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MULTI-OBJECTIVE OPTIMIZATION OF ENERGY EFFICIENCY AND PRESSURE MANAGEMENT IN LARGE WATER DISTRIBUTION NETWORKS

Mario Erik Castro Gama

MULTI-OBJECTIVE OPTIMIZATION OF ENERGY EFFICIENCY AND PRESSURE MANAGEMENT IN LARGE WATER DISTRIBUTION NETWORKS

DISSERTATION

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SUMMARY

Many utilities around the world are required to constantly improve their operations. This is a job which is never fulfilled. Every day demand changes, new elements appear in a system, old elements are replaced and even new sensor technologies are implemented in the field. To better manage these dynamic changes utilities have been shifting towards a digitalization of their daily operations. Within this landscape many different issues which are faced by a utility can be addressed with the help of decision support systems. Such systems may be of particular relevance for issues pertinent to diverse stakeholders such as: operators, customers, decision makers, government and environmental agencies. Among the issues which are more relevant to operators are the continuous supply of water demands, and at an acceptable water quality level. As long as this is achieved, most utilities satisfy their customers. However, this does not come without costs. Reduction of operational costs is always in the loop of discussion of every utility, associated with operational actions such as reducing leakages, reducing energy consumption, reducing pipe breaks and overall improvement of asset management.

This research deals with two different aspects of operations of water distribution networks related to energy minimization and pressure management. Both problems are dealt through model-based optimization via pump scheduling and water network sectorization. The research findings are a stepping stone to improved operation of large water distribution systems where assets are known and there is a need for improvement of energy use. Both optimization problems have been performed using simulations made with EPANET 2.0, linked to heuristic algorithms. Due to the large number of optimization runs, High Performance Computing (HPC) was also employed, using the national computing grid of the Netherlands for research and educational institutions, named SURFSara HPC Cloud, and, to some extent using Microsoft Azure®.

The research was carried out as part of a research project of the European Union’s 7th Framework Programme (EU-FP7), entitled ICeWater - “ICT for efficient water resources management”. This project ran from 2012 until 2015. The outcomes of the research in terms of developed methods have been applied to two different case studies of the water supply system of Milan, Italy: 1) the Pressure Management Zone (PMZ) Abbiategrasso (a sub-system in the south of the city) and 2) Full WDN of the Milan water distribution system. The Full WDN, to our knowledge, was operated in itself as a single PMZ until 2016. The two systems have different topologies and requirements and for each of them a set of options in the form of optimization solutions is proposed.

There is a strong industrial component of this research, as the results were considered for implementation by the project partner, the city of Milan and its utility operator, Metropolitana Milanese S.p.A (MM). The focus on implementation considerations rather than on theoretical computational analysis, or comparison with multiple Multi-Objective Optimization (MOO) algorithms. Furthermore, this research attempts to offer a methodological framework to utilities

looking for planning implementation of future operations, rather than for application of near real-time operations.
Many elements related to the setup of the Water Distribution Network (WDN) models and the vast amount of data which is stored, verified, checked, analyzed and transformed into information within MM, are also covered in this research. This effort proved valuable, as the utility has moved forward with the use of such WDN models for different decision making purposes, even after the finalization of the ICeWater project. The calibration of the smaller system, the PMZ of Abbiategrasso, is also presented. This guarantees that the models can be properly applied in further endeavors of this research and other requirements of the utility. In addition, a test of the obtained results of application of proposed pump scheduling in the PMZ Abbiategrasso was performed in 2015.
Within the research related to pump scheduling, two different optimization algorithms (NSGA-II and AMGA2) have been applied. Both heuristic algorithms are efficient enough to provide solutions in a short amount of time (less than 1 hour). NSGA-II is used as a legacy algorithm, while AMGA2 is applied to have a comparison with a more recent algorithm that is freely available. The optimization problem takes into account two different objectives: total energy and lack of resilience. In terms of problem formulation, real (Variable Speed Pumps) and binary (ON/OFF Pumps) decision variables have been tested. The former corresponds to the potential future operation of Abbiategrasso as an isolated PMZ, while the latter corresponds to the operation of the system until 2015. In addition, two different approaches have been tested for update of the schedules, taking into account a whole day or time step by time step optimization. Last but not least, the pump scheduling problem has been tested with two different types of minimum pressure constraints, Global and Local, the latter one which is represented by the sensors installed in the area in the period of 2013-2014.
The results of pump scheduling show that in the south of the city the utility can save up to 16% energy consumption by changing the pump system to Variable Speed Pumps (VSP). There are additional gains which are expressed in the form of pressure management and Night Flow Analysis (NFA). Results show also that at the time of finalization of the ICeWater project (November 2015), the utility was able to perform gains in terms of operational cost savings associated with large energy consumption and was moving forward with implementations in other parts of the city.
An additional analysis of pump scheduling for the Full WDN of Milan was performed with the goal of identifying whether there is a need to perform additional installations of VSP's in the whole system. These results should be understood as a transition to the time when sectorization will have been completed in Milan. In the meantime, it is better for the utility to perform improved pump scheduling of the system as a whole. Several forms of operation are investigated highlighting certain aspects of the WDN operation.
For the problem of sectorization, a two level optimization algorithm has been custom-designed for the Full WDN. In the first level, the selection of potential sectors is made by opening and closing selected valves. This has been achieved by borrowing components of graph theoretical approaches such as Shortest Path. This allows the identification of what is known in literature as cut-set valves and subsectors. At this point two different formulations were developed for the second level of sectorization:

- The first formulation takes into account a combined set of cut-set decision variables and pump status (ON/OFF). This implies that for each proposed solution a pump scheduling of the Full WDN needs to be performed. This algorithm proved to be challenging computationally and topologically to control. For that reason a second formulation was developed.

- The second formulation takes into account a clustering of smaller subsectors with card collector algorithm (also borrowed from graph theory). This sectorization prepares different sectorization configurations with 2, 3, 9 and 18 sectors.

Results of sectorization are then analyzed to select a single solution which provides the best possible results for energy minimization and pressure management. This is done with the help of Visual Analytics. For this, a MATLAB® library has been developed to perform the selection of optimal solutions and to visualize trade-offs between objectives and performance criteria. The message is to avoid myopic decision making when the number of solutions per sectorization configuration is so vast.

It is also shown that sectorization of such large system with multiple pumping stations inside each sector can be of value for better pressure management. Such insights have not been published so far, as most sectorization methodologies, in vast majority of case studies, are with fixed or gravity sources. To our knowledge, after the conclusion of the ICeWater project the utility has continued the model integration, sensor monitoring and the implementation of the sectorization of the system. This highlights the current needs of utilities for basic, as well as advanced modeling tools combined with optimization algorithms for decision making, as addressed in this dissertation.

The research presents and discusses in detail the outcomes of each of the optimization problems, pump scheduling and sectorization. Identified and potential flaws and limitations are also presented, together with future work required to develop further the proposed methods.

SAMENVATTING

Vele nutsbedrijven over de hele wereld moeten hun activiteiten voortdurend verbeteren. Dit is een taak die nooit eindigt. Elke dag verandert de vraag, verschijnen er nieuwe elementen in een systeem, worden oude elementen vervangen en worden zelfs nieuwe sensortechnologieën in het veld geïmplementeerd. Om deze dynamische veranderingen beter te beheren, zijn nutsbedrijven overgeschakeld op een digitalisering van hun dagelijkse activiteiten. Binnen deze context kunnen veel verschillende problemen waarmee een nutsbedrijf wordt geconfronteerd, worden aangepakt met behulp van beslissingsondersteunende systemen. Dergelijke systemen kunnen van bijzonder belang zijn voor kwesties die relevant zijn voor diverse belanghebbenden, zoals: exploitanten, klanten, besluitvormers, overheid en milieu-instanties. Eén van de kwesties die voor de exploitanten het meest relevant is, is de continue voorziening van de watervraag, met een adequaat kwaliteitsniveau. Als dit wordt bereikt, stellen de meeste nutsbedrijven hun klanten tevreden. Dit gaat echter niet zonder kosten. Verlaging van de operationele kosten is altijd een punt van discussie bij elk nutsbedrijf, in samenhang met operationele maatregelen zoals vermindering van lekkages, verlaging van het energieverbruik, vermindering van leidingbreuken en algemene assetmanagement verbetering.

Dit onderzoek behandelt twee verschillende aspecten van de exploitatie van waterdistributienetten, namelijk energievermindering en drukbeheer. Beide problemen worden aangepakt met modelgebaseerde optimalisatie via pompschakeling en waternetwerksectorisatie. De onderzoeksresultaten vormen een springplank naar een betere exploitatie van grote waterdistributiesystemen waarvan de assets bekend zijn en het energiegebruik moet worden verbeterd. Beide optimalisatieproblemen zijn uitgevoerd met behulp van simulaties gemaakt met EPANET 2.0, gekoppeld aan heuristische algoritmen. Vanwege het grote aantal optimalisatieruns is ook gebruik gemaakt van High Performance Computing (HPC), met behulp van: het nationale computernetwerk van Nederland voor onderzoeks- en onderwijsinstellingen, genaamd SURFSara HPCCloud, en Microsoft Azure® tot op zekere hoogte.

Het onderzoek is uitgevoerd als onderdeel van een onderzoeksproject van het 7e kaderprogramma van de Europese Unie (EU-FP7), getiteld ICeWater-"ICT for efficient water resources management". Dit project liep van 2012 tot 2015. De resultaten van het onderzoek in termen van ontwikkelde methoden zijn toegepast op twee verschillende case studies van het watervoorzieningssysteem van Milaan, Italië: 1) de drukgedrevengebied (Pressure management zone - PMZ) Abbiategrasso (een subsysteem in het zuiden van de stad) en 2) Volledige waterdistributienetwerk (WDN) van het Milanese waterdistributiesysteem. Het volledige WDN werd, voor zover ons bekend, tot 2016 op zichzelf als één PMZ geëxploiteerd. De twee systemen hebben verschillende topologieën en vereisten. Voor beide systemen wordt een reeks opties in de vorm van optimalisatie-oplossingen voorgesteld.

Er is een sterke industriële component in dit onderzoek, aangezien de resultaten in aanmerking komen voor implementatie door de projectpartner, de stad Milaan en haar nutsbedrijf,

Metropolitana Milanese S.p.A (MM). De nadruk ligt op implementatie-overwegingen in plaats van op theoretische rekenkundige analyse of vergelijking met meerdere Multi-Objective Optimization (MOO) algoritmen. Bovendien tracht dit onderzoek een methodologisch kader aan te bieden aan nutsbedrijven die op zoek zijn naar de planning van implementatie met toekomstige exploitaties, eerder dan voor de toepassing van exploitaties in bijna real-time.

Veel elementen die verband houden met het opzetten van de WDN-modellen en de enorme hoeveelheid gegevens die worden opgeslagen, geverifieerd, gecontroleerd, geanalyseerd en omgezet in informatie binnen MM, komen ook in dit onderzoek aan de orde. Deze inspanning bleek waardevol aangezien het nutsbedrijf verder is gegaan met het gebruik van dergelijke WDN-modellen voor verschillende besluitvormingsdoeleinden, zelfs na de afronding van het ICeWater-project. De kalibratie van het kleinere systeem, de PMZ van Abbiategrasso, wordt ook gepresenteerd. Dit garandeert dat de modellen goed kunnen worden toegepast bij opvolging van dit onderzoek en andere eisen van het nutsbedrijf. Verder is in 2015 een test uitgevoerd van de verkregen resultaten van de toepassing van de voorgestelde pompschakeling in de PMZ Abbiategrasso.

Bij het onderzoek naar het pompschakeling zijn twee verschillende optimalisatie-algoritmen toegepast (NSGA-II en AMGA2). Beide heuristische algoritmen zijn efficiënt genoeg om in korte tijd (minder dan 1 uur) oplossingen te bieden. NSGA-II wordt gebruikt als een bestaand algoritme, terwijl AMGA2 wordt toegepast om een vergelijking te kunnen maken met een recenter algoritme dat vrij verkrijgbaar is. Het optimalisatieprobleem houdt rekening met twee verschillende doelstellingen: vermindering van totale energieverbruik en gebrek aan veerkracht (*Lack of resilience*). Wat betreft de probleemformulering zijn reële (pompen met variabele snelheid) en binaire (AAN/UIT pompen) beslissingsvariabelen getest. Het eerste komt overeen met de mogelijke toekomstige werking van Abbiategrasso als een geïsoleerde PMZ, terwijl het tweede overeenkomt met de werking van het systeem tot 2015. Bovendien zijn twee verschillende benaderingen getest voor het bijwerken van de schema's, rekening houdend met een optimalisatie voor de hele dag of voor elke tijdstap. Ten slotte is het pompplanningsprobleem getest met twee verschillende soorten minimumdrukvoorwaarden, namelijk globale en lokale, waarvan de laatste wordt weergegeven door de sensoren die in de periode 2013-2014 in het gebied zijn geïnstalleerd.

Uit de resultaten van de pompplanning blijkt dat het nutsbedrijf in het zuiden van de stad tot 16% energie kan besparen door het pompsysteem om te schakelen op pompen met variabele snelheid (VSP). Er zijn extra winstpunten die tot uiting komen in de vorm van drukbeheer en nachtstroomanalyse (Night Flow Analysis - NFA). Uit de resultaten blijkt ook dat op het moment van de afronding van het ICeWater-project (november 2015), het nutsbedrijf in staat was om winst te boeken op vlak van operationele kostenbesparingen (omwille van het grote energieverbruik) en vooruitgang boekte met implementaties in andere delen van de stad.

Er werd een aanvullende analyse van de pompplanning voor het volledige WDN van Milaan uitgevoerd met als doel vast te stellen of er behoefte is aan extra installaties van VSP's in het hele systeem.

Deze resultaten moeten worden gezien als een transitie naar het moment waarop de sectorisatie in Milaan zal zijn voltooid. In de tussentijd is het beter voor het nutsbedrijf om een betere pompplanning van het systeem als geheel uit te voeren. Verschillende exploitatievormen worden onderzocht waarbij bepaalde aspecten van de werking van WDN worden belicht.

Voor het probleem van de sectorisatie is een optimalisatie-algoritme op twee niveaus op maat ontworpen voor het Full WDN. Op het eerste niveau is de selectie van potentiële sectoren gemaakt door het openen en sluiten van geselecteerde afsluiters. Dit is bereikt door componenten te lenen van 'graph theoretical' benaderingen zoals 'Shortest Path'. Dit maakt de identificatie mogelijk van, wat in de literatuur bekend staat als, cut-set afsluiters en subsectoren. Op dit punt werden twee verschillende formuleringen ontwikkeld voor het tweede niveau van sectorisatie:

- De eerste formulering houdt rekening met een gecombineerde set van cut-set beslissingsvariabelen en pompstatus (AAN/UIT). Dit houdt in dat voor elke voorgestelde oplossing een pompplanning van het volledige WDN moet worden uitgevoerd. Dit algoritme bleek rekenkundig en topologisch een uitdaging te zijn om te regelen. Om die reden werd een tweede formulering ontwikkeld.

- De tweede formulering houdt rekening met een clustering van kleinere subsectoren met een 'card collector' algoritme (ook ontleend aan de graftheorie). Deze sectorisatie bereidt verschillende sectorisatie-configuraties voor met 2, 3, 9 en 18 sectoren.

De resultaten van de sectorisatie worden vervolgens geanalyseerd om een enkele oplossing te kiezen die de best mogelijke resultaten oplevert voor energiereductie en drukbeheer. Dit wordt gedaan met behulp van Visual Analytics. Hiervoor is een MATLAB® bibliotheek ontwikkeld om de selectie van optimale oplossingen uit te voeren en om trade-offs tussen doelstellingen en prestatiecriteria te visualiseren. De boodschap is om myopische besluitvorming te vermijden wanneer het aantal oplossingen per sectorisatieconfiguratie groot is.
Er wordt ook aangetoond dat sectorisatie van zo'n groot systeem met meerdere pompstations binnen elke sector van waarde kan zijn voor een beter drukbeheer. Dergelijke inzichten zijn tot nu toe niet gepubliceerd, omdat de meeste sectorisatiemethodologieën, in de overgrote meerderheid van de case studies, gebruikmaken van vaste of zwaartekrachtbronnen. Voor zover wij weten, heeft het nutsbedrijf na de afsluiting van het ICeWater-project de modelintegratie, de sensorbewaking en de implementatie van de sectorisatie van het systeem voortgezet. Dit onderstreept de huidige behoefte van nutsbedrijven aan zowel basis- als geavanceerde modelleergereedschappen in combinatie met optimalisatiealgoritmen voor besluitvorming, zoals behandeld in dit proefschrift.
Het onderzoek presenteert en bespreekt in detail de uitkomsten van elk van de optimalisatieproblemen, pompscheduling en sectorisatie. Geïdentificeerde en potentiële tekortkomingen en beperkingen worden ook gepresenteerd, samen met toekomstige acties die nodig zijn om de voorgestelde methoden verder te ontwikkelen.

The abstract is translated from English to Dutch by PhD Claudia Agudelo-Vera en Wouter Leduc from *Gemeente Nieuwegein*.

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1 GENERAL INTRODUCTION

1.1 Background

During the last decade the European Union has further strengthened its policies towards more sustainable development and reduction of CO_2 emissions. It has been duly noted that the framework of economic development cannot be expanded further without increasing the internal accountability for clean production. For that reason its countries have agreed in a reduction of 55% of emissions by the year 2030, which would be an important achievement towards the ambitious goal of becoming climate neutral by 2050 (EC, 2019).

To achieve these goals, novel technologies can be used in many areas of different productivity sectors. Further introduction of Information and Communication Technologies (ICT) may lead to increasing efficiency and higher productivity in many of them, although this does not mean that it will be without significant costs. One of the main sectors in which ICT can be applied to increase efficiency is the water sector, where many challenges can be tackled through the use of such technologies.

In this thesis the focus is made directly towards the increase of efficiency of real Water Distribution Networks (WDN). Several partners formed a consortium for a research project of the European Union’s 7th Framework Programme (EU-FP7) named ICeWater, which stands for “**IC**T solutions for **e**fficient **Water** resources management” [1]. One of the case studies in this project was the city of Milan, where the Water Supply System (WSS) operator Metropolitana Milanese S.p.A. (MM), intended to increase the capabilities of system operation with reduced energy consumption. The ICeWater project ran from October 2012 to November 2015.

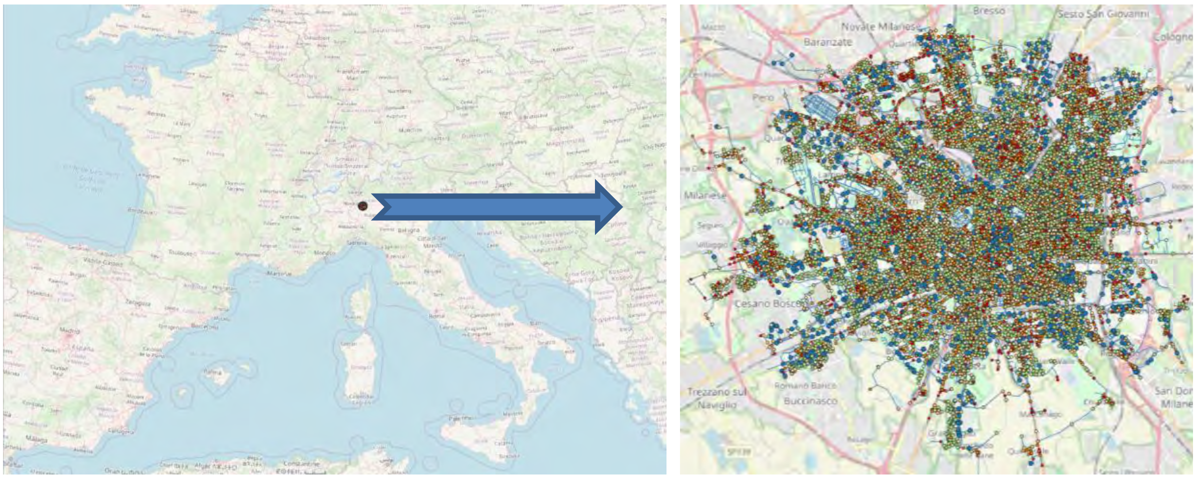


Figure 1-1. General localization of the case study of this research. Milan, Italy. (Source OpenStreetMap)

In many parts of the world there is an increasing need to better manage shortage of water resources. The city of Milan is facing different challenges, as there is both abundancy of water resources available and of possible means to extract, treat and process water for supply. For

[1] http://www.icewater-project.eu/

MM the main problem is the excessive use of energy due to the need for pumping (for extraction of groundwater, and for maintaining required pressures in the WDN). A number of alternatives have already been considered by the operator- MM reduction of energy consumption (and increase of efficiency) in this large Water Distribution Network (WDN), however they were not thoroughly modelled and tested for possible implementation. One could argue that the system, prior to the ICeWater project, was operated in an inefficient way due to lack of appropriate decision support tools. The main focus of the research presented in this dissertation is development of such modelling- and optimization-based tools for testing and proposing more efficient alternatives for system operation. Currently, the developments put in place by ICeWater project and several subsequent projects have increased the capabilities that the operators at MM have for daily operations.

The problem of energy minimization is tackled through the implementation of a combination of two different approaches: 1) through the application of Pump Scheduling (PS), and 2) through the application of a sectorization of the whole system. By sectorization is meant splitting the large WDN into smaller subsectors. Due to the configuration of a system, where multiple pumping stations are the sources, a water company may require options/choices for practical implementation which can satisfy the demand and pressure requirements in the system.

Pump scheduling has gained importance in the last two decades as resources such as water and energy have become scarcer. Nowadays, there is an increasing number of water companies which are replacing ON/OFF pumps with automatically controlled Variable Speed Pumps (VSP), to better accommodate their daily operations to the customer demands. In fact, the decision making towards whether or not exists a feasible business case for such transition is where model-based optimization can help and contribute in the years to come.

Sectorization is done in general either by making District Metered Areas (DMA), or Pressure Management Zones (PMZ). The former correspond to areas where water accounting and operations can be easily performed in the field, while the latter is mostly related to the goal of reducing control de pressure in different areas. Here as well model-based optimization can be helpful and it is certainly playing a role for the improvement of water accounting and energy accounting.

1.2 Motivation

With the growth of population in large cities, not only in the EU but globally as well, in the coming years many utilities will face similar challenges as MM. Systems will grow as population will settle in large population hubs. Particularly in densely populated areas, efficient management of water supply must be able to sustain the growing human population and address the growing water demand. Utilities will need to provide more water to customers, while at the same time being required to keep an efficient water production cycle.

There is one main difference in characteristic of the Milan WDN, compared to most other WDNs. In general, in Milan, there is no intermittency of water supply and there is no water shortage. As mentioned, earlier, the primary challenge in the Milan WDN is reduction of energy consumption for system operation. On the contrary, many systems in EU and in the world need to cope with limited supply of water to satisfy the demands. As examples, just in 2016, California in the US, faced a water crisis due to a large demand or several productivity sectors. Several lakes reported its lowest historical levels in the US such as Lake Powell and Lake Mead. Recently, Across Europe reports of lower levels in the rivers were reported at the Loire River in France, Rhine River, Danube River posing challenges for water supply and agricultural development across the continent. Even in China, its largest freshwater lake, Poyang, was at its minimum surface area in history (25%) in 2022, while one of its major rivers and economical driver the Yangtze, shrunk to almost half of its width during the same summer. But this is not only an occurrence in Europe, the US and China. The African continent, in 2008 the longest drought on the Eastern horn lasted two years, prompting one of the largest famines in recent history. Right afterwards in 2012 drought occurred across the Sahel desert being this the sixth such occurrences in the last 100 years with similar consequences to the one of the Eastern horn. More recently, in 2018, there was yet another drought (mainly in Namibia) which lasted almost 3 years. And to close full circle, a new drought occurred between 2020-2022 once again on the Eastern horn. This indicates that Milan WDN has a privileged situation regarding its water resources availability, but also that better management of its resources can mitigate possible issues which are latent in other parts of the world.

Most of the methodologies to operate and split WDN in DMAs have been formally tested only in small to medium WDN, as presented further in the literature review in Chapter 2. The academic literature is full with demonstrative cases of a couple thousand assets, however when it comes to real systems as the one presented in this thesis, most algorithms are applicable but not efficient for large WDN. In addition, sectorization problems are usually medium size problems where all sources are in fact set as fixed head locations. In the case study presented here, Milano WDN, a multiple number of sources is present. On top of that, all sources are groundwater where the pumping stations have different configurations, complexities and capacities. A problem of this kind is never addressed in the academic literature.

The research addresses mainly an industrial question from a water utility perspective, and presents many features which are of interest for development of WDN models. As a consequence, the research also focuses on this subject, as building such large models is still a cumbersome task for any utility, independently of the software used.

Finally, most of the water supply in European countries is performed by using pumping stations, not gravity systems. In this regard, it is important to develop new methodologies that are able to increase the efficiency of large WDN, with extensive pumping systems, such as the case of Milan. In this research, this subject has been dealt by both proposed approaches (pump scheduling and sectorization), including tests in the field with real measurements.

1.3 Research objectives

One general and three specific objectives are formulated in this research:

General

The objective of this study is to develop and demonstrate methods for optimal operation of large WDNs with respect to energy efficiency and pressure management, using hydraulic simulators coupled with heuristic search algorithms. In particular, three specific goals are presented below.

Specific

- Propose efficient methods for developing model-based pump scheduling for efficient energy management of large WDN's.
- Propose efficient methods for developing model-based optimal sectorization for efficient energy management of large WDN's.
- Propose and provide viable methods for pressure management in large WDN’s with complex topography and multiple sources.
- Integrate validate and test the proposed methods on the case study of Milano.

1.4 Research questions

This research is expected to answer several research questions. Even though the research uses as case study a single large WDN (Milan) it can be easily generalized for other systems with similar characteristics. The following are the proposed research questions:

– Is the energy reduction obtained by model-based optimization of significance in the case of a single PMZ, and which combination of setup and decision variable provides better gains?
– What is the additional gain and return period of investment of intervention of a PMZ by means of pump scheduling?
– Is it possible to perform sectorization for energy reduction in large WDN with current tools?
– Is the energy reduction obtained via model-based optimization for sectorization significant in a fully connected system?
– Is it possible to identify areas of large WDN susceptible to perform installation of Variable Speed Pumps?
– When topography and topology are complex, is it possible to perform gains in energy efficiency with pressure management?
– What is more important in a large WDN with complex topology: to perform pump scheduling or to perform sectorization?

1.5 ICeWater Project

ICeWater aimed to address many other challenges in addition to the research objectives questions formulated above, using a holistic approach to manage the “water energy nexus”. The project consortium was formed by (see Figure 1-2):

four industrial partners:

1) SIEMENS AG, Germany (SAG),
2) TOSHIBA RESEARCH EUROPE LIMITED, United Kingdom (Toshiba),
3) ITALDATA S.p.A. Italy (ITALDATA),
4) K & S GMBH PROJEKTMANAGEMENT, Germany (K&S)

three research institutions:

1) IHE Delft Institute for Water Education, The Netherlands, (IHE). (Nowadays UNITED NATIONS IHE).
2) CONSORZIO MILAN RICERCHE, Italy (CMR),
3) INSTITUTE OF COMMUNICATION AND COMPUTER SYSTEMS, Greece (ICCS)

two utilities:

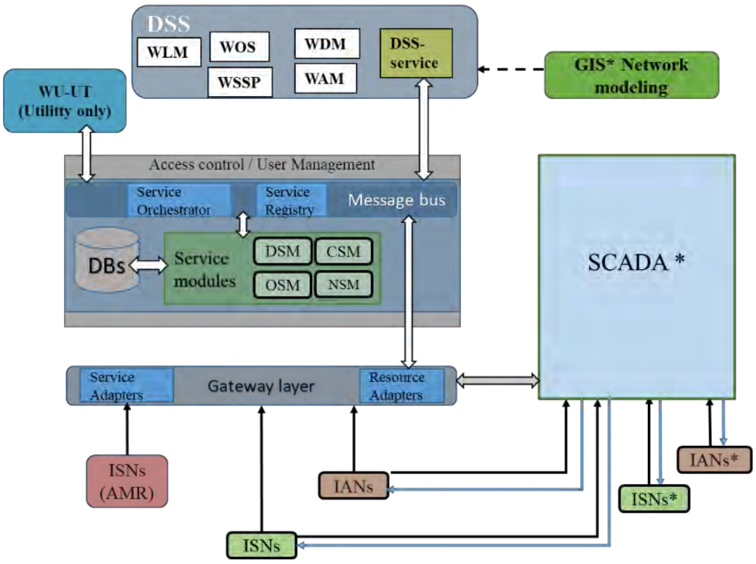
1) SC AQUATIM SA Romania (Aquatim),
2) Metropolitana Milanese S.p.A., Italy (MM)

In particular, ICeWater combined sophisticated ICT solutions to provide real-time monitoring of water supply and demand (see Figure 1-3). The developed Decision Support System (DSS) contains several components providing services such as Water Loss Management, Water Operation Support, Water Supply System Planning, Water Demand Management and Water Asset Management. This DSS is connected to an Access Control/User Management composes of several modules and databases. In order to be able to use information of sensors on the field and historical records located in the SCADA system a Gateway layer was developed. An external layer which displays the network as Geographical Information System (GIS) is connected to the DSS.

To reduce demand-supply mismatch and water losses (both commercial and physical) some additional DSS components were developed. The envisaged demand management and consumption information system through ICeWater was made accessible online to all relevant stakeholders and it allowed the application of different customer demands patterns when it was required.

Figure 1-2. Partners of the ICeWater project consortium .

Energy costs comprise a significant share of the operational expenses of the water utility. Solutions existing today are inadequate as they do not provide capabilities for fine-granular, real-time monitoring and optimisation, and management of the water supply based on customer needs and energy costs. Solutions available in the market today are not interoperable and extendable. Based on sensor data, advanced decision support systems facilitates the optimisation of water networks operation (by providing pumping schedules, system pressures, system flows).



Acronyms	Full name
WU-UT	Water Utility User Terminal
DSS	Decision Support System
WLM	Water Loss Management
WOS	Water Operation Support
WSSP	Water Supply System Planning
WDM	Water Demand Management
WAM	Water Asset Management
*	Water Utility Existing Infrastructure (WUEI)
GIS	Geographical Information System
DSM	Data Service Module (access/store data)
OSM	Operation Service Module (control, setpoints)
CSM	Configuration Service Module (parameters)
NSM	Notification Service Module (alarms, events)
SCADA	Supervisory Control And Data Acquisition
ISN	Intelligent Sensor Node
IAN	Intelligent Actuator Node
AMR	Automater Meter Reading
← - - -	GIS independence of any communication path
↑	Reading from sensor/actuator
↓	Controlling sensor/actuator
⇔	Communication within ICeWater Middleware
⇔	Gateway and SCADA communication

Figure 1-3. Main software and hardware architecture developed during ICeWater project. (Modified from Deliverable 2.5 of ICeWater project).

Innovative services for asset management, such as leakage detection and leakage localization where implemented to reduce water waste, however these were developed outside of this research and will not be discussed in this thesis.

The results presented in this thesis deal with the optimisation problem formulations for Pump Scheduling and Sectorization, and aspects of decision support and additional sensor and middleware layers developed during the project are not considered. It was decided that the final results of the DSS would not be triggered directly to the SCADA system. This means that even though the different modules of the DSS were operational and the results confirmed it was not explicitly redirected to the real system actuators such as pumps and valves. This was to some extent an expected outcome, as the utility did not want to compromise the secure delivery of water to a large number of customers due to potential errors produced by the DSS components that had limited testing during the course of the research project.

1.6 Innovation and practical value

Current research focuses in a specific pair of case studies where water availability is not an issue. This is contrary to what happens in most of the world. However, the methodology can be applied in similar large systems all over the world when there is a need to increase the efficiency, either by energy consumption minimization or to increase the operability of a large WDN.

As practical value of this research four different aspects are seen as innovative implementations:

1) *Implementation of one of the reportedly efficient heuristic algorithms for the PS problem (AMGA-II).* There is a large number of algorithms available and during the

research this genetic algorithm is applied for the problem of pump scheduling, in addition to the NSGAII algorithm that is widely used.

2) *Implementation of the inclusion of pumps when estimation of Shortest Dissipated Power Path (SDPP).* In most of the algorithms used for sectorization there is a lack inclusion of pumping systems as sources. In fact, as the literature review will present, in most cases, it is assumed that gravity sources are enough for the implementation of sectorization. In a system like the Milan WDN, the heterogeneous composition and spatial distribution of the pumping stations across the city makes it hard to define an aggregation of pumps. To circumvent this issue, a methodology where sources with multiple pumps stations is presented.
3) *Implementation of two different formulations for the sectorization problem.* The problem of sectorization has been dealt using different types of methodologies. In this thesis, two formulations are presented. One in which the sectors are automatically created by opening and closing a set of critical valves in the system. In this case there is no control in the number of sectors or configuration of the system. A second approach is also developed in which the user can provide certain parameters for operation with different number of sectors. In both cases the sectorization of such large systems is a Non-Polynomial (NP)-hard problem to address and only a subset of solutions is discussed.
4) *Present alternatives to the utility for the improvement of their current operation.* After using the methodologies for both pump scheduling and sectorization, the utility (MM), was provided with diverse alternatives for the operation of the system into different configurations. In 2017, MM started the implementation of sectorization of the WDN with results obtained from this research. This shows the innovative nature of the research and the practical value for implementation. In this regard, many authors present methodologies in the literature for sectorization of benchmark systems, however such approaches lack the applicability in actual systems. Testing multi-objective optimisation in WDN of a few pipes, may be relevant for some scientific insights, but when a system like the one of Milan, which contains more than 35,000 valves, the direct applicability of results obtained using benchmarks may be limited.
5) *Novel networking concepts* (protocols, management of virtualized network resources) were required to enable better data and information flow management, network resources management and sharing of a complete service oriented architecture. The information gathered with such services allows a better understanding of the operator MM and the effectiveness of water resources management and advanced metering in the city of Milan. The web services developed for the model-based optimisations which are presented in this thesis have been presented in Pan et al., (2015).

1.7 Thesis outline

The thesis has the outline as presented in Figure 1-4. In Chapter 2, a literature review is presented to identify what has been done in the field of Multi-Objective Optimisation (MOO) for Pump Scheduling (PS) and Sectorization. Chapter 3, describes the case studies used for the application of the methodology in the current research. In Chapter 4, the methodological framework of the thesis is provided for both problems addressed. Chapter 5 introduces the specific characteristics of the simulation models developed throughout the research and the challenges on their implementation. In Chapter 6, a complete description of the implementation of PS problem is presented, together with the obtained results. In Chapter 7, a complete discussion of the sectorization MOO formulations and their implementation are presented with the obtained results. The document is finalized with the conclusions and recommendations in Chapter 8.

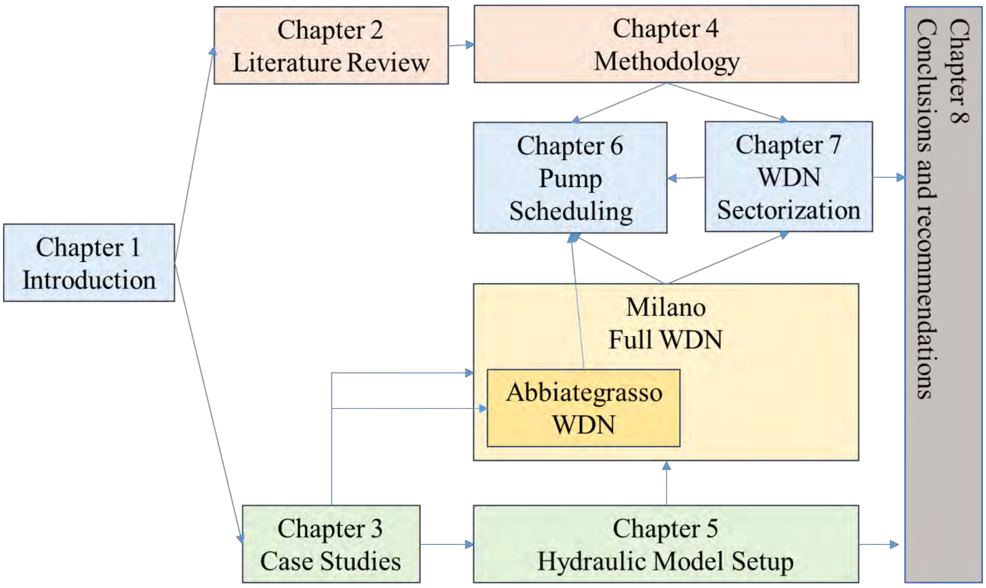


Figure 1-4. Outline of the thesis structure showing relationships among chapters.

2 LITERATURE REVIEW

This chapter presents a literature review of the research. It presents first a literature review on water distribution network simulation, given that this subject is of importance for utilities dealing with large WDNs. Subsequently, the general problems of water distribution networks are presented from an optimisation perspective. After this subsection, literature review regarding two specific problems addressed in this thesis, related to pump scheduling and sectorization, is presented and discussed broadly. Finally a summary is made of current research trends relevant for the subject.

2.1 Water distribution network simulation

When dealing with the improvement of water production, energy consumption and lower operational costs in WDNs it is necessary to perform multiple scenario runs or simulations of the system. Usually, the WDNs are simulated using different criteria and constrains for decision making. Many simulation approaches have been used in the past for WDNs in conjunction with several methods of optimisation.

In the case of energy management, the minimization of total energy costs has often been explored as main objective. Many researchers have sought the solution for cases of single pumping stations or medium scale WDNs. For systems selected for this study (large WDNs) there has been less research emphasis and this is one of the gaps that that this research intends to fill.

State of the art in WDNs modelling involves coupling of simulator of the real system and optimisation approaches using different methods. In the last two decades large efforts have been made to use heuristic and randomized search methods such as Genetic Algorithms (GA). This will also be the main target of the current research, however applied to large WDNs.

It must be established that in the case of operation of large WDN, one common problem is updating the system operation through application optimal control theory, occurring in near real-time. In the current thesis, a different approach is presented in which multi-objective optimisation is performed for purpose of planning future operations, and then obtained solutions are suggested to the utility. For that reason, the results of the current research are not intended to be used for near real-time online update of WDNs.

2.1.1 Brief history of simulation approaches

A WDN is a system composed of spatially distributed elements such as pipes, valves, pumps, tanks and reservoirs, in which the dynamics of the state variables like discharge and pressure are constantly changed by human behaviour in the form of demands. The idea of performing numerical modelling of WDNs comes from the need to understand such systems, to evaluate their behaviour and propose actions for improving their performance.

Since the birth of electronics, numerical modelling of WDNs has been in progress and many algorithms have been implemented through time. Basically all of these algorithms are based on the concept of maintaining a water balance in the nodes and preserving energy losses in pipes or loops (depending on the method). The first algorithms developed for the simulation of WDNs date back to the first half of last century known as loop balance of heads and loop balance of flows (Cross, 1936). With the growth of the digital computers several other algorithms were developed based on Newton's algorithm (Martin & Peters, 1963) and global linearization techniques (Wood & Charles, 1972) until the development of what we know today as the Global Gradient Algorithm (GGA), which was developed initially by (Todini, Un metodo del gradiente per la verifica delle reti idrauliche, 1979). In subsequent research this algorithm has been made more efficient by the use of numerical methods available in the decade of the 1980's (Salgado-Castro, 1988) (Todini & Pilati, 1988), with the introduction of sparse matrix libraries in the calculation of algebraic operations and preconditioners used as reordering schemes of the obtained matrices.

A recent development in this regard has been presented by Todini and Rossman (2012) in which all the algorithms aforementioned were derived under the same analytical approach and notation. The current research will follow only the GGA with solution based on a Newton-Raphson approach. There are three reasons for this. Firstly its ability to reduce the computational effort for the simulation of WDNs, as presented by several authors (Salgado-Castro, 1988), (Todini & Pilati, 1988; Todini & Rossman, 2012). Secondly, the algorithm has the possibility to be used for extended period simulation. Finally, the freely available source code of this algorithm is implemented as EPANET (version 2.0) (Rossman, 2000). Recent enhancements to this algorithm have been proposed for improvement of the pump's Best Efficiency Point (BEP) (Marchi & Simpson, 2013), to its hydraulic engine (Rossman, et al., 2020)and to its water quality engine (Davis, Janke, & Taxon, 2018) among others. This shows the universality of the algorithm and the ease of its use.

2.1.2 Hydraulic paradigms

Two complementary hydraulic paradigms can be used to simulate the behaviour of a WDN, known as Demand Driven analysis (DDA) and Pressure Driven analysis (PDA). The difference lies in the dependence of the nodal demands on the actual pressure of the node.

- Demand Driven Analysis (DDA)

In this approach, the demands are considered as known inputs and fixed in the nodes, and they are independent of the pressure in the system. The EPANET software works using this approach. The drawback of this approach is that sometimes the algorithm forces the heads in the nodes to be negative in order to satisfy the demand. While numerically it solves the problem, in reality this is not what is expected in a WDN, because if the total head in a node reaches zero the expected demand to be supplied must be zero as well (No pressure = No water).

- Pressure Driven Analysis (PDA)

In this approach, the demands are considered as a function of the head in the nodes. Usually this is common in networks which present low pressures and intermittency in the service. The idea behind PDA is that below a certain critical pressure in a particular node the demand cannot be fully satisfied (Germanopoulos, 1985). Many authors have suggested several equations for the dependency of demand and head, but most of the approaches make use of polynomial equations, which makes it easy to be derived and used in GGA (Paez et al. 2018, Paccin et al. 2017).

An extension to EPANET in the form of an additional emitter coefficient for the simulation of PDA was developed as a wrapper to the original GGA solver, and is freely available (Pathirana, 2010). Direct modifications to the numerical solver of EPANET are presented by (Giustolisi, Savic, & Kapelan, 2008) and to commercial packages by (Wu & Walski, 2006) and (Wu, Wang, Walski, Yang, & Bowdler, 2009), as implemented in WaterGEMS software.
During the current research this approach is not considered, mainly because of sufficient available water (and pressures) for supply in both case studies, but the algorithm is presented with the additions required for simulation under this hydraulic paradigm.

2.1.3 Energy and continuity equations in WDN

For the development of any algorithm for the simulation of WDNs it is required to use a set of equations which are able to provide simplified, but sufficiently accurate representation of the system. In standard WDN simulations flows in pipes are considered under steady conditions. The Extended Period Simulations (EPS), used for analysis of WDN under changing conditions in time, are modelled as sequences of steady state simulations. Unsteady flow simulations are needed for special cases such as transient modelling due to water hammer or sudden drop of pressure, and they are commonly built on top of steady flow simulations. The following sections present the steady state simulation equations used.

- Continuity in nodes

The continuity is calculated in each node of the network with an unknown head, the equation used for this is:

$$\sum_{s} \pm Q_{is} = d_i^w$$

Equation 2-1. Continuity in nodes

Where, Q_{is} = flow/discharges of the s −pipes joining in the node i, and the sign of Q_{is}depends on the pipe's positive direction for the pipe s with respect to flow entering the node, d_i^w =fixed/dependant demand in the node i.

- Energy losses in pipes, accessories and pumps

From the hydraulic point of view the energy losses in a system are comprised of major losses, minor losses and pump losses.
Total energy losses in a pipe can be quantified by using a generic energy loss equation like:

$$H_j - H_i + R_k Q_k |Q_k|^{n-1} + K_k Q_k |Q_k| + C_k Q_k |Q_k|^{\gamma-1} = \pm H_k^P$$

Equation 2-2. Energy balance in a pipe including minor losses and a pump system.

Where, H_i, H_j =unknown nodal heads at the upstream (i-th) and downstream (j-th) terminal nodes of pipe k with positive flow/discharge (Q_k) of the pipe k, R_k = resistance coefficient of the pipe k for major losses, n = exponent of energy losses (e.g. 2.0 for Darcy-Weisbach and 1.845 for Hazen-Williams formulations), K_k = minor loss coefficient of the pipe k, C_k = loss coefficient of the pump system (if any) in pipe k, $\gamma =$ Exponent for energy losses in pumps (2.0 for the general case), H_k^p = static head of the pump system (if any) in the pipe k (its sign varies with the direction of the installation of the pump, the assumption is made to follow the direction of the flow in the pipe).

Sometimes pipes can be connected to a tank or a reservoir. In those cases one of the unknown heads in the equation becomes known as a fixed value, and the total energy equation becomes:

$$H_j + R_k Q_k |Q_k|^{n-1} + K_k Q_k |Q_k| + C_k Q_k |Q_k|^{\gamma-1} = H_o \pm H_k^P$$

Equation 2-3. Energy balance in a pipe with a known head node.

where, $H_O =$ known head (is moved to the right side of equation).

Pipe Resistance ($\boldsymbol{R_k}$)

The pipe resistance can be estimated by using several formulae. In particular, the Darcy Weisbach (DW) and the Hazen-Williams (HW) are the most commonly used.

$$R_k = f_k \cdot C_{DW} \left(\frac{L_k}{D_k^5}\right) \text{ with } C_{DW} = \frac{8.0}{g\pi^2} \sim \frac{1}{12.1026}$$

Equation 2-4. Pipe resistance calculated with the Darcy-Weisbach (DW) formulation.

Where, $f_k =$ friction factor of the pipe k, $C_{DW} =$ constant of DW formulation, $L_k =$ is the length of pipe k, $D_k =$diameter of pipe k and $g =$ acceleration of gravity in the unit system of calculation.

The issue with the DW formulation is that to estimate f_k for transitional and turbulent flow, an implicit equation known as Colebrook-White (CW) (Colebrook & White, 1937) needs to be solved:

$$\frac{1}{\sqrt{f_k}} = -2.0 \cdot log_{10}\left(\frac{\epsilon}{3.71} + \frac{2.51}{R_e\sqrt{f_k}}\right)$$

Equation 2-5. Friction factor for turbulent flow (Colebrook-White).

Where, f_k is a function of the non-dimensional Reynolds number (R_e) and the relative roughness of the pipe (ε).

The problem with this equation is that in every iteration of the GGA a new f_k must be calculated which implies more calculations. There are two possible ways of performing the calculation of friction factor f_k, either *implicit* or *explicit* (Giustolisi, Berardi, & Walski, 2011) (Brkic, 2011). The use of implicit formulations require an additional computational time at each iteration of the GGA, and in EPANET a legacy explicit formulation is used (Swamee & Jain, 1976).

2.1.4 Global Gradient Algorithm (GGA)

For the solution of the system of simultaneous nonlinear equations (Equation 2-1, Equation 2-2 and Equation 2-3) the iterative procedure of the GGA is presented, without the derivation of the algorithm.

The equations related to the energy balance in all the network pipes (n_p) and continuity equations in every calculation node either known (n_o) or unknown (n_n) are rearranged in a matrix form like the following:

$$\begin{aligned} \mathbf{A}_{pp}\mathbf{Q}_p + \mathbf{A}_{pn}\mathbf{H}_n &= -\mathbf{A}_{po}\mathbf{H}_o + \mathbf{H}_p^P \\ \mathbf{A}_{np}\mathbf{Q}_p &= \mathbf{d}_n^w \end{aligned}$$

Equation 2-6. Matrix form of energy and continuity equations in a WDN.

where, $\boldsymbol{A}_{pp}\boldsymbol{Q}_p = [n_p, n_p]$ is the matrix of the energy losses in every pipe of the network (Equation 2-2), $\boldsymbol{A}_{pp} = [n_p, n_p]$ is the matrix of the linearized energy losses, $\boldsymbol{Q}_p = [n_p, 1]$is the vector of unknown flows in the pipes, $\boldsymbol{A}_{pn} = \boldsymbol{A}_{pn}^T = [n_p, n_n]$ is the topology matrix of pipes and unknown head nodes, $\boldsymbol{H}_n = [n_n, 1]$is the vector of unknown nodal heads, $\boldsymbol{A}_{po} = [n_p, n_o]$ is the topology matrix of pipes and known head nodes, $\boldsymbol{H}_o = [n_o, 1]$ is the vector of known nodal heads (these ones can be variable in time), $\boldsymbol{H}_p^p = [n_p, 1]$ is the vector of static heads of pump system in pipes, $\boldsymbol{d}_n^w = [n_n, 1]$ is the vector of demands in the nodes.

In the case of PDA a modification must be performed in Equation 2-6, pertaining the continuity equation due to the dependence of demand in total head of the node:

$$\mathbf{A}_{np}\mathbf{Q}_p - \mathbf{d}_n^w(\mathbf{H}) = 0$$

Equation 2-7. Matrix form of the continuity equation for the GGA in PDA approach.

Where, $\boldsymbol{d}_n^w(\boldsymbol{H})$ is the pressure dependant demand. In this case, the demands are dependant of the unknown total head at the nodes ($\boldsymbol{H}_n$), which the algorithm estimates as piezometric head. This is the sum of the pressure head and the vertical elevation of each node ($\boldsymbol{z}_n$).

The solution of the system can be obtained by solving iteratively the following equations (Giustolisi, Laucelli, Berardi, & Savic, 2012):

$$\begin{aligned}
\mathbf{B}_{pp}^{iter} &= \left(\mathbf{D}_{pp}^{iter}\right)^{-1}\mathbf{A}_{pp}^{iter} \\
\mathbf{F}_n^{iter} &= \mathbf{A}_{np}\left(\mathbf{Q}_p^{iter} - \mathbf{B}_{pp}^{iter}\mathbf{Q}_p^{iter}\right) - \mathbf{A}_{np}\left(\mathbf{D}_{pp}^{iter}\right)^{-1}\left(\mathbf{A}_{np}\mathbf{H}_o + \mathbf{H}_p^p\right) - \mathbf{C}_n \\
\mathbf{H}_n^{iter+1} &= \left[\mathbf{A}_{np}\left(\mathbf{D}_{pp}^{iter}\right)^{-1}\mathbf{A}_{pn} + \mathbf{D}_{nn}^{iter}\right]^{-1}\mathbf{F}_n^{iter} \\
\mathbf{Q}_p^{iter+1} &= \left(\mathbf{Q}_p^{iter} - \mathbf{B}_{pp}^{iter}\mathbf{Q}_p^{iter}\right) - \left(\mathbf{D}_{pp}^{iter}\right)^{-1}\left(\mathbf{A}_{np}\mathbf{H}_o + \mathbf{H}_p^p + \mathbf{A}_{pn}\mathbf{H}_n^{iter+1}\right)
\end{aligned}$$

$$\mathbf{C}_n = \mathbf{d}_n^w \text{ and } \mathbf{D}_{nn} = \mathbf{0}_{nn} \text{ for DDA,}$$

$$\mathbf{C}_n = \left(\mathbf{d}_n^w(\mathbf{H})\right)^{iter} - \mathbf{D}_{nn}^{iter}\mathbf{H}_n^{iter} \text{ for PDA.}$$

Equation 2-8. Iterative solution of the GGA for DDA and PDA.

Where, $\boldsymbol{B}_{pp}^{iter} = [n_p, n_p]$ is an intermediate auxiliary matrix, $\boldsymbol{D}_{pp}^{iter} = [n_p, n_p]$ is a diagonal matrix containing the derivatives of the head loss components with respect to the discharges ($\boldsymbol{Q}_p$), $\boldsymbol{F}_n^{iter}$ is an intermediate matrix used for the estimation of heads, $\boldsymbol{C}_n =$ is the matrix of demands which can be built for DDA or PDA. For PDA, $\boldsymbol{D}_{nn}^{iter} = [n_n, n_n]$ is a diagonal matrix whose elements are the derivatives of $\boldsymbol{d}_n^w(\boldsymbol{H})$ with respect to the nodal heads ($\boldsymbol{H}$), while for DDA the same matrix $\boldsymbol{D}_{nn} = 0$.

Nonetheless the algorithm as stated above is established for a single set of initial and boundary conditions. Which raises the question: What to do when a system needs to be solved for changing combinations of unknowns under many loading or demand conditions (as implemented in free and commercial software) are required? This is called an Extended Period Simulation. A second question is what to do when a WDN is large and computational performance is an issue (like in the case of Milan). Two possible enhancements to the algorithm will be presented from theoretical point of view.

- Extended Period Simulation (EPS) & Generalized GGA (G-GGA)

Many WDN issues require the analysis of the system for different loading conditions as they are changing in time. In order to do that the variability of the network demand, set-up of pumps, tank levels and reservoir levels should be addressed in time. The approach that allows to carry out such analysis is known as Extended Period Simulation (EPS). An important issue in EPS is the updating of the computations in every time update.

There are four possibilities used for the estimation of the variables update in GGA in an EPS:

1) The first idea was developed before the birth of the GGA (Shamir & Howard, 1968) and was applied afterwards in most methods for solution of WDN available at that time (Rao & Bree, 1977) (Rao, Markel, & Bree, 1977). It could be interpreted as an Euler method for solution of the system of equations. In this approach, the variability of the system is updated in time, by discretization in time intervals (Δt). Essentially the method could be described as a sequence of steady state simulations and corresponding updates of the boundary conditions. It can be seen as taking a picture (snapshot) of the system, then updating the boundaries by the variation during Δt, then following the procedure of GGA, taking another picture and repeating the process until having covered the time window of analysis (Rossman, 2000).
2) The second idea is to perform an analytic integration of the variation of demand coming from the tanks and reservoirs by use of basic calculus. This approach is known as Explicit Integration (EI), but because of the complexity of the dynamic behaviour of a system of tanks, analytical solutions could not be always obtained (Coulbeck, 1980). Further development of EI has been low and only small improvements have been made on the subject applied to small scale networks (van Zyl, Savic, & Walters, 2006).
3) The third procedure is a logical evolution of the first one, and it takes into account an implicit formulation of the updates of tanks and pumps inside the GGA. This alternative is required to avoid instabilities occurring with the use of the original EPS in its explicit form when direct connections between multiple tanks or multiple pumps exist (as is the case in almost every real system). The system of equations is solved, including the tanks in one step (Todini, 2011) opposite to the two steps procedure of the explicit alternative, with the aid of the θ −method (Stuart & Peplow, 1991) (Barclay, Griffiths, & Higham, 2000). In this approach θ is a time averaging weighting factor for solution of differential equations, discretized as an implicit scheme. The variables in each new time step are estimated as a linear combination of new and old values of the same variable. For the case that $\theta = 1.0$, the EPS-GGA represents the explicit approach. When $\theta = 0$, the solution is fully implicit. No agreement was found in the literature reviewed for the optimal value of θ.
4) An additional improvement of the EPS-GGA in its implicit form came with the development of the Generalized GGA (G-GGA) (Giustolisi, Berardi, & Laucelli, 2012) in which the update of the tanks (or reservoirs) is included. In this approach the update is made for the fluctuation or variation of total head for the tanks (ΔH_o) between time steps ($t_1 \rightarrow t_o + \Delta t$). The drawback of this approach is that fluctuations are set as additional variables and increase the sizes of the matrices in the GGA. In addition, reservoirs must be treated as regular tanks with a large surface area.

In general, the implicit formulations show more stability than the explicit ones in the literature reviewed, but tests on real WDNs have not been documented to date, except for case studies conducted for small benchmark networks.

Given the conditions of the two case studies of the present research, only the basic EPANET formulation can be used due to the size of the case studies.

- Enhanced Global Gradient Algorithm (EGGA)

With increased need to improved operations of water supply, operators in general have become more aware of the necessity to integrate free and commercial computational tools for modelling of their systems. The mixture of these with Geographical Information Systems (GIS) has become more and more common and utilities tend to develop and enhance their hydraulic models by including in their databases as many elements of the hydraulic system as they can, and subsequently develop more and more complex models. As a consequence, when large WDNs require modelling, the EPS-GGA simulation becomes very slow and in some extreme cases impossible to be performed on personal computers.

Recently a new development in the GGA has been introduced (Giustolisi & Berardi, 2011) (Giustolisi & Laucelli, 2011), either for DDA or PDA. The algorithm is known as Extended GGA (EGGA). The idea behind this development is based on a topological reformulation of matrices that allows to perform simulations of large WDNs.

As the first step an aggregation of *serial* pipe resistances (i.e. connected only to nodes in series), is performed. Second, the reduced system of serial pipes is solved with the same GGA iterative procedure. After this, the solution is applied to the original pipes and nodes by disaggregation based on the continuity and energy equations inside the serial pipes, maintaining convergence (conservation of mass and energy), accuracy and numerical precision of the algorithm.

The approach has been tested for large WDNs created from artificial serial nodes added to it (Giustolisi, Laucelli, Berardi, & Savic, 2012). The authors also report that, if in a large network an average of two serial nodes exist in each pipe, a reduction in computation time of around one third (1/3) with respect to the original GGA can be achieved.

The EGGA is different from the skeletonization approaches (SKA) (Anderson & Al-Jamal, 1995). The SKA methods usually perform linearization of the system of equations around selected nodes of the network (Martinez-Alzamora, Ulanicki, & Salomons, 2014), or eliminating nodes by accumulating hydraulic roughness to pipes in series and distribution of the removed node demands in the nodes of the new equivalent pipe (Maschler & Savic, 1999). The problem with these methods is that these (1) tend to induce regularization of demands in the whole network due to the deletion of nodes, and (2) that the linearization causes an artificial numerical fluctuation in the energy balance (Giustolisi, 2010).

Although neither G-GGA nor EGGA are used in this research, both may be relevant for future studies on large WDN. Their application could be useful for saving computational time, especially when performing model-based optimization.

2.2 General problems of water distribution network optimization

Along with improvements in algorithms used to simulate the behaviour of a WDN, and the hydraulic paradigm to use for nodal demands, many research efforts have been made for development of optimal responses to different operational and planning problems. Many optimization algorithms have been used for these purposes, born in other fields such as Operations Research (OR) and Computational Intelligence (CI). A timeline of objectives of the optimization of WDN's is presented with the description of optimization approaches, followed by the review made for each optimization problem formulation in each subsection. This section concludes with a short review on benchmark models.

2.2.1 Evolution of optimization for WDNs

There is a certain timeline of evolution of optimization problem formulation that can be observed. The first formulations were related to the design and rehabilitation of simplified actual systems (Shaake & Lai, 1969). With the increase of involvement of simulation tools and SCADA systems, utilities required optimal operation scenarios that could be applied under budget constrains (e.g. hydraulic structures operations, hydraulic modelling, water quality (WQ) planning and emergency planning). Furthermore, with the aging and evolution of WDNs, the need for optimization algorithms for calibration of all of the above was recognized (Walski, Techniques for calibrating network models, 1983) (Bhave, 1988). Calibration is performed to obtain the hydraulic parameters of elements in the network, based on observed variables like pressure, flows and laboratory WQ tests stored in databases or SCADA systems.

The trend in optimization shifted in time also from Single-Objective Optimization (SOO) (Savic & Walters, 1996) to Multi-Objective Optimization (MOO) in the last two decades (Maier, et al., 2014) (Alfonso, Jonoski, & Solomatine, 2010). This path was followed in order to account for the requirements of various stakeholders related to water supply.

With time, operational problems have become subject of research, but in this regard a division should be drawn here into what is called an *off-line* and an *on-line* optimization approaches for operational purposes. On one hand, off-line methodologies focus on the analysis of a WDN based on stored data of the current and past status of the system, and they are mainly used for planning and design tasks. On the other hand, on-line methodologies refer to the near real-time update of components of the system based on forecast of demand and water availability. This review focuses mainly on off-line methodologies used by diverse authors.

2.2.2 Optimization for WDN design and rehabilitation

The goal of using optimization for design of WDNs is to obtain a minimum cost of new infrastructure that needs to be deployed while keeping as constrains some values of state variables of the network, related to system performance, like minimum pressures at critical points or volumes delivered. These state variables are linked with different reliability indicators of WDNs (Trifunovic, 2010). The literature shows that there is a large amount of research in this field.

Mathematically, WDNs design (or rehabilitation) is an intractable problem (Gupta, Bassin, Gupta, & Khanna, 1993) and its computational complexity is characterized as NP-hard (Eusuff & Lansley, 2003) implying that the solution cannot be found in polynomial time. This means that for large-scale problems a rigorous algorithm used is not practical for this purpose, and random search techniques may be more efficient. The reason for this, lies in the following facts:

1) the feasible region of the integer value diameters (or codes of pipes in a catalogue) considered as decision variables, is non-convex;

2) the constrains are implicit functions of the diameters;

3) the objective function has multiple local minima and

4) the system solution is based on a nonlinear system of equations (e.g., energy losses are inversely proportional to diameter to power five).

In general, for small cases it is possible to find solutions relatively quickly, but for large networks computational complexity remains a problem.

In case of WDNs rehabilitation optimization, the goal is to perform analysis of what part of the network is more in need for being replaced due to poor service or aging of structures. Usually the objective is to obtain the minimum cost of the replacement of structures along the network (such as pipes, valves and pumps) that corresponds to a minimum investment.

The first case study appearing in reviewed literature was the simplified version of the WDN of *New York City* (NYC), a system of tunnels which required rehabilitation. The objective used was the minimization of the total cost of the pipes (either replacement or duplication). The first solution reported used a Linear Programming (LP) approach (Shaake & Lai, 1969).

The second and probably most widely studied case to date in literature is the artificial *Two-Loops network* (Alperovits & Shamir, 1977) which was first modelled using Linear Programming Gradient (LPG). The use of gradients means that a linearization of the mass and energy equations is performed during the solution. The Hanoi network, a simplification of a real case, subsequently appeared. First studied with a two phase decomposition method based on continuous LP (Fujiwara & Khang, 1990), and further analysed by other authors (Sonak & Bhave, 1993) (Eiger, Shamir, & Ben-Tal, 1994). One big problem with Two-Loops, Hanoi and NYC problems is that they focus on a problem without taking into account the variability of the demands.

The first case reviewed in the literature which shows a set of significant characteristics of a real system is named *Anytown*, also a benchmark network, that was part of what is known as the Battle of the Network Models (BNM) (Walski, et al., 1987). The Anytown case introduces a small network in which expansion, replacement and rehabilitation are taken into account. At the same time, a pumping station is used to supply water, but due to shortage, an additional tank required allocation. It was also the first optimization problem for design and rehabilitation under an EPS, using real constrains. It was shown by several researchers, e.g. (Walski, et al., 1987) that hydraulic knowledge cannot be neglected in a hydraulic design problem for WDNs, regardless of the algorithms used.

Since the 1990's the applications of heuristic methods (typically randomized search) were introduced for WDNs design problems. Among the first ones proposed were the Genetic Algorithms (GAs) (Dandy, Simpson, & Murphy, 1996) (Savic & Walters, 1996). They were followed by Adaptive Cluster Covering with Local search (ACCOL) (Abebe & Solomatine, 1998), Simulated Annealing (SA) (Cunha & Souza, 1999), Shuffle Leap Frog (SFLA) (Eusuff & Lansley, 2003), Ant Colony Optimization (ACOA) (Maier, et al., 2003), Harmony Search (HS) (Geem Z. , 2006), Memetic Algorithm (MA) (Banos, Gil, Reca, & Montoya, 2010), Robust Optimization (Reehuis, 2010). All the methods present advantages and disadvantages in relation to computational runtime, proportion of space searched and convergence to global minimum.

In addition, combinations of methods have been also used. These methods are SOO, such as Scatter Search (SS), Mixed SA and Tabu Search (MSATS) and Binary Linear Integer Programming (BLIP) (Reca, Martinez, Gil, & Banos, 2008). The problem with these methods is that they require setting up of algorithm parameters depending on the problem to which they are applied. Subsequently, a Parameter-Setting-Free (PSF) algorithm for HS was also applied to the design problem (Geem & Cho, 2011).

In addition, during the last 10 years, MOO methods have gained popularity. The number of objective functions in literature reviewed are usually two. Minimization of total cost is kept as a first objective and an additional measure of the total pressure deficit or a reliability measure of the WDN, depending on the case, has been applied (Todini, 2000). Case studies of MOO for the design problem are diverse in literature reviewed, but, in general, they show different perspectives than the ones used for SOO. One of the advantages of MOO is that it offers to the decision maker a set of solutions in which trade-offs can be observed and analysed (Farmani, Walters, & Savic, 2005). One of the disadvantages of the MOO in the case of WDNs design is that the number of simulations required for obtaining near-optimal results compared to the SOO increases. In general, GA's and EA's have shown to be poor in handling constrains. Usually this task is performed by applying penalty coefficients. One MOO used for handling constrains in GA was developed by (Prasad & Park, 2004). Other MOO algorithms which have been applied are Shuffled Complex Evolution (SCE) (Liong & Atiquzzaman, 2004), Non-Dominated Sorting GA (NSGA-II) (Atiquzzaman, Liong, & Yu, 2006), Cross Entropy MOO (CE) (Perelman, Ostfeld, & Salomons, 2008) and a hybrid between GA and CE for Combinatorial sets (Perelman, Krapivka, & Ostfeld, 2009).

Other problems, such as rehabilitation of WDNs for medium and long term investment planning have been reviewed as well. These methods are often called Asset Management (AM). In this case, the idea is to select which type of pipes (e.g. depending on material, diameter, age), where (e.g. which sector, area, user type) and when should be replaced (e.g. month or year of infrastructure replacement). For this, MOO has been performed under PDA using NSGA-II (Alvisi & Franchini, 2009), where pipe breaks are simulated using a simple probabilistic Monte-Carlo method (Metropolis & Ulam, 1949).

More recently, an extensive analysis of MOO for WDNs design, performed with 6 objectives (including water age) and applied to the Anytown benchmark case was performed by (Fu, Kapelan, Kasprzyk, & Reed, 2013). The algorithm applied was ε-NSGA-II (Kollat & Reed, 2006). Other authors have even opted for inclusion of objectives related with minimization of Greenhouse Gas emission (GHG) (Kang & Lansey, 2012).

If the decision space becomes large then other techniques are applied for the reduction of the search space such as global sensitivity analysis (Fu, Kapelan, & Reed, 2012) or space reduction (Kadu, Gupta, & Bhave, 2008). A multi-objective design problem of a WDN with multiple sources was solved by (Zheng & Zecchin, 2014) showing that it is possible to reduce the decision space by using graph theoretical approaches.

2.2.3 Optimization of WDN planning for operation and management

This kind of optimization covers the main area of study of this research. As mentioned before, two different case studies are considered, an isolated system in the south of the city, and the full network of Milan. In both case studies, problems were identified that exist in networks after long periods of operation, which fit the solution of an optimization problem. The idea is that some modifications of the current operations will lead to more optimal (more efficient) operational schemes with respect to model uncertainties. Depending on the objectives, many different criteria can be used as objective functions for optimal operations such as closing and opening valves, changing the pump schedule or testing the behaviour of the network under new scenarios of demand, energy cost patterns or added infrastructure (Zessler & Shamir, 1989).

Energy optimization

In terms of optimisation of WDNs operations the first goal reviewed was the energy cost minimization by changing pump schedules. There are two different approaches to perform the optimisation of pump schedules known as the Implicit Pump Schedule Optimization formulation (IPSO) and the Explicit Pump Schedule Optimization formulation (EPSO). In the IPSO formulation, the flows and pressures provided by the pumping stations are treated as the decision variables together with the tanks levels (Ormsbee & Lansey, 1994). In the EPSO formulation, the actual operation times of the pumping stations (either for individual or equivalent curves) are the decision variables (Lansey & Awumah, 1994).
As for the case of WDNs design, the initial approaches were formulated in terms of OR techniques. Initially, LP was used during the 1970's but then a shift towards the definition of integer variables was done until the use of what is known as a Mixed Integer Non-Linear Programming (MINLP) approach (Biscos, Mulholland, Le Lann, Buckley, & Brouckaert, 2003). With the increase of involvement of heuristic evolutionary algorithms for optimization purposes in the water resources field, the WDNs operations followed this path as well (Ormsbee, Lingireddy, & Chase, 2009), first with the use of GA's (Boulos, et al., 2001) and extensions to it such as, Hybrid GA's with Hillclimber techniques (van Zyl, Savic, & Walters, 2004). More recently, Linz et al. (2020) have explored the use of multi-threaded model-based optimization for energy reduction and the necessary platform for such implementation.

On-line Optimisation

When the problem of energy optimization needs to be addressed as an *on-line* solution many other details need to be addressed such as proper demands forecast with time series analysis (Alvisi, Franchini, & Marinelli, 2007) or estimation of the trend of demand inside a predictor-corrector procedure. The predictor-corrector approaches guarantee reliable supply, but, as in the case of any forecasting system, an increase of lead time results in increased uncertainty (Preis, Allen, & Whittle, 2010).
Other type of predictor-corrector approach is the use of Kalman filter for the update of the system first proposed by (Todini, 1999) and updated subsequently for copying with a three step Data Assimilation (DA) of pressures, flows and demands (Bragalli, Fortini, & Todini, 2016) using ensemble Kalman filter (EnKF). Other authors have applied also EnKF for demand monitoring (Okeya, Kapelan, Hutton, & Naga, 2014) and real-time water quality modelling (Rajakumar, Mohan-Kumar, Amrutur, & Kapelan, 2019). Applications of Extended Kalman Filter (EKF) can also be found in the literature for water demand estimation (Shang, Uber, van Bloemen-Waanders, Boccelli, & Janke, 2006), and leak detection (Jung & Lansey, 2015) (Choi, Kim, Choi, & Geem, 2016) (Ye & Fenner, 2014) (Ye & Fenner, 2011). Applications of Particle Filter can be found also for online estimation of demands multipliers (Do, Simpson, Deuerlein, & Piller, 2017) and leak detection (Anjana, Sheetal-Kumar, Mohan-Kumar, & Amrutur, 2015). In addition, a recent review of Real Time Control (RTC) presents different approaches and architectures which can be of interest in such case (Creaco, et al., 2019).

Water distribution sectorization

Another goal of researchers has been the idea to isolate smaller areas of the networks to make them manageable in terms of water balance, leak detection (Night Flow Analysis), pressure management, water audit (non-revenue water quantification), demand management, infrastructure renovations, water quality control, and water quality risk management (isolation for accidental and malicious contamination). As will be presented latter in this chapter, use of optimization algorithms in this area of research is relatively new but the number of approaches is vast.

Water quality optimization

Another goal for operations optimization in the literature is the optimal operation for emergency due to accidental, natural hazard, or, in some cases, due to deliberate attack. This subject area has become of great importance in the last decade due to the interest of stakeholders to reduce the risk of contamination in a WDN. There are two main trends in the development of practices and approaches for managing contamination in a network: 1) how to optimally locate the sensors in a network in order to reduce the number to be installed while increasing / maintaining effectiveness in the issuing correct warnings and 2) how to optimally organise subsequent response with minimum number of manoeuvres with personnel, valves and hydrants (minimize number of necessary operations) for minimizing the spread of pollution throughout the WDN and for effective flushing or taking out of the system the identified pollutant. The largest compendium of techniques in the subject can be found in what has been called the Battle of the Water Sensor Networks (BWSN) (Ostfeld, et al., 2008). Recent advances in the matter using information theory under MOO approaches had been reported by (Alfonso, Jonoski, & Solomatine, 2010), combinations of device operations using Mixed Integer Linear Programming (MILP) (Alvisi, Franchini, Galvanelli, & Nonato, 2012). Research for reduction of residence times in WDN through optimal valve setting is explored by Quintiliani (2018). The latter can have an impact on the reduction of risk of formation of chlorination by-products.

Other approaches which use combinations of flows, heads and quality as state variables are accessible for water quality optimization either using Q-C model (Cohen, Shamir, & Sinai, 2000a), Q-H model (Cohen, Shamir, & Sinai, 2000b) or Q-C-H model (Cohen, Shamir, & Sinai, 2000c). These are intended mainly for simplified networks or for transmission mains of a large WDN where water quality optimization is a need. Recently a comparison of the application of diverse non-linear solvers for Q-C, Q-H and Q-C-H models is presented by Housh (2021).

An interesting study dealing with an hybrid problem of design and operation using as objectives the total cost, reliability and water quality (water age is the average time of water presence inside the system), while at the same time setting the optimal pump schedule and installation of additional tanks, has been applied to the case of *Anytown* network by using NSGA-II (Farmani, Walters, & Savic, 2006). The non-dominated solutions show the trade-off for three different objective functions at no additional computational time, allowing for flexibility in the system for WQ at a reduced marginal cost increase.

2.2.4 WDN calibration

From the mathematical point of view, calibration is an optimization problem in which model coefficients, parameters or inputs need to be estimated to fit a particular response or target. An iterative optimization process updates the parameters and coefficients to achieve better quality with respect to model responses (Atiquzzaman, Liong, & Yu, 2006). An objective function is required to measure the quality of the model response and is commonly described by indicators measuring the sum of differences between observations and simulated results (e.g. RMSE, Root Mean Squared Error). In an extensive review of the calibration problem calibration (Savic, Kapelan, & Jonkergouw, 2009) divide the problem of calibration for hydraulic variables and for water quality variables. In both cases, the tools for optimization used in the past have been of Non-evolutionary type (OR methods) or Evolutionary type (GA methods). The most recent approaches for the calibration of networks is known as Battle of the Water Calibration Networks (BWCN) (Ostfeld, et al., 2012), where researchers from diverse backgrounds, tried to solve a common problem in calibration for medium size WDNs.

The goal of calibration of a WDN is especially important in cases when uncertainty in hydraulic parameters such as roughness and diameters of pipes is high or coefficients related to mechanisms of leakages need to be quantified. This is the case of WDNs that are old, or where the conditions have changed from the original ones as provided in technical specifications. The life cycle of pipes, valves, pumps and storage structures declines in quality so the understanding of the network behaviour in terms of the new status becomes the modelling objective.

Calibration usually requires large data sets of several variables of the system such as pressure and discharges, to guarantee good performance of the calibration process (Giustolisi & Berardi, 2011). In the case that calibration of water quality variables needs to be performed, campaigns need to be prepared in advance, due to the expensive cost of the instruments and the large amount of personnel required. In the ICeWater project data on pressures and discharges was obtained directly from the sensors through wireless networks, which were then stored in databases from where it was possible to extract them, as required.

2.2.5 Parallelization and High Performance Computing

Most of the algorithms discussed in the previous section require large computational times when applied to large WDNs for MOO. Three solutions have been implemented by several researchers to decrease the computational runtime of models: running many simulations in parallel, running parts of the GGA in parallel, and running surrogate models.

Running many GGA in parallel

To overcome the mentioned drawback, computational parallelization techniques such as Global Parallelization (GPC), Island Parallelization (IPC) and Hierarchical Parallelization (HP) for design problems have been explored under the NSGA-II (Artina, Bragalli, Erbacci, Marchi, & Rivi, 2012). All the computational parallelization techniques produce a better performance in the optimization process by reducing the computational time, but the drawback is that the use of these requires an additional calibration process of the parameters of the NSGA-II, and of the parallelization queue between machines (or processors). It needs to be mentioned that the case studies presented in the above reference are small compared to real networks and the representativeness of the results remains to be tested in large WDNs.

More recently a toolkit for EPANET was presented during the WDSA2016 conference (Alvarruiz, Martinez-Alzamora, & Vidal, 2017), using a new design loop-method for the solution of the system of equations.

Running parts of the GGA in parallel

Another idea in this regard was the introduction of High Performance Computing (HPC) and General Purpose Graphics Processing Units (GPGPU) in the hydraulic calculation (Alonso, et al., 2000) (Guidolin, Kapelan, & Savic, 2013). The idea behind this approach lies in the computational time reduction of the hydraulic calculation inside the GGA. There are not many parts of the GGA that are feasible for parallelization. Two particular results were found by (Guidolin, Kapelan, & Savic, 2013). Firstly, contrary to the common belief that the largest proportion of computation time spent in the GGA is the iterative solution of the linear sparse algorithm (used for the inverse matrix calculations), this is rather the case for the hydraulic resistance calculation (Equation 2-2). Secondly, the approach has the potential to be extended for the case of large WDNs while maintaining the efficiency.

Some authors have tried the actualization of the libraries (using commercial and freeware such as: PARDISO, HSL-MA87, CHOLMOD, CXSParse, SAMG, ViennaCL, CUDA) which are used to solve the system of equations either on CPU's or GPU's (Burger, Sitzenfrei, & Rauch, 2015), while others have tested different linear solvers (direct or indirect) applied to EPANET code (Giustolisi & Moosavian, Testing linear solvers for GGA, 2014). A remark is made to the latter authors, as they tested the two hydraulic paradigms DDA and PDA. Besides determining an improvement in the computation for some specific libraries or algorithms on specific configurations (number of elements = size of matrices in Equation 2-6), the regular solver of EPANET still holds for the full range of network scales, and there seems to be no real *winner* library in the race for the determination of best linear solver.

Surrogates of the WDN

A third approach developed recently relies on the idea of performing the simulation of complete systems by use of meta-models such as Artificial Neural Networks (ANN) which emulate the WDN, and a posterior optimization is achieved by using the emulated system (Broad, Maier, & Dandy, 2010) (Broad, Dandy, & Maier, 2005) (Rao & Salomons, 2007) (Jamieson, Shamir, Martinez, & Franchini, 2007).

This meta-modelling had been used mainly to reduce the computation time of the hydraulic solver but usually presents different challenges, such as: 1) being not so accurate with respect to the real systems, 2) requires new optimization with updated ANN emulator in case of system modifications, and 3) such developments are in early stages of research, and only networks with a small number of pipes have been tested. For those reasons, although important, such approaches were not considered during this research.

2.2.6 Benchmark models

Many examples of benchmark case studies used for optimization in WDN have been developed in the last 50 years. The first networks to be used for such purposes were *New York* (Shaake & Lai, 1969), *TwoLoops* (Alperovits & Shamir, 1977), *TwoReservoirsA* (Gessler, 1985), *Anytown* (Walski, 1983) and *Hanoi* (Fujiwara & Khang, 1990). Such networks contained limited number of elements.

Later on, other WDN have appeared as benchmarks for the understanding of problems in different locations such as, *ThreeTanks*, (van Zyl, 2001), *Apulian* (Giustolisi & Todini, 2009), *Balerma* (Reca, Martinez, Gil, & Banos, 2008), *PW06* (Prasad & Walters, 2006) and with time these networks have grown in size and number of elements as *LargeNetwork* (Kang & Lansey, 2012), *One-Reservoir*, *DoubleReservoir*, *ThreeReservoir*s, *FiveReservoirs* (Zheng & Zecchin, 2014), although *FiveReservoirs* is a modification of *LargeNetwork*. Such networks models are useful to serve as a proof of concept for optimization purposes, although these lack the complexities of real systems and deal with a simple problem in water supply at a time.
In the case of *Richmond* and *RichmondSkeletonized* (van Zyl, Savic, & Walters, 2004), *Exnet* (Farmani, Savic, & Walters, 2004), Battle of the water sensors network 1 (*BWSN1*) (Ostfeld, et al., 2008), *Parete* and *Villarica* (Di Nardo & Di Natale, 2011) and *C-Town* (Ostfeld, et al., 2012), these WDN correspond to approximations of real networks with a larger number of elements increasing the computational runtimes.
Other known cases of networks used in the literature for modelling and optimization purposes are *Barcelona*, Spain (Cembrano, Brdys, Quevedo, Coulbeck, & Orr, 1988); *City T*, China (Shihu, et al., 2010); *Goiania*, Brazil (Carrijo, 2004); *Haifa-A*, Israel (Salomons, Goryashko, Shamir, Rao, & Alvisi, 2007); *Madrid*, Spain (Gomez, Cubillo, & Martin, 2014) and *Valencia*, Spain (Martinez-Alzamora, Hernandez, Alonso, Rao, & Alvisi, 2007) and *Cimitile*, Italy (Quintiliani, 2018), although the number of elements as compared with the sizes of such cities is quite low.
In addition, several databases have become available for the testing of multi-objective optimization and operations research in WDN. Just to mention a few there is the case of the Kentucky Dataset[2] (Jolly, Lothes, Bryson, & Ormsbee, 2014), the University of Exeter WDN repository[3], the Texas A&M generator (Brumbelow, Torres, Guikema, Bristow, & and Kanta, 2007), the Pacific City repository (Broad, Dandy, & Maier, 2015b) (Broad, Dandy, & Maier, 2015a) and the examples of the EPANET-MATLAB Toolkit (Eliades, 2017). Also the WDN generators of *Micropolis* and *Megapolis* WDN have been made available for research purposes (Möderl, Sitzenfrei, Fetz, Fleischhacker, & Rauch, 2011).

2.3 Pump Scheduling and Sectorization problems in WDN optimization

There are three different ways in which pressure management of a system can be performed. These are intrinsically linked, however, we will present them separately, as they are in the main focus of this research, in the following sub-sections.

2.3.1 Pump Scheduling

A PS problem can be formulated as the task of determining the operation of pumps in a system during the day: when and where to operate in order to minimize the total cost of energy consumption in a time horizon, reduce the number of pump switches or increase network reliability. Ormsbee & Lansey (1994) presented the first literature review on PS, mostly related to linear programming and operations research algorithms. Boulos et al. (2001) presented a Genetic Algorithm (GA) coupled to a hydraulic simulator as a desktop application. Biscos et

[2] https://uknowledge.uky.edu/wdst/index.html

[3] http://emps.exeter.ac.uk/engineering/research/cws/resources/benchmarks/

al. (2003) presented a model predictive control tool in a case study in South Africa, with an application for a water treatment.

Optimization using a hybrid optimization algorithm (GA and hill-climber strategy) to select the best operational rules was applied for the WDN of Richmond (complete and skeletonized) and for the benchmark *ThreeTanks* WDN using (van Zyl, Savic, & Walters, 2004). A comparison of legacy coded GA’s has been presented by von Lucken, et al. (Pump scheduling optimization using asynchronous parallel evolutionary algorithms, 2004), where, in addition, a parallelization of the optimization algorithms was proposed.

Other algorithms such as dynamic programming (DP) have been applied for a WDN with multiple reservoirs (Ulanicki, Kahler, & See, 2007). Recently, evolution strategies such as Ant Colony Optimization had been used also to PS problem (Lopez-Ibanez, Prasad, & Paechter, 2008a) (Lopez-Ibanez, Prasad, & Paechter, 2008b) (Lopez-Ibanez, 2009). More recent approaches include the possibility to find multi-step scenarios of operation (Napolitano & Sechi, 2021), trigger values (Housh & Salomons, 2019) or determine the optimal time slots of operation (Quintiliani & Creaco, 2019) for daily PS of small systems.

The research presented here follows a similar path in the use of GA's coupled to a hydraulic simulator, but the special characteristics of Milan makes it a unique example of application. The main consideration in water supply, as a constraint, is to preserve a minimum pressure in the system. However, in the last 20 years a great deal of investment has been made in the world for reducing the maximum pressure of operation as well. The latter has the advantages of using less energy, reduction of the amount of leakages, increase of efficiency of the leakages, reduction of pipes bursts, reduction of impact caused by transients in the system (e.g. water hammer), and reduction of customer complains (Thornton, Sturm, & Kunkel, 2008). This is in fact the challenge in Milan WDN, where Optimal PS is sought to determine operational strategies with minimal pressures close to the prescribed constraint value, leading to energy consumption reduction, as well as reducing the problems listed above.

2.3.2 Pressure Management

Pressure management is performed either by controlling the pumps speed using Variable Speed Pumps (VSP) (Marchi & Simpson, 2013) or with the aid of valves to control the pressure of service just after the pumps with the use of Pressure Regulating Valves (PRV) (Germanopoulos & Jowitt, 1989). The trigger in the activation of the operation the PRVs is done in WDNs using measurements at a critical point (or several) of the network or of average pressure in a PMZ. The general idea is to maintain an inlet pressure to the system as low as possible guaranteeing demand and pressure at the critical points.

The main issue with the implementation of PRVs in a model-based approach is the determination of its optimal location in a large network. Some optimization approaches have been used for the determination of best locations of PRVs in a network, based on OR (Sterling & Bargiela, 1984) (Jowitt & Xu, 1990), and based on GA's (Reis, Porto, & Chaudhry, 1997) in single objective approaches, where the objective was the number of PRV required for operation in a WDN.

For the case of MOO (Nicolini & Zovatto, 2009) NSGA-II was used, adding as second objective the total volume of leakages in the system. In these approaches the principal objective of the pressure management was not minimization of energy consumption. However, a comparison between NSGA-II and Epsilon-MOEA was used for the system of Baja (Udine, Italy) where it was proved that this methodology is a cost effective approach for energy reduction (Nicolini, Giacomello, & Deb, 2011). The drawback in all the cases reviewed is that the case studies used are relatively small and cannot be compared with the large WDNs addressed in this research.

2.3.3 Sectorization

Due to different topography and topology in the WDN of Milan, the current operation approach leads to maintaining just above minimum pressures in some parts of Milan network, and higher pressures in other parts of the network. With an optimal sectorization, the WDN can be divided in separate sectors-PMZs, each with optimal pressure (above minimum required) maintained. The supply could be obtained from one or several pumping stations at a time for each PMZ.
There are additional benefits associated with Water Network Sectorization of Milan such as:

i) availability to perform continuous monitoring of leakages for the utility,
ii) increase in reliability,
iii) interconnected system with many sources that can support each other would be better for managing shortages (Fontana, Giugni, & Portolano, 2012), and
iv) improved network protection against malicious or accidental contamination (Di Nardo, Di Natale, Guida, & Musmarra, 2012).

Optimization methods for sectorization have been developed in the last 25 years. Subdivision or partitioning of large WDNs in sectors can be beneficial for other objectives beyond the ones of creating District Metered Areas (DMAs) or Pressure Management Zones (PMZ). In pumped systems DMAs are are small clusters of customers with a provision to monitor the water supplied and consumed, PMZs are zones where energy, pressure and leakages can jointly be managed in an optimal way (Thornton, 2004). Other benefits experienced wit sectorization are: improved system design, better estimation of consumer demands, pressure management, water quality management (isolation of contaminants), dealing with emergencies (e.g. pipe or pump failures), improved design and implementation of monitoring networks. A summary of optimization approaches is presented in Table 2-1.
Many researchers have addressed the problem of dividing large WDNs into sectors by a class of methods based on graph theory. Sectorization introduces changes in the WDN configuration, in particular the connectivity and topology of the system. Such methodology is known as the 'layout problem' (Ostfeld A. , 2005), (Giustolisi, Kapelan, & Savic, 2008). From this point of view, sectorization brings issues related to *connectivity* of nodes in the network (e.g., whether certain node is connected to a particular water supply source, or contamination source, etc., depending on the problem analysed) as well as *reachability* (probability that water / pollution will reach a given node in the network). Single DMAs can be either connected or isolated from the entire network, depending on whether connection exists, which can be modified by operation of valves.
The concept of DMA was first introduced by UK researchers at WAA (WAA, 1980). Steadily, in time, other approaches have been developed based on trial and error methodologies, which usually perform the sectorization by using empirical suggestions coming from knowledge of experts. In such category one may find the UK's (WAA/WRC, 1985), (Wrc/WSA/WCA, 1994), European (WIR, 1999) and US (IWA, 2007) guidelines for DMAs. All of the above are

related almost entirely to the goals of leak minimization and water audit for water utilities, using variables such as number of connections, number of properties/households, number of customers, and number of pipes in an area or total pipe length in a sector.

Given the structure of WDNs, as a collection of pipes and nodes, since the 1970's researchers have performed homologous analysis to the ones existing in Graph Theory approaches for water distribution simulation in steady state or EPS (Chandarshekar & Kesavan, 1972) (Chandarshekar & Stewart, 1975) (Rahal, 1995), and for analysis of transients (such as water hammer) using system dynamics analysis (Onizuka, 1986) (Gupta R. , 2006). In this manner, a WDN can be analogously treated with the same concepts and principles laid by mathematicians in graph theory, constrained by the need to guarantee supply in a system with hydraulic variables.

Recently, some authors have presented algorithms for creation of sectors based on the analogy with graph theory approaches under mechanical failure (e.g. pipe failure, pipe replacement, pipe replacement with valves). Also, some authors have introduced a model of water distribution sectorization based on a decomposition of the network into several trees (Deuerlein, 2008). The trees starting point are sources (e.g. tanks and reservoirs) and then the creation of *bridges* between the different trees allows a full connectivity of the network, however the method does not include isolation of the sectors with respect to the sources. According to the author, the method requires only mass balance in the first steps. If that is the case, *a priori* states of the flows must be known (as the energy losses) and given that the decomposition affects the flow directions in the pipes, the final configuration after introducing the *bridges* between the sectors will not be the same. In this regard an iterative procedure would be more suitable until convergence is obtained for the flow directions in the system after sectorization.

Achieving sectorization is enabled by insertion of isolation valves in a WDN. For this problem, a model using a MOGA taking into account cost and reliability as objectives already exists (Creaco, Franchini, & Alvisi, 2010). In this case, decision variables are the valve locations (binary variables). While many objectives were tested by (Creaco, Franchini, & Alvisi, 2010), the total cost of valves and the water demand shortfall (a similar measure to reliability) showed to be the most relevant in the case studies where such methodology was applied. Since the actual sectorization in WDNs is achieved by closing links in the network, using valves, the sector identification is guided by the topological analysis combined with optimization algorithms. The optimal valves location for isolating of parts of the network was studied by Creaco (2010) also for maintenance purposes. Other authors applied a similar technique for location of the isolation valves (Mays & Ozger, 2004), although using Simulated Annealing (SA) to generate different configurations.

A useful distinction was introduced in (Di Nardo A. , Di Natale, Santonastaso, Tzatchkov, & Alcocer-Yamanaka, 2013), between Water Network Partitioning, related to DMA creation, and Water Network Sectorization (WNS), which is leading to creation of isolated sectors, with their own water supply acting as PMZs (Di Nardo & Di Natale, 2011).

Some generic graph theoretic approaches for WDNs sectorization for better network management irrespective of the actual purpose have been proposed in (Giustolisi, Kapelan, & Savic, 2008), (Perelman & Ostfeld, 2011), (Giustolisi & Savic, 2010), (Herrera, 2011), (Deuerlein, 2008) and (Giustolisi & Savic, 2010).

A recent approach taking concepts from both graph theory and complex systems decomposition theory (Fontana, Giugni, & Portolano, 2012) using community detection (Fortunato, 2010) was used as an alternative for automated DMAs development. Note that these methods use some hydraulics–related variables for the analysis, but they do not include hydraulic simulations or model-based optimization approaches as they have been introduced in the previous sections. In a sense, such methods correspond to topological analysis of physical parameters of the WND. Simulation models may be used here for verifying and testing the obtained results.

Di Nardo et al., (2011), (2013a) (2013b) present WDN sectorization by graph theory using minimum distance analysis. The minimum distance in this case corresponds to the sum of the hydraulic gradients between two given nodes. The algorithm of minimum distance used is the one of Dijkstra (1959) coupled with a GA for the selection of the nodes interfacing between DMAs. However, Dijkstra's algorithm requires certain conditions that most WDNs do not possess. First, in an EPS of a real network, flows cannot maintain a certain direction throughout the day, and second, if the flow changes direction the energy losses becomes negative and is not possible to perform the minimum distance estimation as the algorithm requires exclusively positive values. In that regard the Dijkstra algorithm should be replaced by the *Shimbel* algorithm (Shimbel, 1955). The latter is able to deal with negative weights in the edges of a graph. Such algorithm is commonly known as Bellman-Ford-Moore, although it precedes the publications of each of the authors on the subject (Bellman, 1958) (Ford, 1956) (Moore, 1959).

Table 2-1. Summary of Sectorization approaches found in the literature.

Author	**Year**	**Main description**	**Solution Method**	**Hydraulic paradigm**	**Optimization Algorithm**	**Objective Functions or Performance Criteria**	**Case studies**	Source / type
Goulter et al.	1986	WDN design	Shortest path	DDA	LP	Network cost	Two loops	Synthetic
Reis et al.	1997	Location of valves for leakage reduction	Hydraulic based	DDA	GA	Leakage reduction	Three Sources	Germanopoulos and Jowitt, 1989
Mays and Ozger	2004	Long term operation against failures through valve location	Simulation of failures through statistical generation (Poisson)	Semi PDA	Simulate Annealing	Network Reliability Network Availability	Network I	Synthetic
Ostfeld	2005	Connectedness to source Avoid failures	Adjacency matrix Digraph partitioning	DDA	GA	Flexibility Score	Case 1 Case 2	Synthetic Synthetic

Author	Year	Main description	Solution Method	Hydraulic paradigm	Optimization Algorithm	Objective Functions or Performance Criteria	Case studies	Source / type
Liberatore and Sechi	2009	Location of new valves	Pressure reference method	DDA	Scatter search, meta-heuristic	Weighted of pressure performance and cost of interventions	Burcei, Sardinia	Italy
Murray et al.	2010	Connectedness to source Adding or Closing pipes Size constraints	Manual	DDA	Manual	Water Security Water Age Resilience Index Fire Flow	BWDSN1	Ostfeld et al. 2008
Herrera	2011	Connectedness to sources Size constraints	Computational Int. Graph partitioning Kernel-based Agent-based	DDA	Semi-supervised learning	Number of sectors	Celaya	Mexico

Author	Year	Main description	Solution Method	Hydraulic paradigm	Optimization Algorithm	Objective Functions or Performance Criteria	Case studies	Source / type
Di Nardo and Di Natale	2011	Connectedness to source Pressure constraints Size constraints	Shortest path	DDA	Heuristic	Available Power Dissipated Power Resilience Index Resiliance Deviation Index Statistics on DMA pressure RMS of pressure deviations Mean Pressure Surplus Mean Frequency of pressure deviations	Villarica	Italy
Perelman and Ostfeld	2011	Simplification of a WDN into smaller subsystems	Depth First Search Breadth First Search	None	Clustering unsupervised	Connectivity	BWSN1	Ostfeld et al. 2008

Author	Year	Main description	Solution Method	Hydraulic paradigm	Optimization Algorithm	Objective Functions or Performance Criteria	Case studies	Source / type
Gomes et al.	2012	Location of PRV's Reinforcement Replacement of assets Water loss management	Heuristic Constraints on pressure	DDA	Simmulated Annealing	Net Present Value of investment Intermediate calculation of Benefit and Cost	Case 1 Case 2	Synthetic Arulraj and Rao 1995
Ferrari et al.	2013	Connectedness to source Closing pipes Size constraints	Breadth First Search	DDA	Recursive Bisection	Minimum Pressure	BWDSN2	Ostfeld et al. 2012
Diao et al.	2013	Closing pipes Size constraints	Modularity Community detection	DDA	Heuristic	Minimum Pressure Water Age Fire Flow	BWDSN2	Ostfeld et al. 2012
Di Nardo et al.	2013	Connectedness to source	Depth First Search	PDA	GA	Resilience Index	Parete	Mexico

Author	Year	Main description	Solution Method	Hydraulic paradigm	Optimization Algorithm	Objective Functions or Performance Criteria	Case studies	Source / type
		Closing pipes				Pressue Index Flow Index	San Luis, rio Colorado	Mexico
Di Nardo et al.	2013	Closing pipes Number of Zones	Graph Partitioning	DDA PDA	GA	Resilience Index Pressue Index Flow Index	Villarica	Mexico
Alvisi and Franchini	2014	Closing pipes Size constraints	Breadth First Search	DDA	Enumeration	Minimum Pressure Resilience Index	Castelfranco, Modena	Italy
Giustolisi and Ridolfi	2014	Closing pipes Number of zones	Modularity Community Based	PDA DDA	MOGA	Modularity Index Number of Modules	C-Town	Ostfeld et al. 2012
Gomez et al.	2014	Closing pipes or valves	Hydraulic analysis	DDA	MOGA	Level of service (Vulnerability)	Madrid	Spain

Author	Year	Main description	Solution Method	Hydraulic paradigm	Optimization Algorithm	Objective Functions or Performance Criteria	Case studies	Source / type
		New elements / Interventions	Redundancy, Reliability and Resilience			Cost of interventions		
Perelman et al.	2015	Connectedness to source Closing valves Size constraints Minimum connections	Graph partitioning	DDA	LP	Hydraylic measures Robustness Metrics Resilience Indexes	BWDSN2	Ostfeld et al. 2012
Di Nardo et al.	2015	Connectedness to source	Shortest path	DDA	Automated	Energy dissipation Pressure Variation Fire flow deficit Water Age (mean, max, std) Mechanical Redundancy	Parete Matamoros	Italy Mexico

Author	Year	Main description	Solution Method	Hydraulic paradigm	Optimization Algorithm	Objective Functions or Performance Criteria	Case studies	Source / type
Wright et al.	2015	Resilience PRV settings	Control theory	DDA	Sequential convex programming	Minimize Average Zone Pressure	Real DMA	Unknown
Herrera et al.	2016	Aggregation of demand nodes	Graph theoretical Decomposition	DDA	Semi-supervised	Multi-scale Resilience Hydraulic indexes	Case A Case B	Unknown Unknown
Scarpa et al.	2016	DMA creation with multiple sources	Graph theoretical	DDA	GA	Resilience Index Entropy Index Hydraulic Performance	Milan (North extraction)	Italy
Di Nardo et al.	2017	Clustering Number of sensors	Graph Partitioning	PDA	Multi-recursive bisection	Energy criteria Economic criteria	San Luis, Rio Colorado	Mexico

Other authors have also used similar techniques based on graph theory, with the goal of dealing with network uncertainties (e.g. demand increase and climate change) (Seneshaw, 2013). Such a methodology is named Genetic Algorithm based Flexibility Optimization (GAFO). The important aspect of this particular research is the ability of the methodology to build optimal clusters of future networks, which are able to respond independently to alterations in a cost effective way. However, the word *future* refers to the design (and expansion) problem for WDNs and not to the optimal actual operation problem for WDNs per se.

Classification algorithms from computational intelligence have also been used for sectorization. Examples are K-means, Graph Spectral Clustering Algorithm (GSCA) (including Markov Cluster Algorithm "MCA") and Multi-Agent Approach (MAA) (Herrera, 2011). However these techniques relate to the connectivity of the network, leaving the hydraulic behaviour of the network to the further steps of analysis, as it was the case of Fortunato (Community detection in graphs, 2010).

Other authors (Perelman & Ostfeld, 2011), have used a topological clustering algorithm which was used to divide a small benchmark case study (126 nodes, 168 pipes, 8 valves) into several subsystems based on a classification by connectivity analysis. The connectivity can be described as either weakly or strongly connected sectors. Strongly connected sectors refers to the fact there are multiple paths from which water can reach all the nodes within the sector from the source, while weakly connected sectors are mainly related to tree-branched water supply (i.e. irrigation networks, water supply of European block houses).

The use of *modularity* (Newman & Girvan, 2004) as a measure of density for the determination of the pipes belonging to each sector of a WDN has been also investigated by some authors (Diao, Zhou, & Rauch, 2013). This approach is similar to the one of spectral clustering discussed previously (Herrera, 2011).

Some advances have been reported on energy optimization using Artificial Neural Networks as simpler surrogate models of the complex hydraulic simulation models, which are then coupled with GA optimization, as in the case of the optimization in sectorization of the system of Valencia, Spain (Martinez-Alzamora, Hernandez, Alonso, Rao, & Alvisi, 2007).

Sectorization for optimal valves location, but in this case for leakage reduction, with topological analysis and a Genetic Algorithm (GA) is presented in (Reis, Porto, & Chaudhry, 1997), optimal Pressure Reducing Valve (PRV) placement for pressure management is presented in (Liberatore & Sechi, 2009) and optimal valves placement for reliability assessment after pipe failures using heuristic.

Other examples of design problems using similar approach are given in (Kadu, Gupta, & Bhave, 2008), where GA was combined with graph theory algorithms for optimal WDNs design (pipe selection); (Krapivka & Ostfeld, 2009), where a spanning tree identification algorithm was combined with GA-LP, again for least-cost pipe selection; (Zheng, Simpson, & Zecchin, 2011), where shortest distance tree approaches were combined with Non-Linear Programming – Differential Evolution (NLP-DE) for the same problem. A multi-objective design problem of a WDN with multiple sources was solved by (Zheng & Zecchin, 2014), where graph-theoretic approaches were used for WDNs sectorization and afterwards NSGA-II was used for optimizing two objectives per sector (total cost and reliability index).

2.4 Summary

In the current research, the Water Network Sectorization (WNS) approach is most relevant for the problem in a large WDN, where the attempt is to find optimal sectorization that will minimize the costs for energy consumption due to pumping, and satisfy the pressure reliability. The sectors in this case are created by valve closures (binary decision variables) and they will be operating as completely isolated, with one or several sources of water supply (wells and booster pumping stations). From this point of view the Milan WDN sectorization fits a WNS problem where graph theory approaches could be combined with multi-objective model-based optimization.

One of the main elements which is not discussed in any literature on sectorization, is the need to include pumps in the selection of the boundaries of each Pressure Management Zone (PMZ), as their operation may affect the maximum delivery from a particular source. In this research, a simple algorithm is presented for inclusion of pumps as part of the sectorization problem.

Regarding the simulation models used in the literature for these kinds of problems, it should be noted that most of them are similar in nature, and very frequently EPANET 2 (Rossman, 2000) was be used as the network simulator, as this is widely available as free and open source software. This hydraulic simulator has also been used here. Although some advances were made in the development of new EPANET versions, regarding bug corrections and the development of an Open Software initiative, such developments came after the finalization of ICeWater project (late 2015) and are not considered in this work. For example, Marchi and Simpson (2013) developed extensions to the EPANET code regarding the identification of best efficiency point, however such analysis are not considered here.

As for the optimization algorithms used, for PS optimization the choice made was to test two algorithms: 1) NSGA-II, which had a proven performance in many multi-objective optimization problems, including those related to WDNs and 2) AMGA2 (Tiwari, Fadel, & Deb, 2011), a relatively new meta-heuristic optimization algorithm. AMGA2, stands for 'Archive based Micro-Genetic Algorithm' and uses a reduced number of objective function evaluations while showing better convergence to the real Pareto set in MOO benchmarking problems. To the knowledge of the author, AMGA2 has not been applied broadly to problems of WDN (Marquez-Calvo, et al., 2018). The performance of both algorithms has been compared and subsequently the decision was to continue with the use of NSGA-II for the majority of the research regarding sectorization.

3 CASE STUDIES (ABBIATEGRASSO AND MILAN)

Two case studies are considered in this research: the first one concerns the full WDN of the city of Milan, in the north of Italy, and the second one is a sub-system in the southern part of the same WDN known as Abbiategrasso. Both systems have their own particularities and problems that are presented in the following sub-sections. While in this chapter the characteristics of the system are presented, the model building and the assumptions made are presented in Chapter 5.

3.1 Characteristics of the water supply system

3.1.1 Milan

The city of Milan is located in the region of Lombardia, Italy (see Figure 1-1). The water supply is administered and operated by the company Metropolitana Milanese S.p.A (MM), which was part of the ICeWater project consortium. Energy management in the supply system is the main challenge for the utility and the research is focused on this task.

The WDN is completely supplied from water coming from groundwater. A total of 550 wells are spread across the city. The system operates completely as a pressurized system and there are no intermittencies in the supply. The water availability and the capacity of the system is enough to provide water to its customers and even deliver to neighbouring cities.

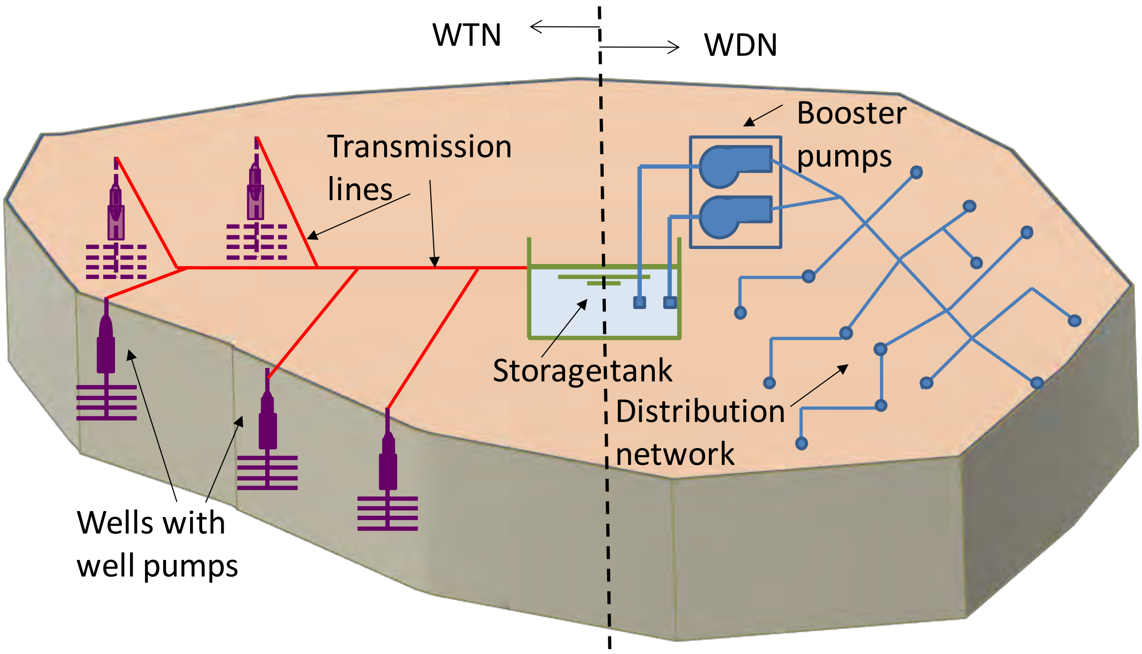


Figure 3-1. Schematic representation of the components of Milan Water Transmission Network (WTN) and Water Distribution Network (WDN).

In a schematic way the system can be split in two (Figure 3-1). First, it is the Water Transmission Network (WTN), corresponding to the system of wells which provide water up to the storage tanks which belong to each station. The second part of the system, the WDN, is composed of the storage tanks from where water is pumped to customers using 103 booster pumps.

A total of 34 booster pumping stations are located in the city, however, only 28 were operational at the beginning of the research, to convey the water to the customers. Every pumping station contains also its own treatment plant, associated with at least one storage tank. One important aspect is how heterogeneous the system is regarding its configuration, because there is no uniformity in the number of wells or boosters belonging to each pumping station. In addition, all pumps in the system (wells and boosters) possess quite different pumping characteristics in terms of head curves. This implies that there is a high variability on the amount of water which can be supplied from each pumping station.

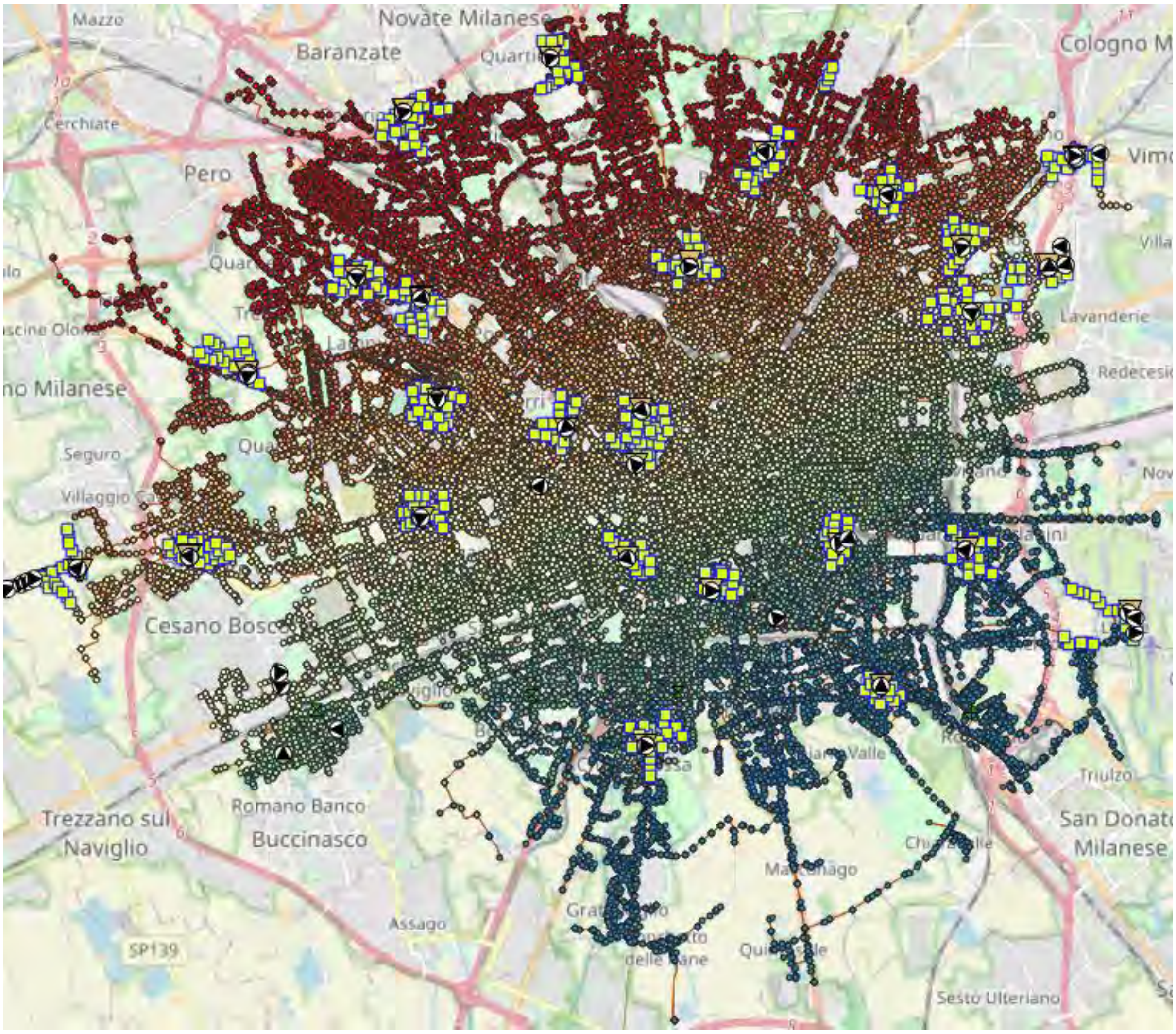


Figure 3-2. Plan view of Milan WDN. Full Network Yellow squares are wells locations, while booster pumping stations are presented as circle-triangle symbols in the WDN. Coloring of junctions is presented from higher elevations (red) to lower elevations (blue).

The storage tanks are located underground and have a low total storage capacity ($Vol \leq 10^4 m^3$) and operational head (in average ~3.75m), for a city of around 1,250,000 inhabitants (Milano, 2014). The system is operated entirely as a single Pressure Management Zone - PMZ where all pumps are operated as ON/OFF pumps. The network is presented in Figure 3-2, with pipes of

WDN in green, yellow squares representing well pumps, while the combo triangle circle represent the pumps in each case. Nodes are presented showing the elevation of the nodes from the hills (red) to the lowest parts of the city (blue).

The system at present has enough water for meeting all demands because:

- There has been a reduction of the total water demand of the city, because over the last few decades, large industries have moved out of the city boundaries. This has created the situation that there is sufficient availability of water for human consumption for a long time.
- This argument is confirmed by the statistics of *Censimento Italiano* (Milano, 2014), which show that the city population has decreased steadily since 1971. Since former industries had their water supplies from groundwater, after their removal the groundwater table has raised due to under-exploitation. In fact, apart from the water supply wells of MM, there are at present additional wells that operate solely for the purpose of maintaining low groundwater table in the underlying aquifer.
- The infrastructure installed is old but is capable of coping with higher water consumption than the current one.

One of the important features of the system is that the city of Milan is located over a hilly topography. The system is located between 64.9 m.a.s.l. and 143.2 m.a.s.l. The average elevation of the WDN of Milan is 120.1 m.a.s.l. Thus the topography plays a role in the daily operation of the system. Figure 3-3, shows the elevation of all pump stations. Given a required pressure of about 30 m (in column of water), for reliable supply of the system, when the whole system is connected and operated as one PMZ, the lower pipes (linked to the lower tanks) are located approximately 40 m below the higher pipes (linked to the higher tanks), thus receiving unnecessary high pressure. This is the problem that will be addressed in this research regarding energy savings and optimal pressure management. In this situation, for reasons of maintaining pressures close to the minimum required in the whole network, the second stage of sectorization optimization combined with pump scheduling needs to be considered.

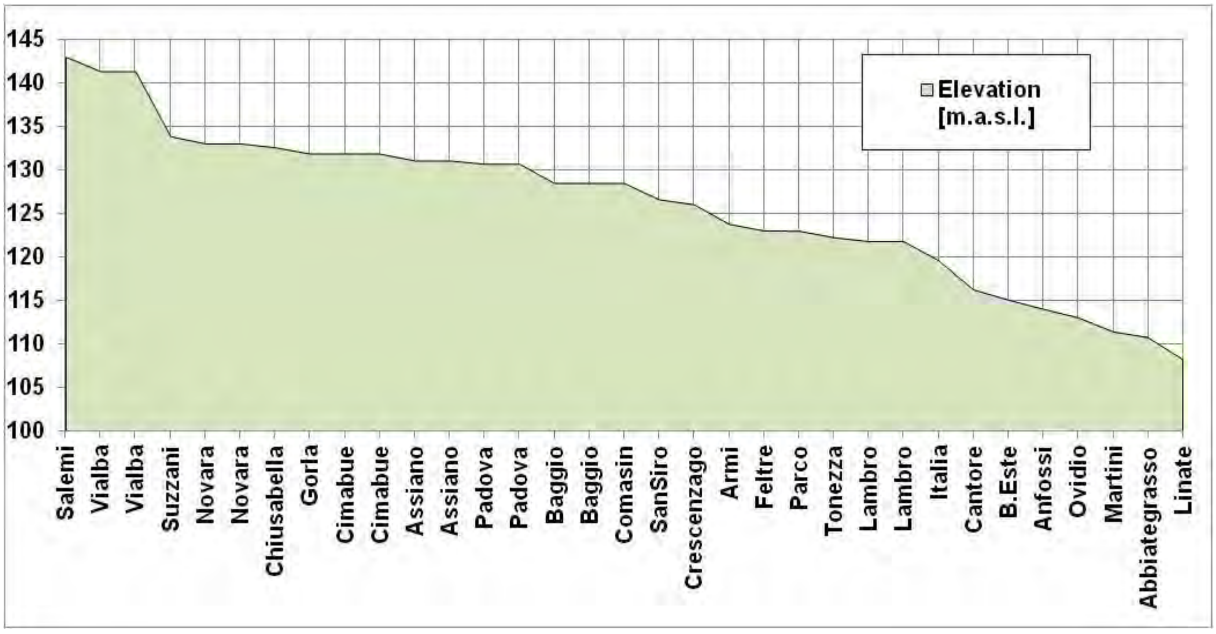


Figure 3-3. Profile view of tanks located in the WDN of Milan (from North-South).

- Daily water production and demands

The total and average daily demand was estimated from historical records. It varies between $7.3 m^3/s \pm 4.0 m^3/s$ on a hourly basis. More than 50,000 customers (among households and industrial) are supplied while the median customer demand is 0.28 l/s. Figure 3-4 presents the demand patterns as demand multipliers, representing proportion of the average demand. Three different demand patterns are identified Spring/Summer (which presents the highest consumption), Fall/Winter (which is obviously delayed 1 hour due to the change between summertime and wintertime), and the Summer Break (prior to *Ferragosto*[4]).

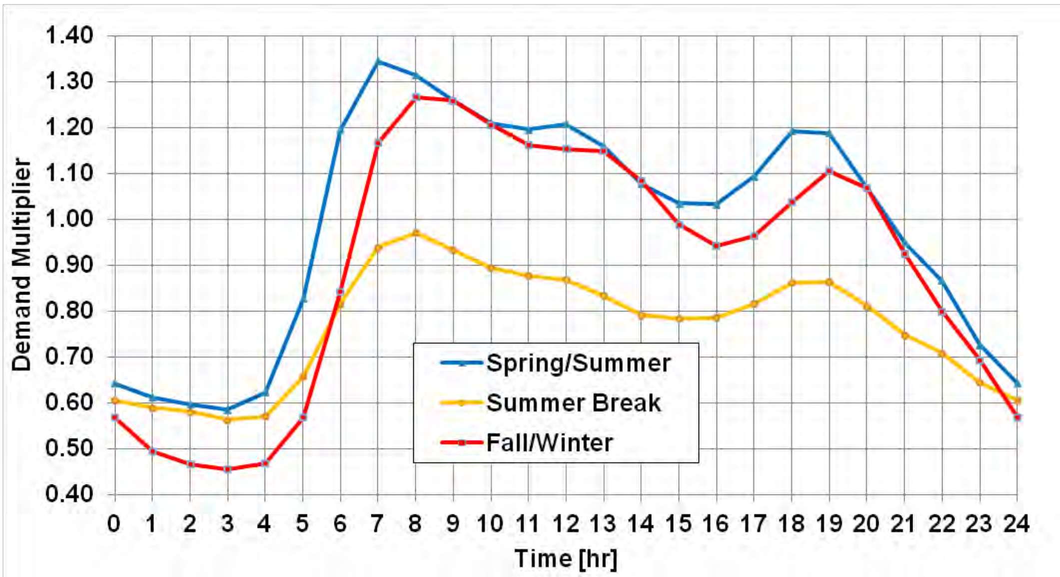


Figure 3-4. Average demand patterns in the city of Milan based on historical records of MM.

- Wells

In total there are 544 wells. However, of these there are only 493 that are active. The groundwater table in the wells changes due to drawdown caused by well pump operation (as well as due to seasonal variations in groundwater recharge). A preliminary analysis of static groundwater levels was used to simulate the water tables, and this was not extended further.

- Storages

The system operates with 33 storage tanks between the WTN and the WDN. From these tanks, only 23 have known volume curves. This accounts for 177,800 m^3 of total storage. For tanks with missing volume curves the total volume has been estimated at 43,400 m^3. The total volume of the system has been estimated at 221,200 m^3 at maximum capacity. However, the actual volume is only 93,300 m^3 due to the minimum and maximum operational levels in the tanks, required at every pumping station. The tanks are located all around the city between elevations 108.22 m.a.s.l. and 143.02 m.a.s.l. (see Figure 3 2). The tank equivalent diameters vary between

[4] It originates from *Feriae Augusti*, the festival of emperor Augustus, who made the 1st of August a day of rest after weeks of hard work on the agricultural sector. Ferragosto became in modern Italy a public holiday which is celebrated on 15 August in all of Italy. As a tradition most people in Milan take their leave of work for holidays at the end of July and beginning of August.

13.0 m and 58.0 m. The ranges of their operational levels are also variable, between 2.45 m and 8.00 m.

- Pipes

The system has 119,118 pipes. Number and total length of pipes per diameter (in the range of 20-1200 mm) are shown in Figure 3-5. The total length of the pipes in the full model of Milan is 2,298 km.

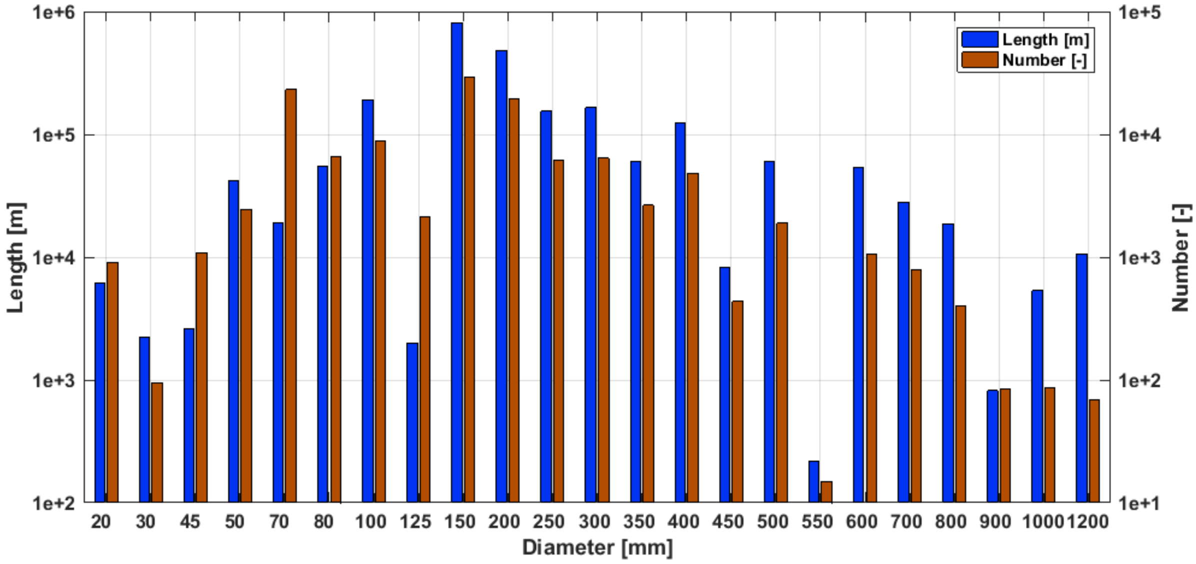


Figure 3-5. Pipe length and pipe total per diameter in Milan system.

- Valves

The WDN of Milan has 36,557 valves. The valve diameters range from 20-1200 mm as presented in Figure 3-6. The most predominant valves are of 70 mm and 150 mm which correspond to 28.8% and 23.5% respectively. Only 6% of the valves have a diameter equal or larger than 350 mm.

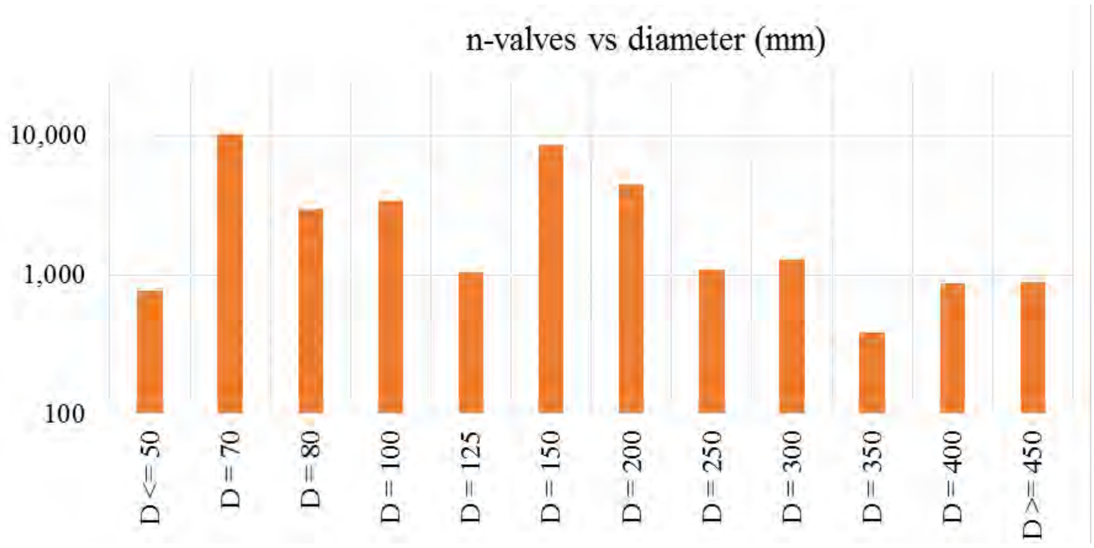


Figure 3-6. Distribution of number of valves per diameter in the model of Milan WDN.

- Time of Day tariffs for consumption of electrical energy

Two different Time of Day (ToD) tariffs were provided by MM for the years 2009 and 2014. These are presented in Figure 3-7. For a full day of operation the new ToD tariff of 2014 has the advantage of being cheaper than the one of 2009.

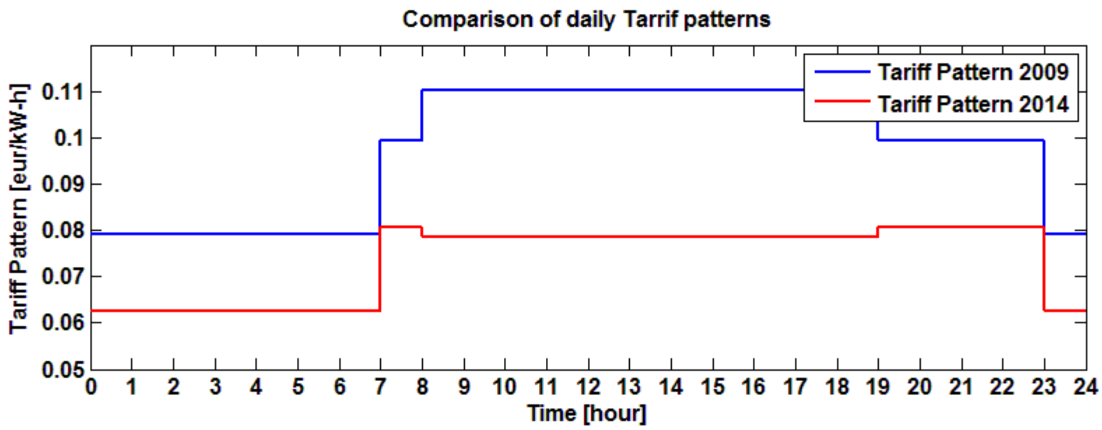


Figure 3-7. ToD electricity tariff patterns for the years 2009 and 2014.

3.1.2 Abbiategrasso

For the purposes of pump scheduling analysis, testing the sensor deployment and the ICeWater components, as well as for gaining experiences with isolating one sector from the whole WDN, a pilot area has been selected, named Abbiategrasso. This pilot area is supplied by a pumping station of the same name and it is located in the southern part of the city (Figure 3-8). This subsystem is considered Pressure Management Zone (PMZ) as most of the interventions are intended for pressure management. Inside this PMZ an area on the north was used for the installation of AMR's, and that one is considered a representative District Metered Area (DMA) within Abbiategrasso.

The booster pumps at Abbiategrasso pumping station draw water from a local ground storage tank, which is fed by a field of 20 wells. Each well is equipped with a well pump supplying water from the well's ground water table to the storage tank via a transmission pipe. The network of transmission pipes connecting well pumps to the storage tank is referred in this thesis as the Water Transmission Network (WTN) of Abbiategrasso. Figure 3-9 presents more precise structure of this WTN. The single ground storage tank is located near Abbiategrasso pumping station and has a storage capacity of about 3,300 m^3.

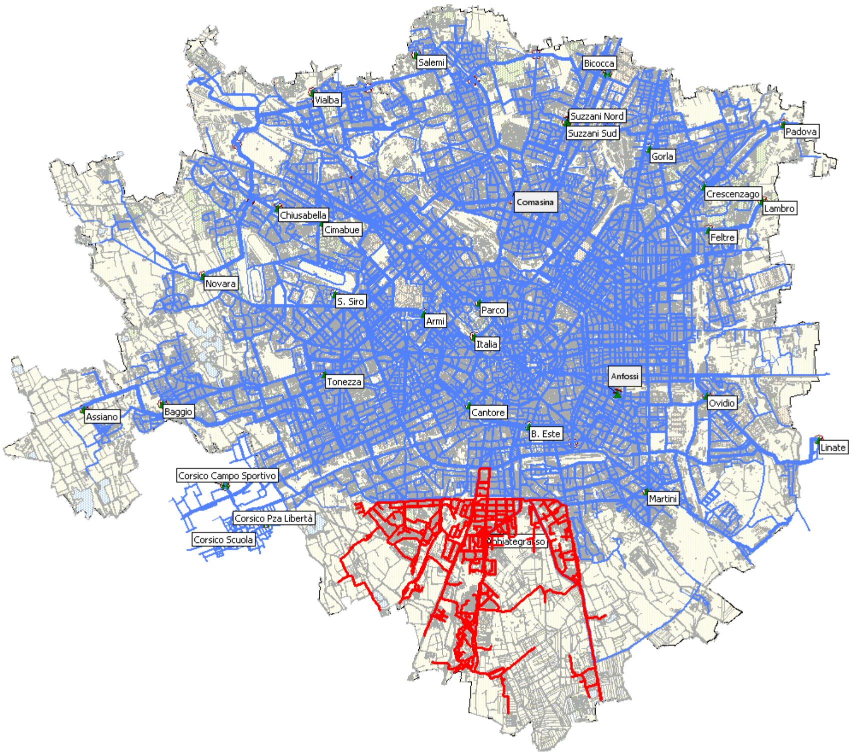


Figure 3-8. Plan view of the Abbiategrasso pilot area (in red) inside of Milan WDN.

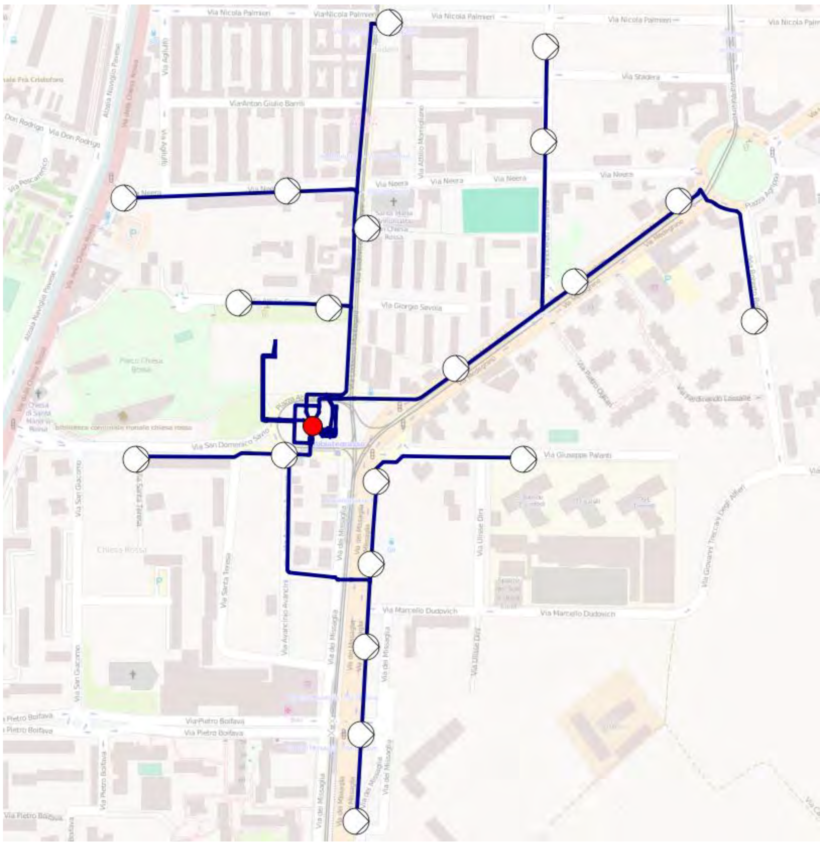


Figure 3-9. WTN in Abbiategrasso (blue), well pumps (white), ground storage tank (red).

More detailed information about the subsystem Abbiategrasso is provided in the following subparagraphs.

- Demands

Two demands time series were available from MM: one for the year 2009 ($D_{b\text{-}2009}$=355 l/s) and another one for year 2014 ($D_{b\text{-}2014}$=367 l/s). However, demands are constantly changing due to the stochastic behaviour of customers. In order to adapt in future conditions, data of demands is available from the AMR devices installed in the Abbiategrasso pilot within ICeWater project. The spatial distribution of the demands is the same for $D_{b\text{-}2009}$ and $D_{b\text{-}2014}$. It is presented on Figure 3-10 below:

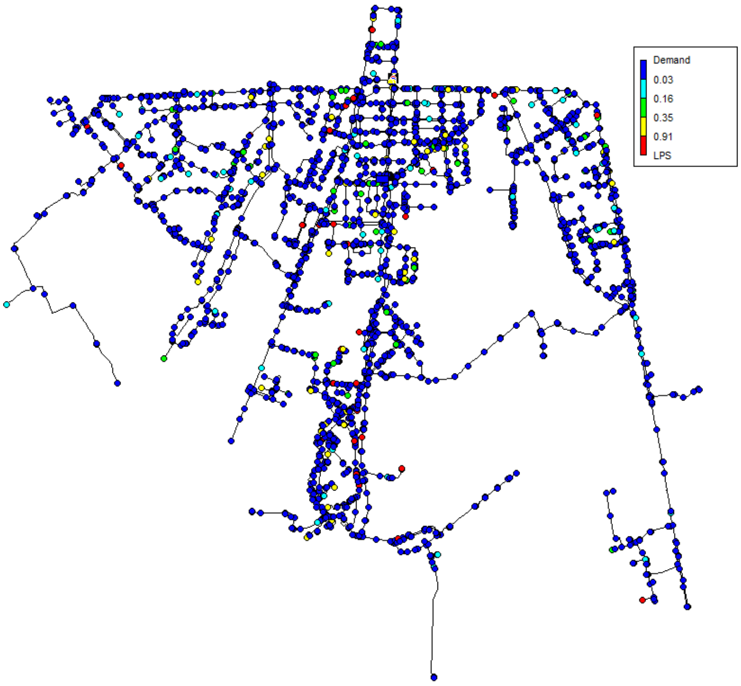


Figure 3-10. Spatial distribution of demands in Abbiategrasso during 2009 and 2014.

The patterns of demand consumption are available at 1 minute resolution. In Figure 3-11, the hourly demands are also specified as: dotted line (···) for the maximum hourly, dashed line (---) for hourly average and dashed-dotted (-.) for minimum hourly demand. In the simulation model, which was run with time step of 1 hour, the maximum hourly demands were used. The system where all demands were stored during the ICeWater project was shut down in 2018, and all data remains kept by the utility in their SCADA system.

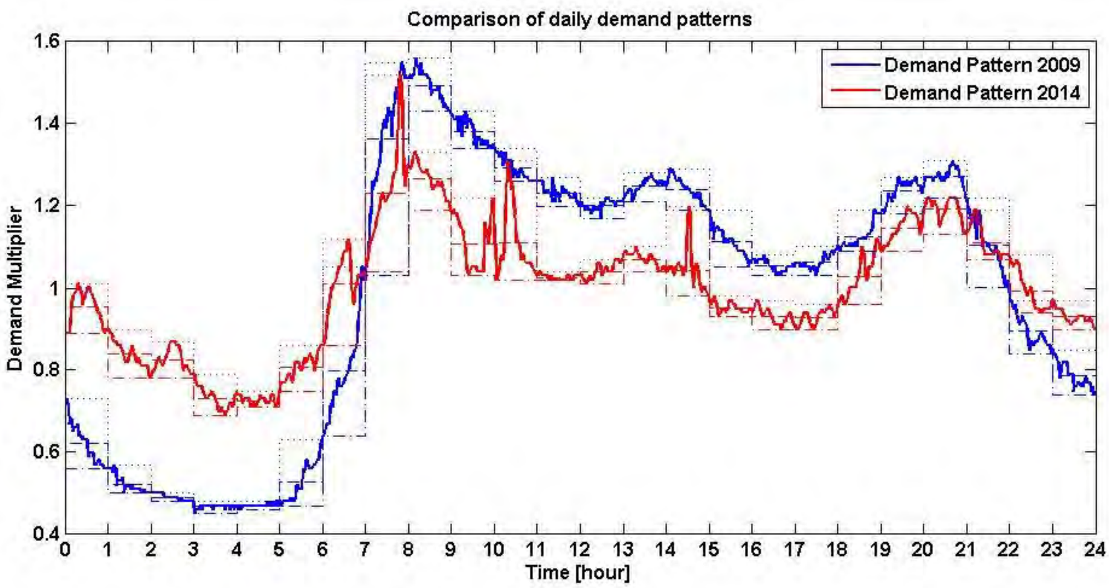


Figure 3-11. Daily demand patterns in Abbiategrasso district at 1 minute resolution

- Wells

There are 20 wells in Abbiategrasso which represent the source for the WTN. Data from sensors was available after the finalization of the project for each of the wells, time series of the dynamic groundwater levels can be used by the utility to better understand groundwater variations in the future.

This research deals only with the model-based optimization of the WDN of Abbiategrasso. The WTN was not taken into account to test the optimized PS optimized, elaborated in later chapters. Mainly because other ICeWater partners were considering well pumps PS optimization as a separate task.

- Storage

The subsystem has one storage tank, which represents the storage tank of Abbiategrasso between the WTN and the WDN. It has a maximum volume of 3,300 m^3. Figure 3-12 shows the linear relationship between tank level and tank volume. Figure 3-13 shows a measured daily tank filling (and emptying) pattern (corresponding to the demand pattern $D_{pt\text{-}2009}$ measured on the 18th of November, 2009).

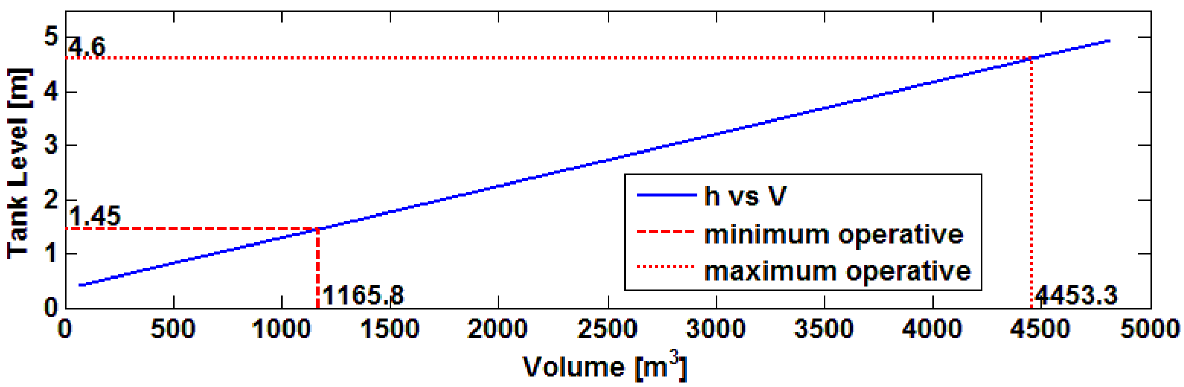


Figure 3-12. Tank level vs volume at Abbiategrasso.

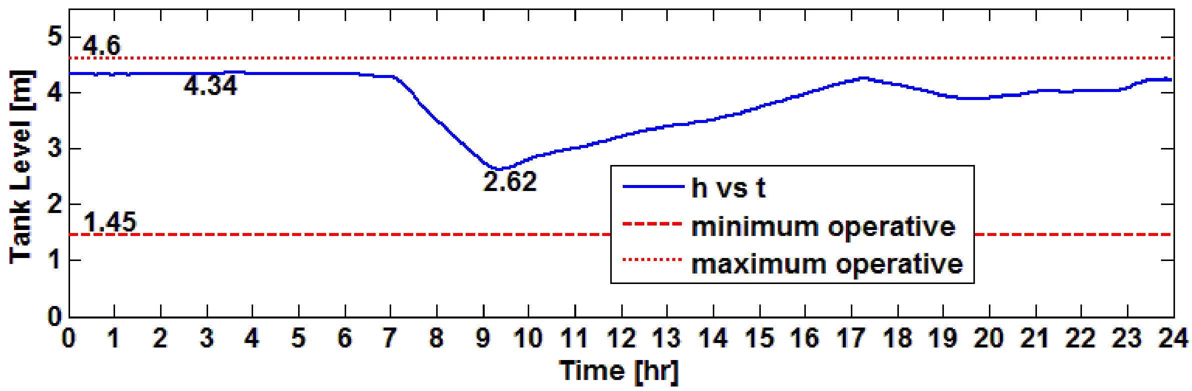


Figure 3-13. Daily tank filling pattern at Abbiategrasso.

- Pipes

The subsystem of Abbiategrasso has 6,073 pipes. Number and total length of pipes per diameter (in the range of 20-900 mm) are shown in Figure 3-14. The total length of the pipes in Abbiategrasso is 127.83 km.

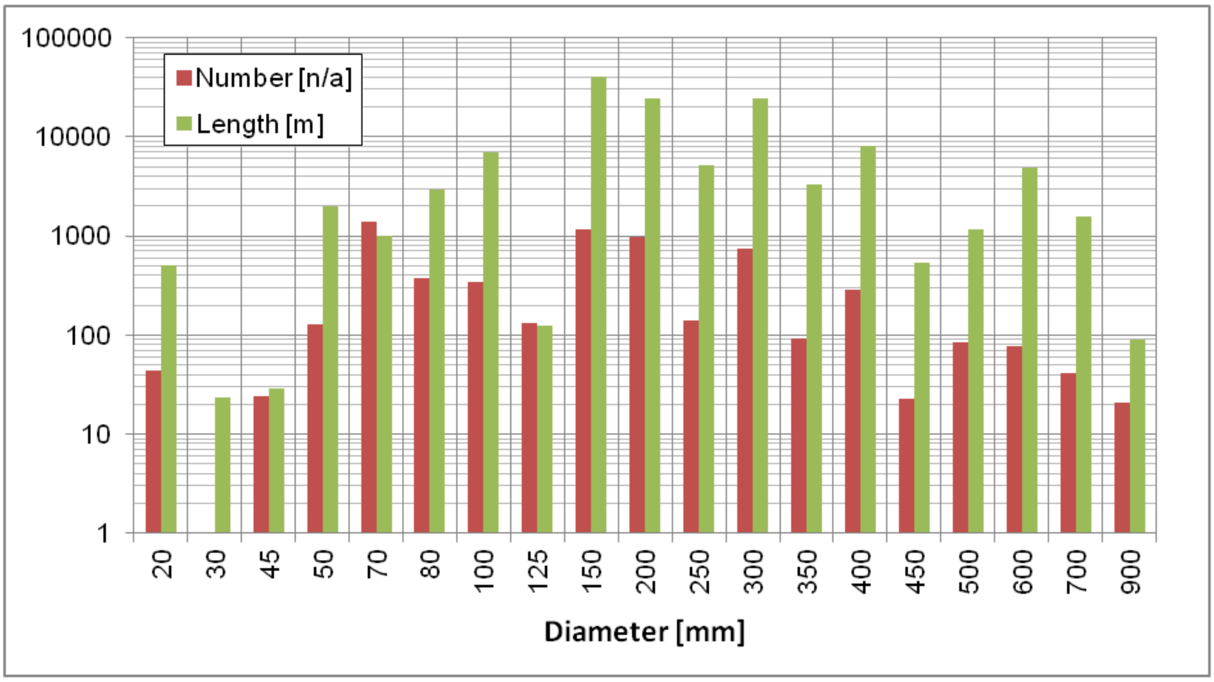


Figure 3-14. Distribution of pipes per diameter: Number of pipes and total length[5].

- Valves

This subsystem has 1,961 valves. Their diameters range from 20-900 mm as presented in Figure 3-15. According to the utility, valves are either completely open or completely closed. After a thorough in-situ verification by operators of MM, it was discovered that in the district five valves were closed, all of them located in the WTN.

[5] There is only one pipe with D=30 mm.

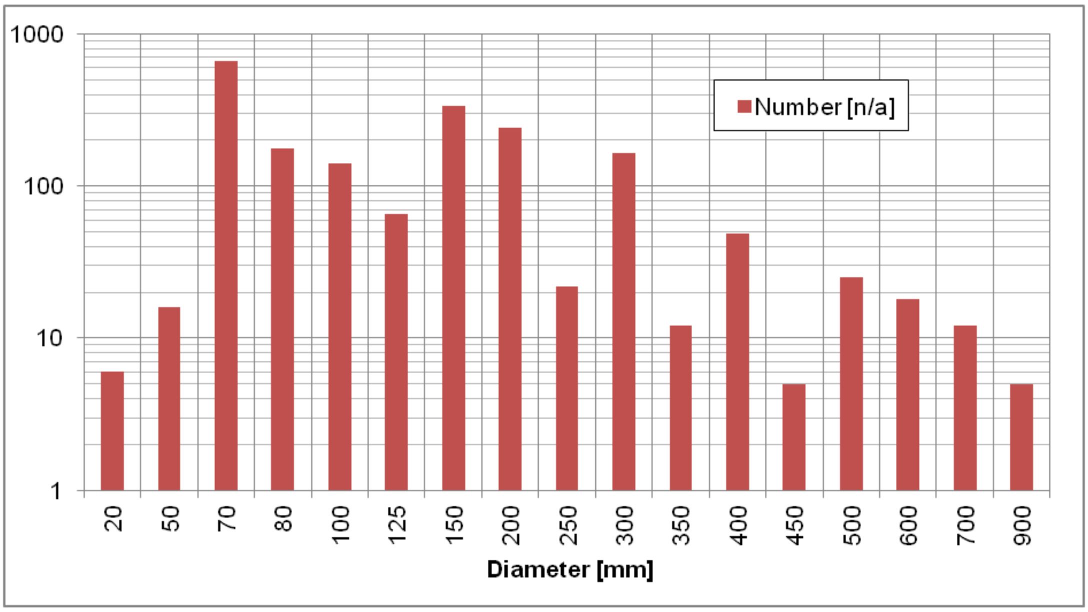


Figure 3-15. Distribution of number of valves per diameter in the model.

- Pumps

The subsystem contains 24 pumps. There are 20 well pumps, and 4 booster pumps. The new system configuration, which was developed within the ICeWater project, had two of the booster pumps replaced by new pumps, which were equipped with variable speed drives and worked as VSPs. For the pumps, the following data was available:

- H-Q curves of all 20 well pumps
- H-Q curves for the 4 booster pumps (old system)
- H-Q curves for the 2 new booster pumps (new system)
- Efficiency curves of the 2 new booster pumps (new system)

Efficiency curves of the old system (both well pumps and booster pumps) were not available. A constant pump efficiency of 75% was assumed.

An example H-Q curve for one of the well pumps is provided in Figure 3-16. However, as it will be presented in Chapter 6, setup for WDN is prepared with both the old and the new configuration with respect to the booster pumps. Figure 3-17, presents the head-flow curves related to the booster pumps.

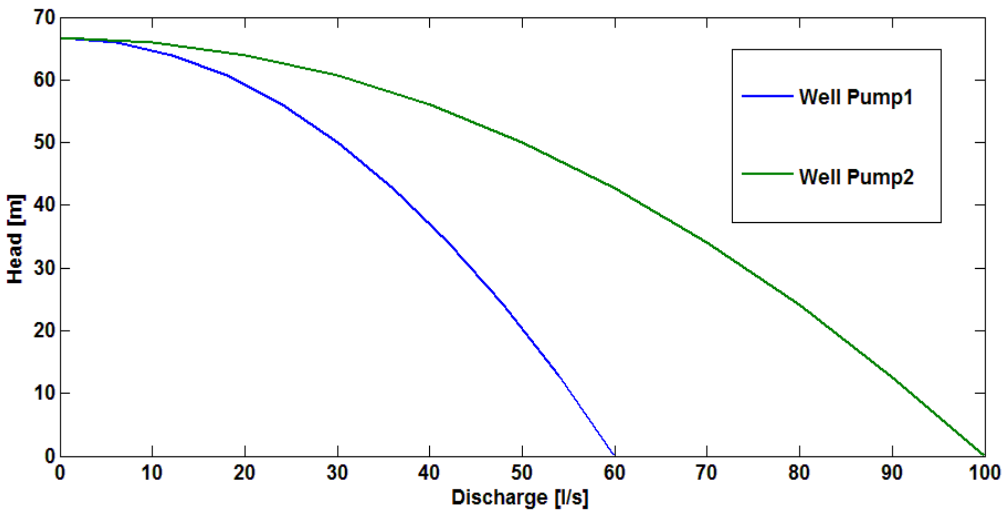


Figure 3-16. Example H-Q curves for two of the 20 well pumps.

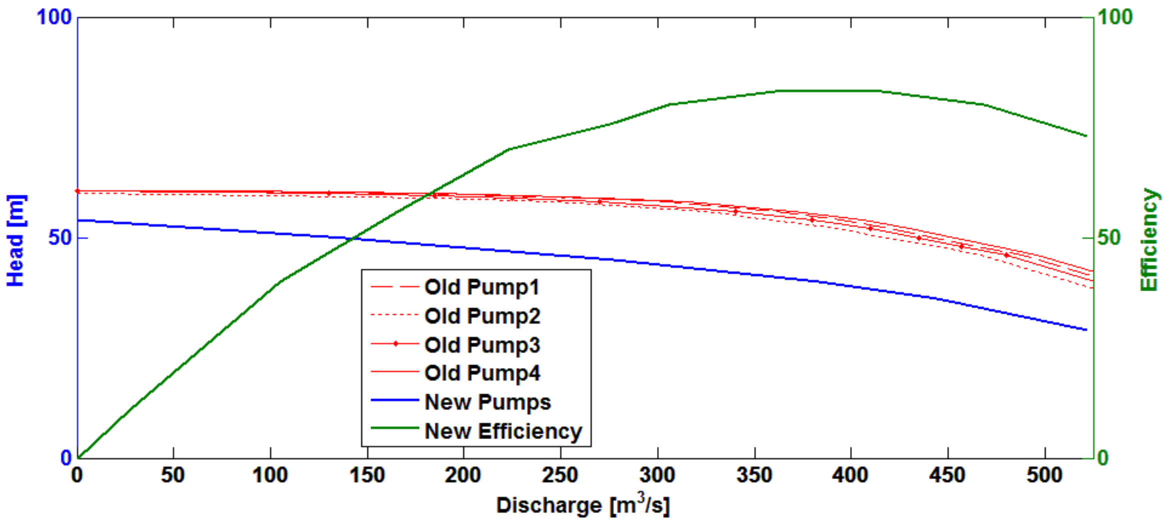


Figure 3-17. Head curve and efficiency curve of the old and new booster pumps in Abbiategrasso.

3.2 IT infrastructure for managing the water supply system

In order to test the capabilities introduced by the ICeWater research several implementations came into place in the city of Milan / the Abbiategrasso pilot. Up to 2013, the data of pumps and wells, and treatment plants was integrated in a Supervisory Control and Data Aquisition (SCADA) system, which was available for the purposes of this research. Pressure loggers, volume meters, two new pumps with Pressure Regulating Valves (PRV) and Automated Meter Readers (AMR) were installed between 2013 and 2015 See Table 3-1 for more details on the elements installed in Abbiategrasso.

a. Abbiategrasso pump inverters

b. PRV chamber, from above

c. PRV chamber, from inside

Figure 3-18. Diagram of installation of the inverters and Pressure Regulating Valve (PRV) chamber for managing the 2 new Variable Speed Pumps (VSP) in Abbiategrasso. Such installation was made in order to improve and test the pump scheduling approach. a) location of inverters for the old system (ON/OFF pumps) and the new one (VSP pumps), b) PRV chamber under construction, and c) PRV chamber after performing installation.

Table 3-1. Other sensors installed in Abbiategrasso during ICeWater project.

Class	Unit	Quantity	Acronym	Location	Brand/Model
Level sensor	m	20	PTP	Wells	BCM LV36
Flow meter	m^3/s	20	PTP	Wells	ISOIL MS2500 | ISOIL ML250
		5	PTRP	Transmission	
		2	PCC	DMA	
		2	PCPRV	DMA	
Pressure sensor	m	20	PTP	Wells	Nuova Firma ST18 | BCM 131S
		5	PTRP	Transmission	
		12	PTM	PMZ*	
		2	PCC	DMA	
		4	PCPRV	DMA	
Smart water meter	l/s	64	AMR	DMA	-
Noise logger	dB	20	-	DMA	Primayer Phocus.sms

DMA: District Metered Area; PMZ: Pressure Management Zone; dB: decibels. *The location of this sensors is presented in Chapter 5.

In addition, it was required to isolate the sector from other parts of the Full WDN. For that purpose the valves which isolate the sector were identified through field measurements and additional valves which were required were installed. This allowed the operator to perform the tasks of pump scheduling testing, but also, in case of requiring to perform maintenance of the pumps in Abbiategrasso, the supply could be performed entirely from the North of the city. Three different segments of Abbiategrasso were intervened: Abbiategrasso-Center, Abbiategrasso-West and Abbiategrasso-East (see Figure 3-19).

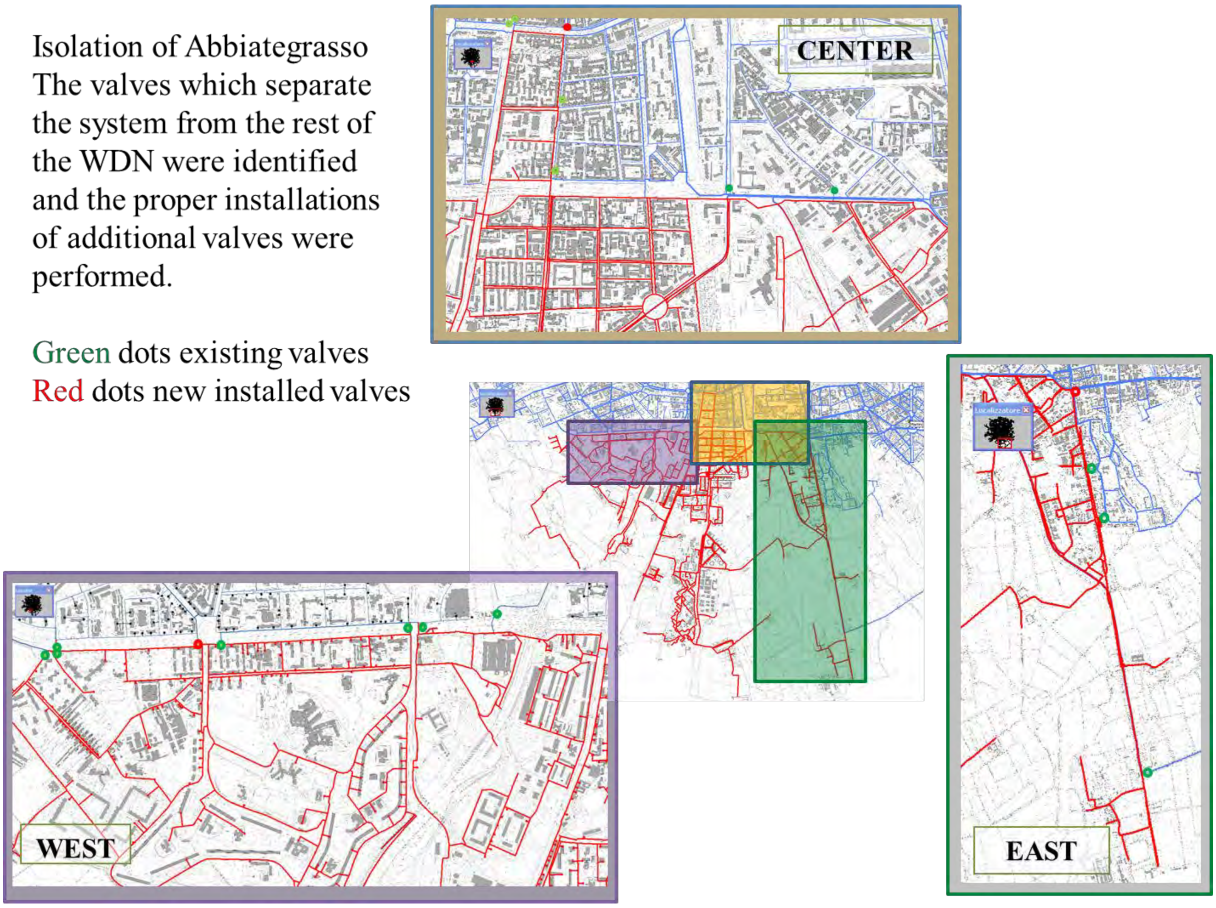


Figure 3-19. Interventions performed to isolate Abbiategrasso from the rest of the system when necessary.

At the start of ICeWater project and of this research, the pump schedules of the system where mainly handled by operators on the field based on experience. As such, there was no integrated approach towards global system operation. The two new pumps installed, in 2014 are presented in Figure 3-18. This allows for the comparison of the old pump scheduling approach with ON/OFF pumps, versus a more modern and reliable Variable Speed Pumps (VSP) approach. By the beginning of 2014, MM has also integrated measurement of sensors presented in Table 3-1. An additional calibration process of the WDN models was performed using such data from the SCADA system from 14th November of 2014. In fact, the operators become more aware of the advantages of a simulation-optimization approach for decision making.

3.3 Summary

According to the operators of MM, most of the pipe breaks during the last 15 years have been caused due to the increase of pressure in the system. More specifically, the southern part of the system where the pumping station of Abbiategrasso is located, is characterized with this problem. As will be presented in the following chapters, efficient pressure management plays a key role to avoid this. For purposes of this research, as well as for improved operations in future, the isolation of Abbiategrasso brought for two important benefits:

1) It offered a case study for field tests of pump scheduling. Most utilities are very reluctant to transform the form in which they operate their systems. There is a tacit mentality among operators that dictates *"if it is not broken, do not try to fix it"*. However, it is impossible to perform innovation on water resources management without interventions on the field.
2) It serves to the operator as an experience to recreate the splitting of the system into sectors. Not having prior experience isolating a sector of the city is challenging. The understanding of the actions to take place, in order to perform further isolation of sectors within the whole WDN of Milan, without disturbing customer supply can foster a better water management.

4 METHODOLOGICAL FRAMEWORK

The methodology presented here comprises several different components. Broadly, it has been implemented as a model-based MOO. In the following chapters the simulation model and optimization algorithms are presented in detail. Here only the general formulations of the optimization problems are addressed.

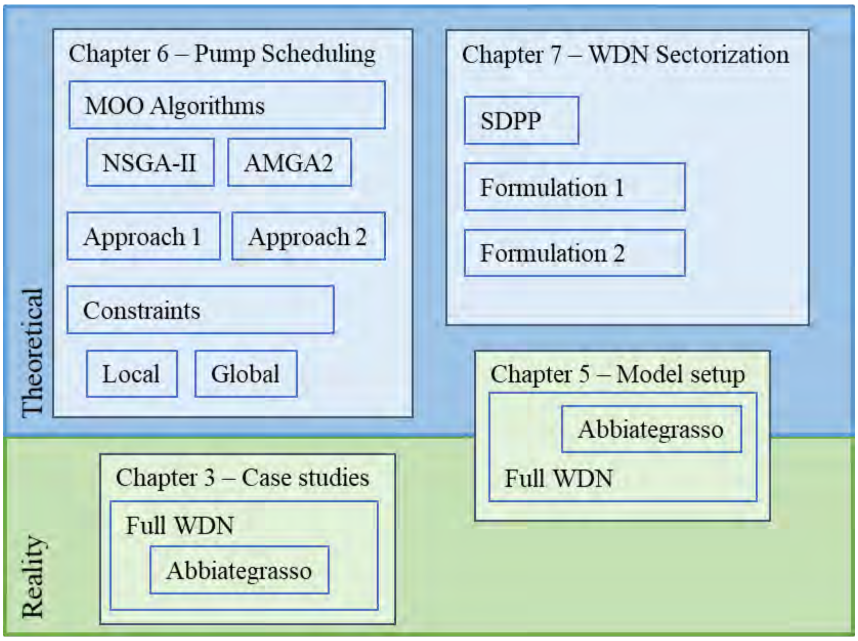


Figure 4-1. Links between theoretical formulations of this research and reality (practical) aspects for implementation in large WDN.

The methodology can be split in two different blocks: one with theoretical aspects (blue) and another with real and practical (green) aspects (see Figure 4-1). For the theoretical blocks, the methodology includes several distinct aspects of optimization for both pump scheduling and sectorization of large WDNs. Most important aspects for both of these subjects have already been introduced in Chapter 2 - Literature Review. For sectorization, relevant aspects of graph theory are very briefly introduced in the following section. The cases studies belong completely to the real and practical aspects of this research. Chapter 3 – Case studies, introduces the practical aspects of each case study and why different methods are used for each case study. It is a presentation of the existing problematic and available information in each case. In Chapter 5- Model setup, the required setup of each of the case studies, as WDN models. For the application of the methodology is described for the period of 2014-2016 a combination of theoretical and practical aspects are presented. Chapter 6 – Pump Scheduling presents the application of this methodology for energy consumption reduction in the two different case studies. Chapter 7 – WDN Sectorization, introduces the different results obtained by performing sectorization with two different formulations, only for the case study of Full WDN

Milano. In both cases, the results correspond to theoretical model-based optimization formulations, however the results also highlight different options in the form of possible WDN configurations for pump scheduling and sectorization to be used in actual systems.

4.1 WDN as a graph

For solving the problem of Sectorization a graph formulation of the WDN of Milan has been used. It has been applied initially to identify a set of cut-set valves which allows splitting the system into smaller subsectors by means of a shortest path algorithm. Such algorithm has been adapted to the case in which the sources are dependent on pumping stations and not solely on gravity sources, based on the head losses of the pipes and valves. This is what is known as Shortest Dissipated Power Path (SDPP).

In the second formulation of sectorization an additional graph theory abstraction is made to create larger sectors from previously identified subsectors. All of the analysis were done using MATLAB® which facilitates greatly the graph theoretical analysis. The reader will find the presentation of this content in Chapter 7.

4.2 Simulation models

In order to perform model-based optimization EPANET 2.0 was used (Rossman, 2000). This software is the most broadly used tool for decision support of pressurized water supply systems. The argument for the need to use a PDA instead of DDA can be override by the fact that the system of Milan operates at pressures much larger than 20 m of column of water. For that reason a DDA is used throughout this research. For more information on the different hydraulic paradigms for WDN modelling the author refers the reader to §2.1.2, and for the mathematical formulations of the algorithm of solution of WDN to §2.1.3 and §2.1.4.

An executable of the simulation run was built using C/C++ for the case of pump scheduling and for sectorization as well. This reduces the time of computation with respect to other programming languages for which wrappers are available.

4.3 General description of Optimization problems

Life is made of choices, sometimes you make good choices and sometimes you make bad choices and always our decisions are biased. In physical systems it is possible to formulate mathematically decisions to be made and define criteria to evaluate the outcome. When dealing with multiple criteria there is the possibility to select among many multiple solutions among which there is a pre-existent trade-off. One cannot just improve a criterion, without decreasing one of the many others considered for quantification of the decision made. It is impossible (in most cases) to propose a decision which satisfies all of the considered criteria for the better. When this happens there is a complete branch of mathematics known as Multi-Objective Optimization which could be used for this purpose. A typical mathematical formulation of a Multi-Objective Optimization (MOO) for a problem with *M* criteria is defined as:

$$
\begin{aligned}
&minimize\ F(x) = \{f_1(x), f_1(x), \dots, f_M(x)\}\\
&x \in \Omega\\
&subject\ to\ \begin{cases} G_i(x) = 0, & \forall_i \in n_{eq} \\ H_j(x) \leq 0, & \forall_j \in n_{ineq} \\ x_{min} \leq x \leq x_{max} \end{cases}
\end{aligned}
$$

Equation 4-1. General mathematical formulation of a MOO problem.

Where, x = is a vector of decision variables, Ω is the decision space. Here, $F(x)$ is the vector of criteria or objective functions. The set of constraints is $G_i(x)$ and $H_j(x)$, where n_{eq} and n_{ineq} are the number of equalities and inequalities of the problem respectively. Here x_{min} and x_{max} are the minimum and maximum values which can be given to each decision x.
The optimality of different decisions is expressed in the form of a Pareto set, or a Pareto front generated in the objectives space. It is said also that among two different objectives F_A and F_B, F_A dominates F_B, if and only if $\forall i \in 1,2,\ldots,M$, $F_A \leq F_B$. This is usually expressed as $F_A \prec F_B$, where the symbol $\prec$ is read as dominates (see Figure 4-2 for a simplified example with three decision variables and two objective functions). When using MOO algorithms the convergence is obtained by improving progressively the Pareto dominance among objectives or until some pre-defined number of function evaluations is reached.

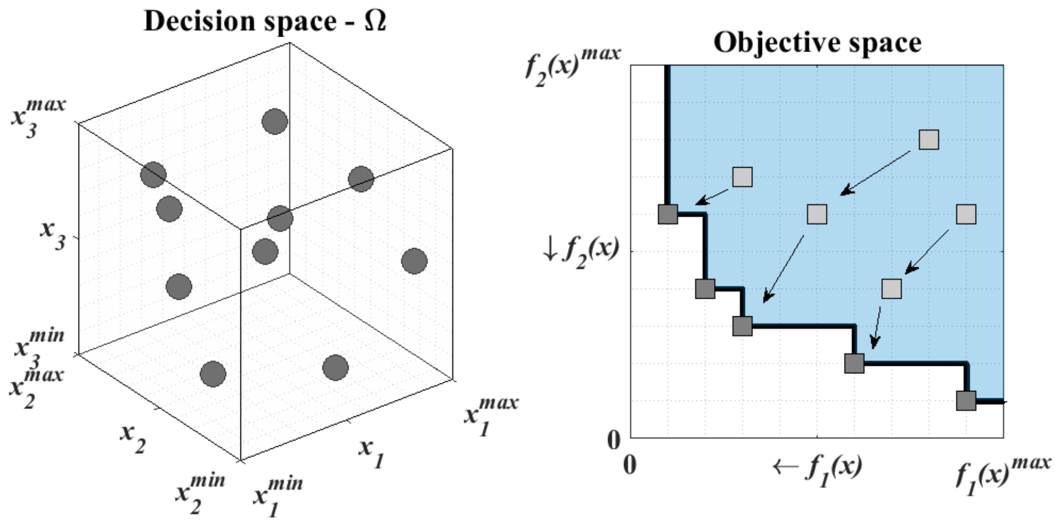


Figure 4-2. Simplified visualization of the decision space and the objective space in a multi-objective optimization formulation. (Left) scatter of decision variables (3) for each solution a function evaluation is performed. For each solution (circle) there is a corresponding point on the objective space. (Right) scatter of the objective functions (2) where both of them are set for minimization. There are 5 solutions which dominate the other 5. The line connecting the most dominant solutions is known as Pareto front.

4.4 Optimization Algorithms

In general, a model-based MOO for WDN follows the procedure of Figure 4-3, where three different blocks are required. The first block corresponds to the pre-processing of the WDN models, the second block correspond to the MOO coupling of optimization algorithm with simulation model, and the third block corresponds to post-processing made to select the solutions.

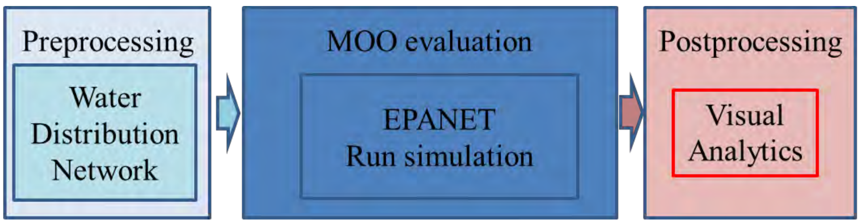


Figure 4-3. Flowchart of Model based MOO for WDN, preprocessing, simulation and postprocessing.

4.4.1 Preprocessing

The preprocessing allows to generate the right setup files and hydraulic input files which are required during optimization. In the case of pump scheduling problem a pre-processing of the WDN is made to match the old system with ON/OFF pumps in Abbiategrasso and for Full WDN. When discussions are made about the new system the setup is made such that the hydraulics can make use of Variable Speed Pumps (VSP) in Abbiategrasso. When the sectorization problems are addressed the preprocessing contains a list of preselected valves for opening or closing. Closing valves is set in two different formulations as it will be presented in §7.2.

4.4.2 MOO evaluation

The second block corresponds to the evaluation of the MOO. For this the objective functions are evaluated from a compiled executable created in C/C++ as it was discussed in §4.2.
For this research two different heuristic MOO algorithms are used. First is NSGA-II which has been applied throughout as presented in Chapter 6 and Chapter 7, and AMGA2 which has been applied only in Chapter 6. Both algorithms can be categorised as randomized search algorithms being NSGA-II a legacy algorithm, while AMGA2 is a more recent algorithm.

NSGAII	AMGA2
Initialize a population P_t of size *N,* $R_t = P_t \cup Q_t$, combine parent (P_t) and offspring (Q_t) population $\mathcal{F}$ = non-dominated sort of R_t $P_{t+1} = empty$ and $i = 1$ Until $\|P_{t+1}\| + \mathcal{F}_i$, the parent population is filled - calculate crowding-distance in $\mathcal{F}_i$ - $P_{t+1} = P_{t+1} + \mathcal{F}_i$ include i_{th} nondominated front in the parent population - $i = i + 1$, check the next front for inclusion Termination Sort ($\mathcal{F}_i \prec_n$) in descending order using $\prec_n$ $P_{t+1} = P_{t+1} \cup \mathcal{F}_i[1: N - P_{t+1}]$, choose the first $N - P_{t+1}$ elements of $\mathcal{F}_i$ Q_{t+1} = make new pop (P_{t+1}), use selection, crossover and mutation a new population Q_{t+1} $t = t + 1$, increment the generation counter	Initialize a population P_t of size *N,* $R_t = P_t \cup Q_t$, update archive (R_t) from initial population P_t. Until - $R_t = P_t$, create parent (P_t) population from (R_t), use for mating pool - Create offspring population P_{t+1} from the mating pool. Crossover followed by mutation. Then evaluate P_{t+1}. - $R_{t+1} = R_{t+1} \cup P_{t+1}$, update the archive. Using $\mathcal{F}$ = non-dominated sort of R_t Termination Report *N,* desired number of solutions from the archive

Figure 4-4. Pseudocode of both MOO algorithms used on this research.

For the cases of pump scheduling the use of NSGAII is not novel, while the use of AMGA2 is. The application of new optimization algorithms is of relevance as time of computation in larger WDN tend to increase exponentially. Any reduction in the total time that would be necessary to provide the right decision in a water supply system can greatly improve operations. The drawback on the use of AMGA2 is the fact that Binary decision variables are not suitable, while this is not the case of Real decision variables as presented in Chapter 6. In addition, the Sectorization problem is a planning problem for long term operations in a WDN, the computation time gains of AMGA2 are not really cumbersome, when compared with the objective function evaluations. In the Pump Scheduling and Sectorization of Full Milano WDN the evaluation is computationally expensive. For that reason, the analysis in Chapter 7 and beyond are performed only with NSGA-II.

Decision variables

For the pump scheduling optimization there are two types of variables which are considered, namely Real and Binary. Real corresponds to the pump speed of each pump in the system in the range of {0.70; 1.00}, this type of variable has been applied to VSPs. Binary {1; 0} corresponds to the simple case when pumps are either active/inactive: ON/OFF as the pump switches of the current pumping system.
In the case of sectorization, decision variables are Binary {1; 0}, corresponding to isolation valves, in this case only two settings are allowed for each valve, valves open or valves closed.

Objective functions and performance criteria.

Two different objectives are used throughout this research as the focus is on energy minimization and pressure management respectively. For that reason the total energy consumption (E_T) is considered, while for the pressure management the resilience index (I_R) is used (Todini, Looped Water Distribution Networks design using a resilience index based heuristic approach, 2000), expressed as Lack of Resilience ($1-I_R$).
In addition, for the case of pump scheduling of the Full WDN of Milan and the sectorization, 3 different performance criteria (PC) are also taken into account, namely minimum pressure (*Pmin*), maximum pressure (*Pmax*) and average pressure (*aveP*) in the whole system.
One aspect of importance is that for sectorization, what is named as Formulation 2, corresponds to a non-exhaustive search as only some optimization cases are performed. This is necessary as the number of possible sectorization cases grows exponentially with the number of final sectors to be created and number of possible scenarios of sectorization.

4.4.3 Post-processing

When running MOO two different aspects are considered. First of all, how to best organize and present the multitude of generated results (e.g. decision variables, objectives, performance criteria and constraints), secondly, which of the solutions available to select and recommend for possible implementation. In both cases, the analysis is made using the Visual Analytics for Multi-Objective Optimization Solutions (VAM**OS**) developed by the author and available on GitHub. The main aspects and references of the methods included in the library are presented in Table 4-1. This methods have been specifically applied for both optimization results of Pump Scheduling and of Sectorization.

4.5 Summary

This chapter presented the main methodological framework of the research, including different aspects of Multi-Objective Optimization and decision making for selection of solutions. More specific aspects for each problem formulation, namely pump scheduling and sectorization, are presented in Chapters 6 and Chapter 7. The following Chapter 5, focuses on the different models created for pre-processing to be applied during the MOO for each of the case studies.

Table 4-1. List of visualizations performed using VAMOS library in this research.

Visualisation	Description	References
Scatter2D	Visualization of the evolution of the objective function evaluations as a function of the different objectives and other performance criteria. Classified by color and by size.	(Miettinen, 2014) (Tukey & Tukey, 1981a) (Tukey & Tukey, 1981b).
Scatter3D	Visualisation of the evolution of the objective function evaluations as a function of the different objectives and other performance criteria. Classified by color and by size.	(Woodruff, et al., 2013) (Shah, et al., 2011) (Fu, et al., 2013)
Parallel Plot	Visualization of the evolution of objective function evaluations as trajectories. It serves to check trade-offs among objectives and performance criteria. If a MOO problem is set as minimization the best possible scenario is that all the objectives would acquire the minimum value resulting in an horizontal line. However this is not possible.	(Inselberg, 1985)
Trade-off Index (λ)	In order to be able to identify trade-offs among solutions, the last 2,000-3,000 function evaluations are selected and the Trade-off Index is estimated. Trade-off index is a measure of the percentage of trade-offs among individual solutions in MOO. A large value of λ (close to 1.0) indicates that the solutions between 2 criteria display a significant trade-off. Otherwise low λ values indicate that the two objectives or criteria are significantly correlated.	(Unal, et al., 2016)
Level diagrams	Visualization of unbiased selection of the best possible solution(s) among a large set of solutions, where a high dimensional objective space is reduced to a single criteria using either 1-norm or Euclidian norm.	(Blasco, et al., 2008)
Hyper-Radial Visualization (HRV)	Visualization of unbiased selection of solutions using Hyper-Radius. This corresponds to a full comparison of possible Euclidean norms of subsets of objectives (and criteria) via permutation. The analysis performs a total enumeration to display the solution indexes which present a higher relevance independent of the combination of objectives or criteria.	(Chiu & Bloebaum, 2008)

Visualisation	**Description**	**References**
Dendrogram with Hamming distance	Visualization of simultaneous pump schedules and Pareto front. In order to estimate the difference in pump schedules between the different solutions obtained in the Pareto front of a particular run, a dendrogram is calculated based on a distance between elements of the pump schedules using Hamming distance.	(Morse, 1980) (Hamming, 1950)

5 HYDRAULIC MODEL SETUP

Most developments for WDNs modelling purposes refer to optimization approaches for design, rehabilitation or operation. However, most case studies presented in the literature are rather small and represent only a small portion or simplification of a network. The WDN of Milan is an example where many phenomena occur simultaneously and where the deeper understanding of the underlying daily and long term operations is required. The main goal of this research is identifying operational strategies leading to reduction of energy consumption in Milan, using Multi-Objective Optimization (MOO) on a model of the system. While sectorization will be applied to the Full WDN, the pump scheduling was broadly tested in Abbiategrasso model.

Until 2012, the system of Milan operated as a single Pressure Management Zone (PMZ), limiting the amount of energy that can be saved on a daily basis. For this reason, in 2012, MM agreed to develop a new EPANET model of their system, under the framework of ICeWater project. Such model for the WDN of the city of Milan was developed between MM and IHE Delft Institute for Water Education (in 2012 named UNESCO-IHE), during 2012-2015. Several sources of information were used, presenting additional challenges for both parties involved. This chapter presents not only the process of model building, but also the challenges for the calibration process, open issues and tasks to be developed in future.

This Chapter is based on the following publication:

- Castro Gama, M., Lanfranchi, E.A., Pan, Q., Jonoski, A. (2015) Water distribution network model building, case study: Milan, Italy. Procedia Engineering. Proceedings of the 13th International Conference on Computing and Control for the Water Industry, CCWI2015. 119(2015)573–582.

5.1 Model Building

With the investment of utilities in Geographical Information Systems (GIS), for management and visualization of their WDN, the number of elements in a network increases and operational rules become more complex (Savic & Banyard, 2011). However, in most cases, WDN simulation deals with a simplification of the real systems or with a limited number of pipes, pumps and sources.

Literature reviewed up to August 2017 for model development shows the model developed in collaboration with MM was the largest model implementation based on real data. Some test cases and benchmark problems are larger, however these are built based on idealizations of larger systems adding intermediate demand nodes. Given the increase in computational capabilities available, it is suggested that this model will be just one of many which will be used as decision support tools for real systems. After 2018, through personal communications it was established with many utilities that manage even larger models. In most cases different utilities have non-calibrated models with a larger number of elements. The landscape of model

development is rapidly changing as many more utilities realize the importance of keeping their models updated on an annual or bi-annual frequency.
When building a model of any WDN it is necessary to collect much information regarding the elements and assets that compose the system. In the case of Milan, most data has been integrated in GIS geo-database (DB) by the IT division of MM. This division is in charge of updating the DB as soon as new elements are identified. For example, if the construction of a new residential complex was approved by the municipality, the drawings of the corresponding connections are available for MM. Since 2013, a system is being implemented for Asset Management denominated MAXIMO, so it was responsibility of the author to export and import its data into a WDN model as soon as it was available. Most of the data were available in DB's from MM and it was converted into the simple but reliable EPANET data model.
From a research perspective it was necessary to portray the WSS of Milano as accurate as possible. For this reason, results of the calibration in the most critical zone of the system (Abbiategrasso) are presented. This particular area is of interest as it is the focus of the pump scheduling. This guaranteed that the results obtained through MOO can be meaningful for the operators of the real system. Also, in case that other researchers want to investigate the behaviour of this particular WDN, the models will allow for replicability of results. Given the age of the pipes in some parts of the city dating to beginning of last century, some limitations are also present in the development of WDN models.

5.1.1 Data sharing

The first hurdle in the development of such model was the confidence among institutions which allows data sharing and clear ways for communication among managers, operators, researchers, IT developers, hydroinformaticians and technical staff on the field, to deliver information that added value to the model. In this category, contractors were also in the loop, given that the utility had, at the time of ICeWater project, special requirements for sensors and equipment installation. There was also an additional factor, namely the security of the data.
As an example, the information of an early version of the topology of the network was leaked. Although it was used only for research purposes, it still opens the question of what would have happened if there was ill intent on the people who stole this information.
Another example of this is the data on billing and demand consumption, which is fundamental information for the commercial division of a utility, but must not become open for obvious reasons.
A third example in the data sharing privacy is the extreme case of terrorism treat to the system. Critical assets and pumping station locations in the WDN, may create a vulnerability for a whole city.
The second aspect of data sharing, for purposes of model building, was the early stage negotiation and definition of standards of data and models. While MM has invested in Infoworks WS software tools[6] for WDN modelling purposes, it was of the interest of research to use open software as much as possible. For this reason, the final decision was to develop together all models in EPANET. This change of philosophy increases the challenges because some features are not the same in the two software packages (e.g. valves are nodes in Infoworks

[6] Commercial software produced by Innovyze (http://www.innovyze.com)

WS, while in EPANET are considered links), although their hydraulic solvers are similar. The advantage of such decision is that both research and the operators at MM, do not require additional licenses to make models run, they have a common ground to establish communication of flaws, topological errors, and are able to perform future implementations and elaborate new outcomes. In case that the utility decides to participate in new research projects, the data will be ready for use by others in a common data standard.

A third example of data sharing among partners was the case of communication of sensor data for model developers. The standard selected for data sharing was WaterML2.0[7] and SensorML2.0[8]. Some adaptations were required to both standards, because neither of them contained some variables related to WSS equipment. As a consequence, some variables in the standards were added. In this way, it was possible to fetch and modify raw sensor data in a clear way. Since there is a documented standard and source codes to read WaterML and SensorML file schemas it is possible then to generate scripts for the extraction and extensibility of such standards.

The disadvantage of such approach is that the mark-up languages (xml files) present a challenge to the network transfer queue and hardware involved in ICeWater infrastructure, due to the large size of files to be generated. For example, a file containing the data of measurements of pressure or flows in a particular part of the network, with a time resolution of 1 min for a total observed period of 9 months has an approximate size of 75 Mb. As it is required to process data from multiple sensors, as it was the case of this research, then the network with the sensors gets saturated. As an extrapolation of such system for fetching and exchanging data during a continuous operation for the coming ten years, will force a user to fetch the same data of that particular set of sensors installed during ICeWater project with a requirement of ~1.0 Gb of storage (for a single sensor). In this case, data available chases Moore's law and the amount of data edges on the boundary of Big Data for post processing and analysis, if during a couple of years such information becomes available to operators.

5.1.2 Topology corrections

All topological data (connectivity, elevations, etc.) were prepared in close cooperation with MM, on the basis of their existing GIS databases and updated measurements up to 2014. Data of the system was transformed into a working WDN model, which was calibrated.

One of the first challenges of the model building of Milan WDN was the large amount of elements (assets) and its transformation into model elements. In total, there were around 30 iterations among MM and IHE Delft for the update of the model. In most cases, information that was displayed in GIS was not corresponding with the topology of the WDN. What it is evident for the GIS operator of the DB at MM may not represent the hydraulic connectivity of the system. Most computer engineers lack knowledge on basic hydraulics, so every time that a new topological inconsistency was found, it required an update iteration. Starting from GIS data, a complex export and import of all the features was performed. The data verification chain that was used is presented in Figure 5-1.

Typical errors that may compromise simulations are related to incorrect schematizations such as: pipe locations and vertex (used to give shape to pipes), wrong elevations (corrected with

[7] https://www.ogc.org/standards/waterml
[8] https://www.ogc.org/standards/sensorml

proper topographic studies), misplaced elements in the pumping stations (due to lack of proper asset management), pipe's friction factor and pipe diameters (also related to asset management), lack of knowledge about current status of the valves (common in utilities all over the world). Such errors require an expensive iterative update. Most of the checks performed in WDN models, revealed many geospatial inconsistencies inside GIS, which were corrected to improve GIS DB and model reliability in order to reduce subsequent tasks of calibration.

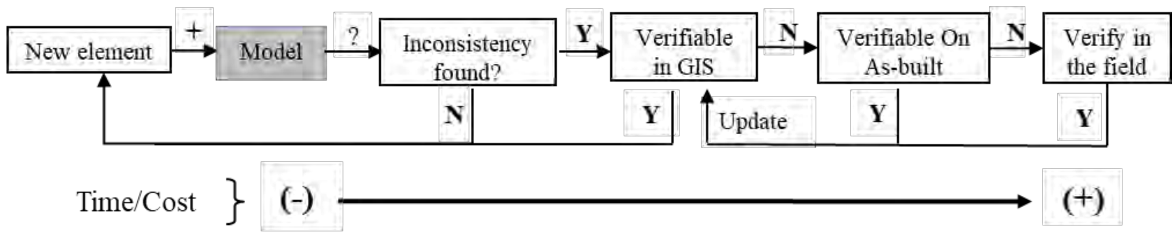


Figure 5-1. Process of model update element by element. More data validations required for a particular element required more time and additional costs expenses.

First, as soon as a new element was identified, it was added to the EPANET model. If an inconsistency was found, there were three levels of verification (see Figure 5-2 for typical errors found during the model building stage). The first and most simple verification was to check the GIS databases to validate and correct the inconsistency. If such inconsistency persisted, then it was verified on drawings *as-built*. If after this verification there were doubts about the inconsistency, and, as a last resort, a field worker was sent to verify the topology of the element. Figure 5-1 also shows that most expensive verifications are obviously the ones made on the field. For basic elements such as pipes and valves, most of the time a simple verification on *as-built* drawing was the highest level reached. However, the utility prepared topographic surveys in 2012-2014 for vital elements such as tanks, wells, booster pumps and valves (e.g. geometry, localization, pump curves and efficiencies).

Even more, the elevations of some elements were surveyed using geodesic precision. Such measurements were performed by external contractors and verified internally by the utility. The focus at MM during such survey were the coordinates and elevations of pumping stations. There were in 2014, 26 active pumping stations in Milan, and 2 pumping stations which deliver water directly into the system. This required extensive fieldwork at MM. It was confirmed also that some pumping stations (four to be precise) have been abandoned due to its age and low efficiency and their elements were not considered in the model.

In an additional effort by the utility, 60% of the valves in the pilot area *Abbiategrasso* where verified one by one, on the field. For this, a procedure was agreed between the author, the utility and their field workers in a process in which larger diameters were verified first, and then smaller ones. A total of 1,100 valves were checked on the field. To our knowledge such an effort has never been made in published research to match a model with a real system. As a total, up to February 2015, approximately 12,000 topological corrections were made in the model and were submitted for update of GIS DB of MM through the contact persons. Afterwards the author lost track of the counting as new elements were added directly in the

GIS system. The WDN keeps growing at the utility, but at least a process was put forward to perform the verification of new elements on the field.

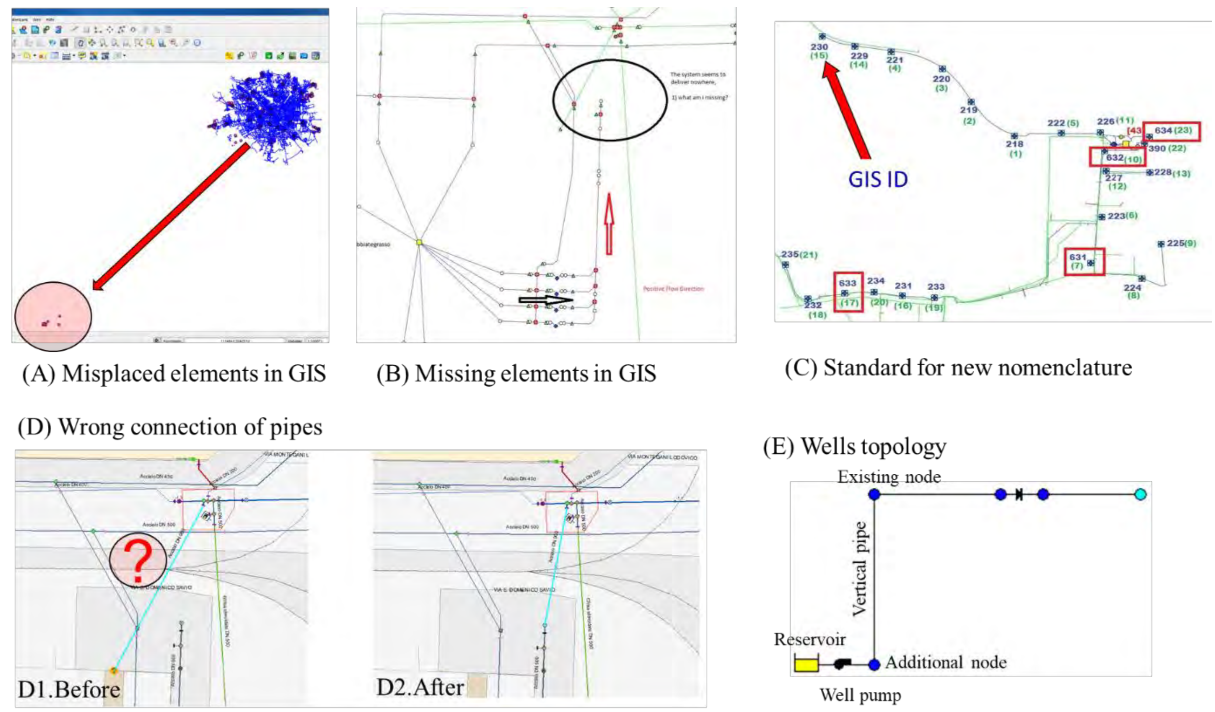


Figure 5-2. Typical errors found while building the models. A) Misplaced elements in GIS, due to the use of wrong coordinate system. B) Missing elements in GIS were a common issue for most pumping stations (26 of them). In this snapshot of GIS, the pumping station delivers water nowhere. C) Many elements in the network had the same numerical ID, for this reason a minimum level of standardization was required to avoid misinterpretation when transferring from GIS to Epanet (and Infoworks). From this thorough inspection, it was possible to identify which well pumps were active and which ones were inactive. D) In addition, some parts of the system also contained elements not connected to the right location. This required intensive verification as in many cases this created instabilities in the Epanet model. D1 shows the status of the pipe before and D2 presents the final configuration of the pipe after verification on as built drawings. E) within GIS a well is just a node of a simple location, while for Epanet a configuration using reservoir-pump-pipe was required. This was added to more than 500 locations in Milan.

The prepared simulation model for the Abbiategrasso pilot served as a basis for the PS optimization in the WDN. Consequently, the model described above was also split into WTN and WDN, and for model-based optimization only the WDN was considered. The proposed WDN PS optimization algorithms use the developed EPANET model for the WDN part as it is, using the tank filling pattern as a given boundary condition and provided based on sensor measurements provided during ICeWater project.

5.1.3 Demand consumptions

Demand consumption with its spatial distribution and variability was known from the billing data of the utility. The historical records of billing data cover the range between 2010 and 2014 for this research. Sensor data was available only until November of 2014. A customer connection does not literally transfers into a model junction, so a spatial allocation process was performed in concertation with the utility. This allocation of customer demands into model junctions was performed using shortest distance using the spatial analysis. In that case, the spatial distribution of demands was solved and the magnitude of the average base demands per junction was obtained based on historical averages contained in the registry of commercial consumption by the utility.

For the daily pattern of demands, there were two alternatives available. The first option was a Demand Forecast performed by project partners Consorcio Milanese Recherche (CMR). In this case the daily demand pattern is obtained through a Decision Support System – DSS that performs spectral analysis of the historical records and projects them for the following day (Candelieri & Archetti, 2014). This option, allows the operators to update the model demands based on their own historical records and some seasonal factors (e.g. summer, winter, working day, weekend, holiday break). The main drawback of the demand forecast is the fact that it cannot provide a finer time resolution than one hour. However, in general, with the results presented in this research for pump scheduling that resolution proved to be fine enough.

The second alternative was the extraction of flow data from the sensor located at the exit of the pumping station, from a Database developed during ICeWater by other project partners. This option allows to obtain the historical records directly from the field. Then a pattern based on a specific daily operation of the system with a resolution of 1 min can be used. This proved to be an advantage for the calibration of the model for Abbiategrasso. For the case of the Full WDN this resolution is too high to be handled. For that reason aggregation to larger time intervals was used in the full model (1 hr).

5.2 Model 1- Milan full network

As mentioned in Chapter 3, the system is composed of two different subsystems: the Water Transmission Network (WTN) and the Water Distribution Network (WDN). Although the whole model was built, in the end, for application of sectorization, only the WDN is used for the purposes of pump scheduling and sectorization. The total number of elements of the model is presented in Table 5-1. As part of the research it was found (and verified on the field) that actually 51 well pumps were inactive. This proved to be important for the utility, as knowing which pumps work and which ones do not can help plan for future investments in separate areas of the city.

In addition, a complete specification of the number of pumps per pumping station is presented in Table 5-2. Notice that the list is presented in alphabetical order and not by capacity, or topographic elevation as in Figure 3-3.

Table 5-1. Total number of elements of Model WDN Milan

Elements	Item	Subtotal	%
Nodes	Junctions	149 642	100.00%
	Demands	21 530	14.39%
	Reservoirs	501	0.33%
	Tanks	33	0.02%
Links	Pipes	118 885	100.00%
	Pipes	118 240	99.46%
	Check Valves	645	0.54%
	Pumps	647	100.00%
	Active	596	92.12%
	Booster	103	15.92%
	Wells	493	76.20%
	Inactive	51	7.88%
	Valves	36 260	30.50%

Table 5-2. Specification of number of pumps per pumping stations for both transmission and distribution. Last column presents the number of tanks per pumping station.

ID	Pumping Station	Transmission			Distribution	Storage
		Inactive	Active	Subtotal	Boosters	Tanks
4	Abbiategrasso	1	19	20	4	1
6	Anfossi	0	16	16	2	1
9	Armi	3	17	20	3	1
14	Assiano	1	24	25	5	2
18	Baggio	1	22	23	4	2
21	Cantore	1	15	16	3	1
24	Chiusabella	2	18	20	3	1
28	Cimabue	0	21	21	4	2
32	Comasina	7	16	23	4	1
36	Crescenzago	5	19	24	4	1
38	Este	1	14	15	2	1
42	Feltre	0	22	22	4	1
45	Gorla	1	19	20	3	1
48	Italia	0	20	20	3	1
53	Lambro	3	21	24	5	2
56	Linate	2	19	21	3	1
59	Martini	2	14	16	3	1
63	Novara	0	21	21	4	2
67	Ovidio	2	18	20	4	1
71	Padova	1	19	20	4	2
75	Parco	3	18	21	4	1
79	Salemi	4	16	20	4	1
83	San Siro	0	24	24	4	1
88	Suzzani	7	20	27	5	1
91	Tonezza	1	19	20	3	1
95	Vialba	3	22	25	4	2
99	Bicocca	0	0	0	4	0
103	Corsico	0	0	0	4	0
	Subtotal	**51**	**493**	**544**	**103**	**33**

The model contains a total of 150,698 junctions, from which 21,530 have allocation of demands. The rest are used for connectivity purposes. In order to simulate the full behaviour of the system, the wells are represented in the model as reservoirs. Each well is represented by the combination of a reservoir and a pump (see Figure 5-2E). Storages are simulated as tanks with cylindrical shape for simplification as there shapes are prismatic and the filling is proportional to the water column in it. All pipes have roughness specified for each of the materials of the pipes. This was extensively discussed and agreed with operators of MM, for the purposes of applying head losses based on Colebrook-White friction formulation. Valves in the model are set as Throttle Control Valves (TCVs), which in principle allows simulation of partially opened valves. Setup was agreed with operators at MM. In the coming Chapters when referring to tariff it is the one of 2014 which is used for modeling purposes. In all model configurations the simulation period has been set to 24 hours, with a time step of 1 hour.

5.3 Model 2 Abbiategrasso pilot

Given that ICeWater project established the goal to be able to test the functionalities suggested by developed research, it was necessary to have a model of the southern part of the city of Milan. This model was built originally taking into account the WTN and WDN of this PMZ. The WTN of Abbiategrasso was developed but used by another project partner (not presented here) for other research purposes of ICeWater project. Abbiategrasso model refers to the WDN, and it is used for optimization of pump scheduling in Chapter 6.

Out of the total number of junctions in this model (7,855), 846 have specified demands. The base demand used corresponds to the one of 2014 in the model setup and in different optimisation cases of following chapters.
There are 20 reservoirs in the simulation model of the WTN. Similar to the case of Milano Full WDN, wells were modelled as a combination of reservoirs with fixed elevation of the water surface and pumps. Static groundwater levels were used. However, only the WDN is considered from this point on. The storage characteristics (Figure 3-13) were used in the simulation model and in the model-based optimization cases. The daily tank filling pattern was used as a given boundary condition to the WDN simulation model to the reservoir which it represents.
At the moment of starting the research a database from MM contained limited information of pipes have roughness and material. After discussion with the contact person of the utility, it was decided to use roughness using Colebrook-White friction formulation.
The valves in the model are set as Throttle Control Valves (TCVs), which in principle allows simulation of partially opened valves. These settings are applied in accordance to findings made by field operators of MM between 2013 and 2014.

5.3.1 Model Calibration

The calibration of the model of Abbiategrasso was performed using data of December 2014. Data form the pressure and the flow sensors located in the real system were available. The flows were used to determine the demand in the system in the form of a pattern, while the pressures were used to estimate how accurate the model represented the real system. In Figure 5-3, the location of pressure sensors is presented.

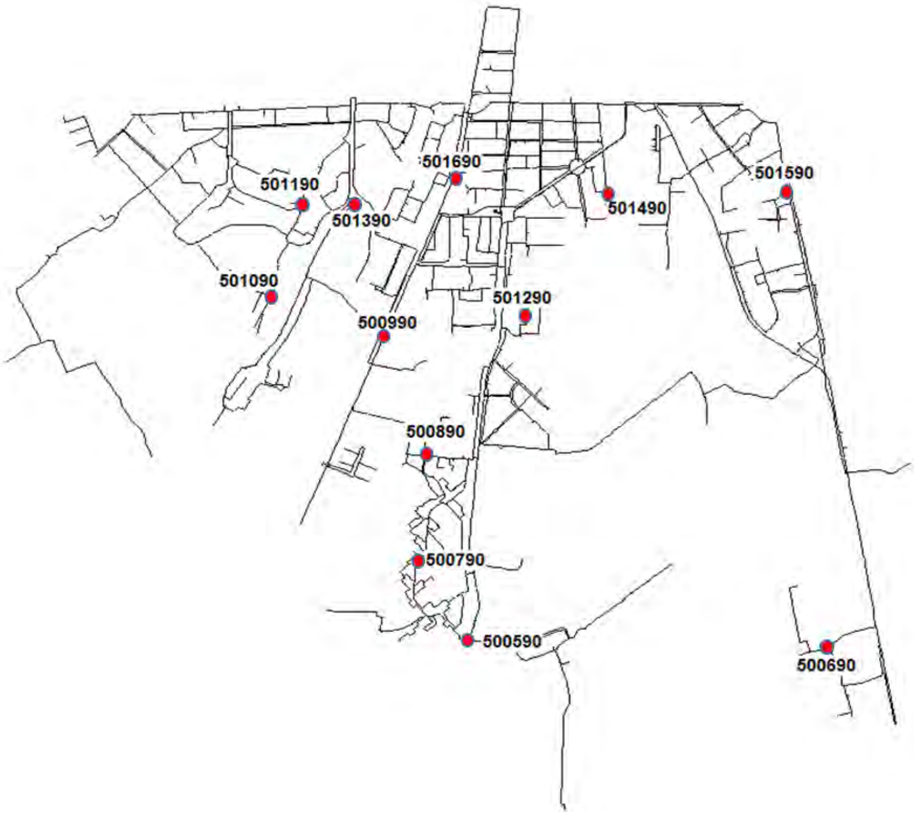


Figure 5-3. Location of pressure sensors in Abbiategrasso used for calibration.

For calibration the time series of pressures in each sensor where compared with the model results. The calibration was done by iteratively adapting the status of elements (such as valves) and pipe roughness's. The final result is presented in Figure 5-4. There is good correspondence for almost all pressure sensors, and only sensor 500590 was found to be outside of the limits of acceptable error. No possible explanation was found for this, however the time series comparison shows that there seems to be a systematic bias in the measured signal of around 10 m column of water.

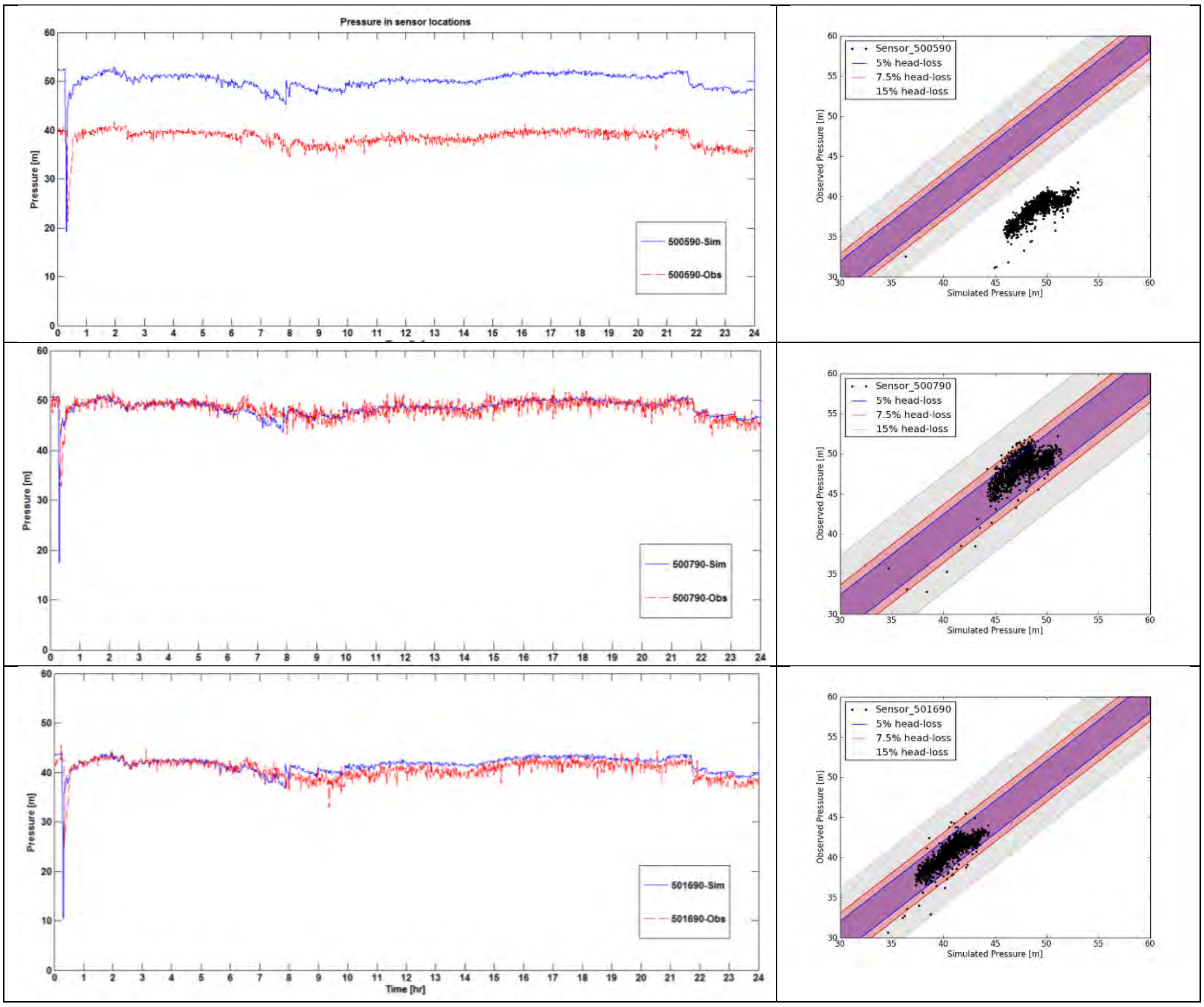


Figure 5-4. Time series and errors of calibration of Abbiategrasso WDN model. Only 3 out of sensors are presented. Sim = Simulated, Obs = Observed.

It is of notice also that the time series follow closely the behavior of the observed values even when specific events such as changes in pump operation (at 00:20) or changes due to the stochastic nature of demand in the real system.
Table 5-3 presents the percentage of points simulated which fall within certain bounds of error with respect to the observed values of each pressure sensor. Three different bands are considered 5.0%, 7.5% and 15.0%. The results at sensor 500590 show no correspondence, however, as mentioned before there is a bias in the model which can be easily subtracted. The rest of the sensors show that the model simulates at least 88% of the time stamps within 7.5% of error.

Table 5-3. Results of percentages of measurements which fall within a band of error with respect to the model.

Sensor number	Percentage of points with Difference within percentage of head-loss (%)		
	5% head-loss (%)	7.5% head-loss (%)	15% head-loss (%)
500590	0.0	0.0	0.1
500690	97.6	98.7	99.4
500790	90.5	98.5	99.8
501090	81.1	92.6	99.7
501190	79.7	93.0	99.7
501290	88.5	99.4	99.8
501390	71.4	88.4	99.6
501490	89.2	98.4	99.7
501590	98.0	99.4	99.8
501690	97.2	98.7	99.8

5.4 Limitations of the models

The dynamic of all major cities in the world is to increase its population, making the extension of a WDN an integral part of the process of the development of water supply. The main emphasis in the growth of the WDN of Milan corresponds to the outcome of rehabilitations and installation of new elements in the city of Milan. Although the model has been calibrated, the number of elements may have changed dramatically in the last 5 years. However, the utility has been presented with a methodology to constantly update and refurbish its WDN models.

One of the major drawbacks in the use of the models for optimisation is the lack of knowledge of the total demand of the system. A WDN demand fluctuates every second of the day and it becomes really difficult to track through optimization all the possible combinations of total demand of the system at a particular hour. However, it is always possible to take into account that the satisfaction of demand can be made for a certain total volume of water, making the assumption that the spatial variability of the total demands will remain unchanged in a the long run. In this particular case that assumption seems to be feasible, given that there has been a steady reduction in the demand due to socio-economic factors which made of Milan a city of services rather than an industrial city.

Many different demand patterns can be used for the estimation of pump schedules and sectorization in the city of Milan. After collecting data from the utility, two different patterns in 2009 and in 2014 where identified having different behaviour (see Figure 3-11). Here models are run coupling with the demand forecast developed within the funding project ICeWater. In principle, that helped reduce the uncertainties for further operation of the utility. Further methodology on the demand forecast applied to the city of Milan can be read in Candelieri and Archetti (2014).

One drawback for the application of sectorization for the full WDN of Milan, is the fact that besides the pumps located in the sector of Abbiategrasso, the pump efficiencies of the rest of the system are not known. Only approximations obtained from energy audits have been applied. In fact, due to the variability of the pump types and age, it was impossible to display the base case. For that reason the base case scenario of pump scheduling in Abbiategrasso can be trusted, while the base case for the sectorization of the full WDN can be seen as a demonstrative tool for decision support. Pump efficiencies are unknown, for that reason together with the experts of MM it was decided to use a value of 75% for old pumps. There is an exception as two new pumps were installed in 2013 in Abbiategrasso.

During early stages of discussion of the ICeWater project, the possibility of having a calibrated model of Milan network triggered a discussion among the utility experts into other subjects of importance. For example, it was considered to use the WDN model for other pertinent issues such as leak detection and leak localization, water quality simulation, integrated asset management (as the utility was heavily invested in a new Customer Relationship Management – CRM commercial service). This is an advantage, as the more questions arose, having a WDN model can have more value to perform decision making and define future scenarios of operation. The more credibility the operators of the utility and decision makers give to WDN models, the more relevance these will have. Models have become more than a tool, and nowadays discussion have started to develop toward the use of WDN for Model Predictive Control or even with the integration of additional data as Digital Twins for operation.

One aspect to consider for the reduction of computational times in the further chapters of this document, is the possibility of using skeletonization approaches. Several authors have dealt with this subject as presented in section 2.1.4. So, Why skeletonization is not performed? The main reason is the fact that it was possible to make use of two large HPC services Microsoft Azure® and SurfSARA HPC Cloud. With the help of these services which have permeated the digitalization of all sorts of industries, including the water industry, it will become less relevant to run simulations in desktops and laptops. Being that the case, the use of reduced models pertains research which could be addressed in a future research project. On top of that, it is evident that the commercial vendors of commercial software are also moving in the direction of online tools. Such is the case of InfoWorks, Sinergy and WaterGems the ones most commonly used by utilities in the European context.

5.5 Summary

This Chapter presents the Model Development for the research. Several steps are followed as there was intensive work required to realize both models for the subsequent Chapters. On one hand, the research benefits from the implementation and the steps followed for data validation as presented in Figure 5-1. The automatization process of the issues presented in Figure 5-2 is outside of the scope of this research, however as utilities face the digitalization of their assets this may very well become a revenue stream research institutions and consultants. In addition, a calibration based on collected data is performed for the model of Abbiategrasso showing that it is a viable representation of the system. This leads the author to think that at the base of poor operations by other utilities is the lack of a standardization process of model building practices. Although this Chapter is rather short and very limited to a couple of specific cases, it may very well be extended to other topologies and locations.

6 OPTIMIZATION OF PUMP SCHEDULING

The chapter is organized as follows: in Section 6.1 the NSGA-II and AMGA2 MOO algorithms are described, and sections 6.2 6.3, 6.4, 6.5 and 6.6 present the elements of the optimization problem formulation (decision variables, objective functions and constraints) and the optimization approaches. Section 6.7 presents the optimization results and the associated discussion. The algorithms have been applied for Abbiategrasso, and field tests which were performed in 2015 there are presented. A particular setup has been applied for the Full WDN model. Main findings are then summarized at the end of the chapter.

This Chapter is based on the following publication(s):

- Castro-Gama, M., Pan, Q., Lanfranchi, E.A., Jonoski, A. and Solomatine, D.P. (2017) Pump scheduling for a large water distribution network. Milan, Italy. Procedia Engineering. Special Issue of the WDSA2018 Conference, 186, 436-443. DOI: https://doi.org/10.1016/j.proeng.2017.03.249.
- Castro Gama, M.E., Pan, Q., Fadl-Elmola, S.A.M., and Jonoski, A. (2015) Multivariate optimization to decrease total energy consumption in the water supply system of Abbiategrasso (Milano, Italy). Environmental Engineering and Management Journal 14(9)2019-2029.
- Castro Gama, M., Popescu, I., Jonoski, A., and Pan, Q. (2015) Towards increased water and energy efficiencies in water distribution systems. Environmental Engineering and Management Journal 14(6)1271-1278.
- P. Kulkarni, T. Farnham, A. Jonoski, D. Soldi, A. Candilieri, M. Allmaras, E. Lanfranchi, M. Fantozzi, M. Marcu, M. Sarno, (2016) The ICeWater Approach to Managing Urban Water Distribution Systems: Experiences from Pilot Trials and Cost Benefit Analysis, Proceedings of the 14th International Conference on Computing and Control for the Water Industry (CCWI).

6.1 Algorithms used

Two evolutionary heuristic algorithms were selected to perform the optimization for PS: The Non-dominated Sorting Genetic Algorithm (NSGA-II), developed by Deb et al., (2001), and the Archive-based Micro Genetic Algorithm (AMGA2), developed by Tiwari et al. (2011). Further, both algorithms were part of the same DSS components of ICeWater project.

The two algorithms correspond to the shaded square of Figure 6-1. Such algorithms are population-based where population is composed of “chromosomes”. In a basic set up, if 2 pumps are used and the operation is set at hourly time steps for a duration of 1 day, the chromosome length is 48 (24hr x 2 pumps). Each of the values of the chromosome are decision variables. In order for the algorithm to evolve, a set of criteria are required. These are presented in §6.3. The algorithms are run until a certain number of evolutions stages called generations has been reached. The initialization of the population is made at random based on the type of decision variable.

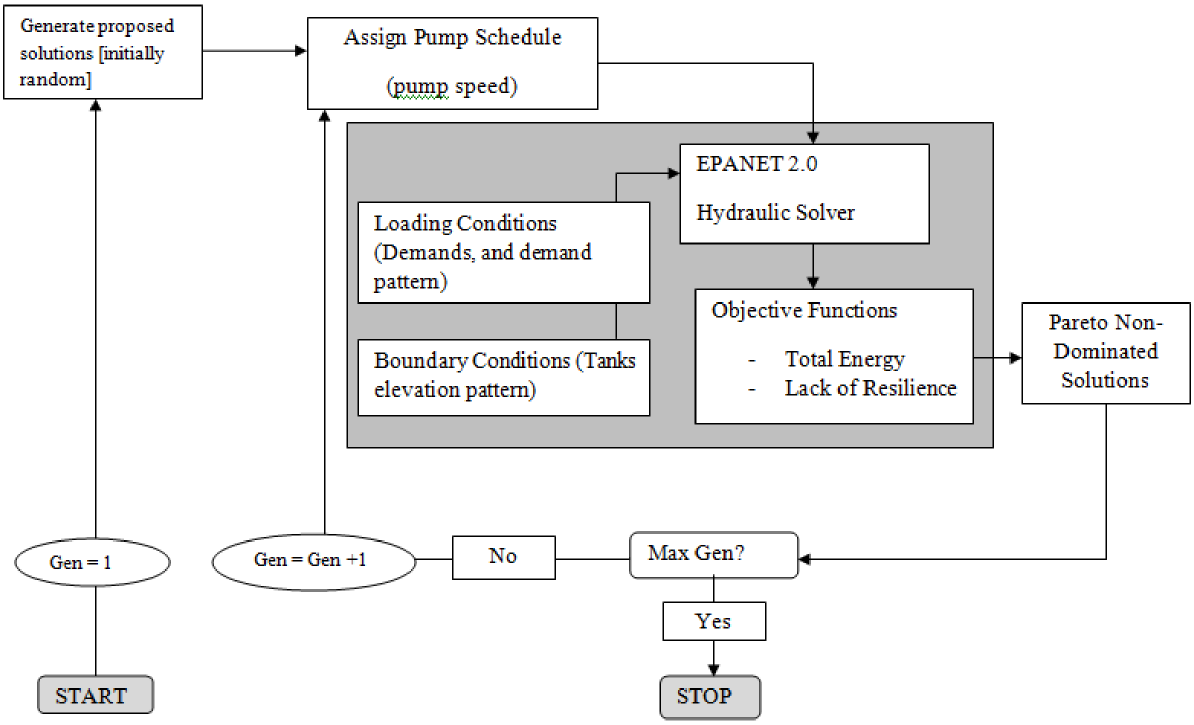


Figure 6-1. Flowchart of pump scheduling optimization using evolutionary algorithms. Gen = Generations.

- NSGA-II

NSGA-II, corresponds to Non-dominated Sorting Genetic algorithm (Deb, et al., 2002). This algorithm has been broadly applied to water resources problems and corresponds to a legacy implementation. NSGA-II has been applied in the past for water resources optimization problems such as water allocation, reservoir operations (Schardong & Simonovic, 2011) and water distribution network design and rehabilitation (Zheng, et al., 2013) among others. It was also selected due to its availability, as it is freely available online in multiple programming languages.

- AMGA2

AMGA2, corresponds to an Archive-based Micro Genetic Algorithm (Tiwari, et al., 2011). At the beginning of the research (2012) this was more efficient algorithm compared with NSGA-II when applied to benchmark test functions. AMGA2 has been applied only in benchmark problems and not for water resources. Recently AMGA2 has been applied also for robust optimization but not for Pump Scheduling (Marquez-Calvo, et al., 2018). Its application for pump scheduling is limited to Real variables. For that reason, subsections of this chapter related to the Full WDN do not make use of this algorithm.

No other algorithms were explored for the purposes of research although it is known that there is a broad landscape of them[9].

[9] It is evident that many other MOO algorithms exist. Parallel to the research and funding project a particular algorithm known as Borg MOEA (Hadka & Reed, 2013) was developed in the USA. It has demonstrated its applicability in multiple problems of water resources including one by the author on reservoir operation (Castro-Gama, Bernal-Quiroga, & Machado-Hernandez, 2019). However, given that there was the need to develop a DSS for the utility and that there was a patent pending (at the time) on such algorithm, only the two open source algorithms discussed in this document were used for the purposes of research.

6.2 Decision Variables

To change the operation of the pumps, setting of pump speeds must be updated using a one day long pattern of the pump speed ($\boldsymbol{x}$). Two different types of decision variables can be used:

i) *Binary*, when $\boldsymbol{x}$ is set ON/OFF, or 1/0,

ii) *Real*, when $\boldsymbol{x}$ is set as in the case of Variable Speed Pumps (VSP). A realistic operational range for x is [0.7, 1.0], where the bounds represent proportions of pump's nominal speed. No over-throttle (x > 1.0) is allowed during simulation. A limit of x = 0.7, is set to limit the operational pump head above 49% of its normal speed value through affinity laws.

In this research, the system was simulated both with Binary and Real variables. Binary has been used only in NSGA-II. AMGA2 is based on a Differential Evolution operator which is particularly inefficient for such variable type. Real variables have been used for both algorithms.

In order to test initially the pump scheduling, the model of Abbiategrasso was used. This model uses just four pumps, however, during early stages of the research it was discovered that only two pumps are required to satisfy the demand of Abbiategrasso. The number of decision variables is a function of the number of time steps of simulation. If time step is set to 1.0 hour, and the number of hours required of pump schedule is one day (24 hours), then the total number of decision variables is 24 per pump.

6.3 Objective functions

Two different objective functions have been formulated during the research:

$$\boldsymbol{f_1(x) = minimize\ Energy}$$
$$\boldsymbol{f_2(x) = minimize\ Lack\ of\ resilience}$$

Equation 6-1. Problem objective functions.

Where, x are the decision variables, $f_1(x)$ is minimization of Total Energy (E_T) and $f_2(x)$ is minimization of Lack of Resilience ($1 - I_R$) calculated based on the Resilience index (I_R) (Todini, 2000). This setup on Resilience is made as the optimization algorithms used only allow for minimization. Both objective functions are evaluated after running the EPANET model (see Figure 6-1).

There is a trade-off between both objectives because the more water is pumped the higher I_R of a WDN is, but, at the same time, more energy is used. If the system is operated at low energy consumption, the resilience index of the system decreases.

- Minimization of Total Energy

The total energy of the system can be estimated as:

$$E_T = \gamma \Delta t \sum_{t=1}^{nt} \sum_{k=1}^{npumps} Q(x)_{k,t} H(x)_{k,t} / \eta(x)_{k,t}$$

The selection of MOO algorithms is highly related to the academic school of thought and as such their application is biased by it.

Equation 6-2. Total energy estimation for a system operated with multiple pumps at multiple time steps.

where, E_T = Total Energy (kW), Δt = time interval (1 hour), $Q(x)_{k,t}$ = flow at pump speed x (m^3/s), for pump k, at time interval t, $H(x)_{k,t}$ = head at pump speed x (m), for pump k, at time interval t, $\eta(x)_{k,t}$ =efficiency at pump speed x, for pump k, at time interval t, and γ specific weight of water.

- Lack of Resilience

Minimization of Lack of Resilience $(1 - I_R)$ refers directly to the estimation of the resilience index (I_R) (Todini, 2000) as presented in Equation 6-3. I_R is the proportion between the amount of power dissipated in the network to satisfy the total demand and the maximum power that would be dissipated internally in order to satisfy the constraints in terms of demand and head at the nodes. Both the numerator and denominator are given in units of power per unit of water volume (kW/m^3).

$$I_R = \frac{\sum_{i=1}^{nnodes} q_i \left(h_{ava,i} - h_{req,i}\right)}{\left(\sum_{j=1}^{nres} Q_j H_j + \sum_{k=1}^{npumps} \frac{P_k}{\gamma}\right) - \sum_{i=1}^{nnodes} q_i h_{req,i}}$$

Equation 6-3. Resilience index equation

where, q_i = is the demand at node i, $h_{ava,i}$ = is the available pressure at node i, $h_{req,i}$ = is the required pressure at node i (20m), Q_j =is the flow supplied by reservoir j, H_j = is the head supplied by reservoir j, P_k = power supplied by pump k. The I_R is calculated for each hour but in order to report a single value it corresponds to the average during the day.

6.4 Constraints

Two types of hard constraints (Kramer, 2010) have been used, using Global pressure constraint and Local pressure constraint.

The constraints were formulated using penalty function values given the result of EPANET simulation. In both cases, a minimum required pressure target was set, independent of the algorithm, or decision variables. After each EPANET simulation the pressure is checked as a constraint in the nodes (Local = 1 node, Global = All nodes). If pressure was lower than the required pressure, the objective function for E_T was assigned a penalty value of 10^6, and the objective of Lack of Resilience was given a value of 1.0. This guaranteed that such solutions were dismissed from the set of feasible solutions during evolution of the algorithm.

- Global Constraints

Global pressure constraint refers to penalizing the objective functions of a simulation when a node in the system with minimum pressure is below a required pressure. Different PS applied to the network result in different locations of minimum pressure in the network, which needs to be detected.

- Local Constraints

The pressure in a single node is used to constrain the optimization, assuming that the node selected for application of the local constraint is a pre-determined critical node (with expected minimum pressures). This does not require checking the pressures in all nodes, but it also does not guarantee that the constraint is applied to the node with lowest pressure.

6.5 Approaches

A pump scheduling problem was formulated with the use of two Genetic Algorithms (GA), with two different approaches. These two approaches are presented in Figure 6-2.

The first approach for PS is one in which each population is composed of chromosomes of length (lc) equal to $npumps * ntimesteps$. For the case of an hourly PS with two pumps, the number of decision variables is 48. Such approach has the advantage of evaluating the whole schedule in a single EPANET run.

The second approach for PS is the one in which each population is composed of chromosomes of length (l equal to $npumps * 1$. In this case k is equal to the number of $ntimesteps$ or number of parallel optimizations needed to be run in order to estimate the full schedule for a day.

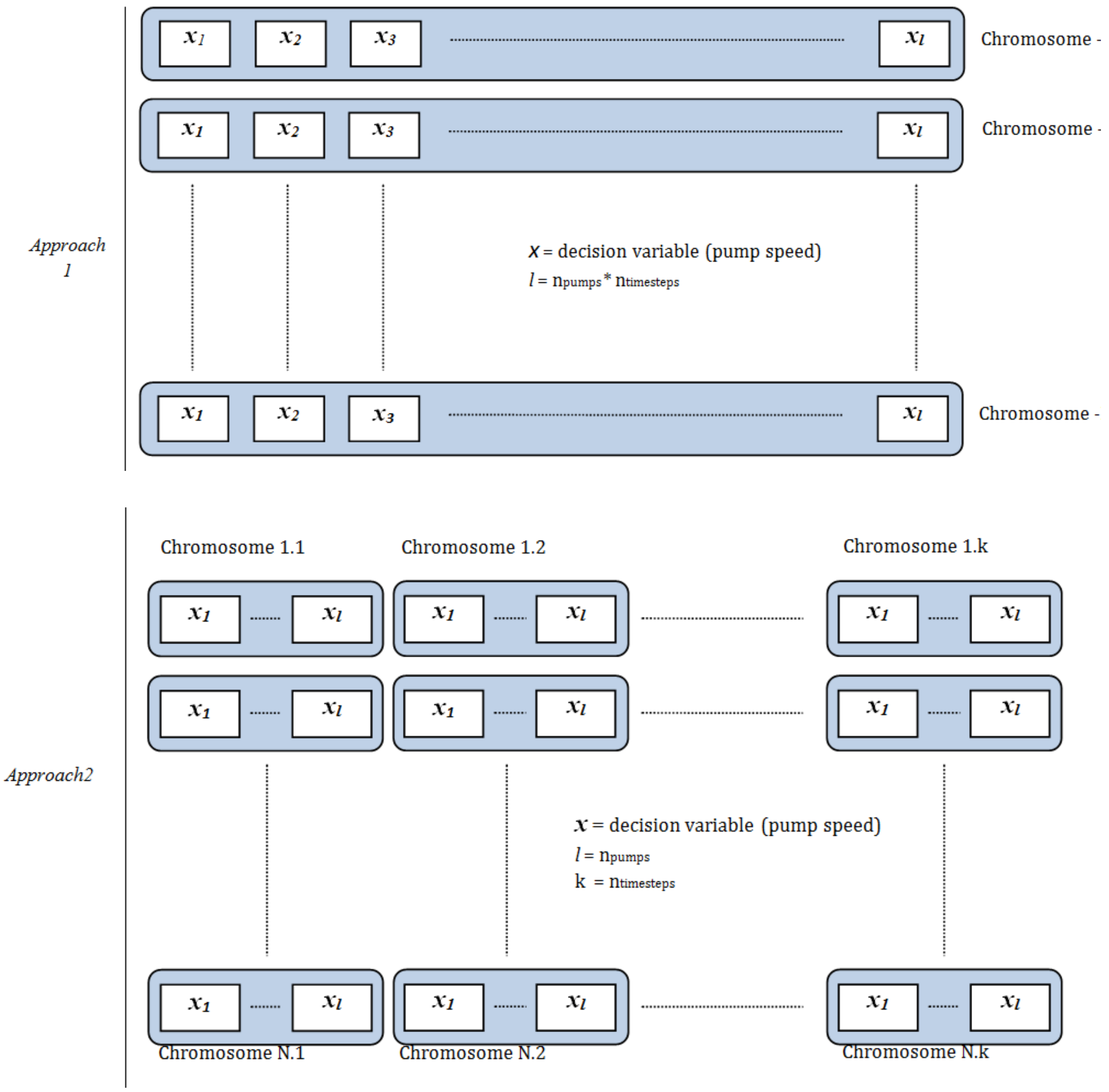


Figure 6-2. Flowchart of approaches of a population for the two approaches of Pump Scheduling used. Approach 1, a chromosome is composed of the pump speeds for all pumps at all time steps simultaneously. Approach 2, a chromosome is composed of the pump speeds of the pumps in the system for a single time step.

Both algorithms are tested for both ON/OFF pumps (Binary) and VSP pumps (Real). At the same time the two types of constraints are applied to the PS problem.

6.6 Other optimization parameters

To make the optimization runs comparable, three settings were fixed for both algorithms when applied to Abbiategrasso WDN:

a) For both NSGA-II and AMGA2 the crossover probability and mutation probability were set to 0.9 and 0.1. Other parameters of both algorithms were fixed to the optimal values given in the literature for benchmark problems (crossover index = 15, number of parents = 2, number of offspring = 2).
b) In the case of NSGA-II, a population of 20 and a total number of 100 generations was set, for a total of 2,000 function evaluations. For AMGA2 the algorithm updates the Pareto front directly, so its selected elite size was set to 20, with a maximum of 2,000 function evaluations. In this way, both algorithms results are comparable in terms of number of function evaluations. The number of function evaluations is relatively low, but here it should be reminded that the algorithms are intended for real use by operatives of the utility. In fact most of the runs are obtained in less than two hours. In order to prove the convergence after a low set of function evaluations Figure 6-3 shows the Hypervolume (HypV) of the Pareto front after each generation for a precooked run where 100 generations correspond to the setup proposed for Abbiategrasso. HypV is equal to the volume of the dominated portion of the objective space between different generations.

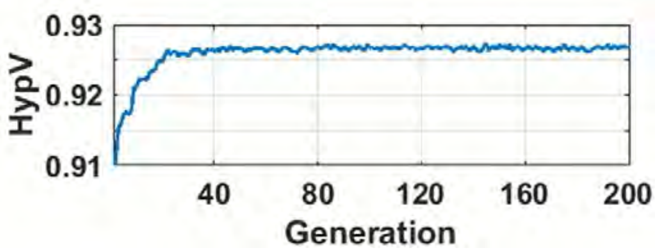


Figure 6-3. Hypervolume (HypV) for a PS run with a population of 20 and 200 generations.

c) The random generator of both algorithms was fixed to be the same for both algorithms. In this way by using the same random seed, all the solutions start from the same initial set of decision variables.

For the case of pump schedule of the Full WDN of Milano the setup follows the following settings:

a) Only NSGA-II was tested, with operation of pumps as ON/OFF (or Binary), while the crossover probability and mutation probability were set at 0.9 and 0.1, respectively.
b) A total of 103 pumps (28 pumping stations) are used as decision variables for each hour of the day.
c) Only Approach 1 was applied. The hard constraint was applied with a minimum pressure of 30m,
d) A population of 100 members with a total number of 200 generations was set, for a total of 20,000 function evaluations. In early runs, it was identified that the solutions

obtained by the MOO become stagnant after around 15,000 function evaluations. Anyway the MOO runs were left to run until the end.

6.7 Results and discussion

The pump scheduling has been applied to Abbiategrasso and tested on the real system. The pump scheduling has been also attempted on the Full Network with some additional computational effort. The former set of results were intended for operational purposes and as part of water operation service of ICeWater, while the latter was performed in order to be able to understand the operation of the full WDN of Milan with a thorough pump scheduling and to set the stage for additional sectorization presented on Chapter 7.

6.7.1 Optimization results of Abbiategrasso

A total of 12 different scenarios of PS were set for the WDN of Abbiategrasso. Table 6-1, summarizes the complete list of scenarios performed, algorithm, approach, decision variables and constraints and their computational runtime per function evaluation.

- Computational running times

The computational running time for Approach 2 is on average 9.1 times higher than the one for Approach 1. This is because during the process of simulation of the WDN as surrogate in each of the optimization algorithms it is required to call 24 times more EPANET 2.0 to simulate each time step. Approach 2 requires between 79 and 105 minutes. In the case of Approach 1, the required time is between 8 and 11 minutes. This is a significant difference, which poses a first disadvantage for Approach 2 with respect of Approach 1.

Table 6-1. Optimization scenarios for PS in WDN of Abbiategrasso.

[1] Algorithm	[2] Approach	[3] Decision Variables	[4] Constraints	[5] Population/ Elite size	[6] Generations	[7] f.eval*	[8] Running Time [s]	[9] Ave. Time [s/f.eval]
AMGA2	1	Real	Global	20	-	2,000	653.7	0.33
NSGA-II	1	Real	Global	20	100	2,000	658.7	0.33
NSGA-II	1	Binary	Global	20	100	2,000	610.1	0.31
AMGA2	1	Real	Local	20	-	2,000	469.6	0.23
NSGA-II	1	Real	Local	20	100	2,000	469.6	0.23
NSGA-II	1	Binary	Local	20	100	2,000	551.9	0.28
AMGA2	2	Real	Global	20	-	2,000	4991.0	2.50
NSGA-II	2	Real	Global	20	100	2,000	4976.3	2.49
NSGA-II	2	Binary	Global	20	100	2,000	6328.7	3.16
AMGA2	2	Real	Local	20	-	2,000	4781.4	2.39
NSGA-II	2	Real	Local	20	100	2,000	4755.5	2.38
NSGA-II	2	Binary	Local	20	100	2,000	4759.1	2.38

*The number of function evaluations (f.eval) of Approach 1 is for a full day, while Approach 2 is per time step

In general, computation times using Global constraints are always higher than using Local constraints, independently of the approach and decision variables. This can be explained because the Local constraint loads only a single vector of pressures for a particular node and compares it with the target pressure. The use of Global constraints requires loading all pressures of all nodes for each function evaluation, and only after that it is possible to perform the comparison with the target pressure. The range of saving computational time by using Local constraints instead of Global constraints is 4.4% to 28.7% for NSGA-II and 4.2% to 28.2% for AMGA2.

When comparing NSGA-II and AMGA2 for the same approach and constraints (only possible for Real decision variables), there is no clear time of computation difference, ranging between -0.8% and 0.5%. In fact, both algorithms have similar behaviour from this perspective, given the same MOO setup. Taking into account that both algorithms start from the same initial condition, this is an advantage for a user, as it allows him/her to choose the algorithm of preference.

- Pareto fronts

The optimal Pareto fronts (set of all non-dominated objective function values) of this combinatorial problem are not known. For this reason, the only possibility was to compare the suboptimal Pareto fronts obtained from the 12 scenarios after the 2,000 function evaluations of E_T vs *1-Ir*. This Pareto fronts may serve to decide whether to use lower energy or guarantee a more resilient system operation. Figure 6-4 and Figure 6-5 show the Pareto fronts for Approach 1 and Approach 2, respectively, with both algorithms.

Figure 6-4, A, B and C, present results with the use of Global constraint, while Figure 6-4, D, E and F, present results using Local constraint. Figure 6-4, A and D, present AMGA2 simulations, Figure 6-4, B and E) present NSGA-II for Real decision variables and Figure 6-4, C and F, for Binary decision variables. All scenarios show also the number of solutions in the Pareto front and dominated solutions in each case, and the minimum E_T obtained.

Figure 6-4A, does not reach a total elite size of 20 at 2,000 function evaluations. NSGA-II with Real variables (Figure 6-4B and E) presents a larger number of solutions than AMGA2 in the Pareto front. On the other hand, AMGA2 converges faster to a lower energy than NSGA-II.

When comparing the operation of the pumping station between Binary and Real pump speed values as decision variables, it is evident that Real decision variables, equivalent to VSP, minimize energy use in area. This implies that the installation of the new pumps by MM at Abbiategrasso, produces a reduction of energy consumption. In the case of Approach 2 (Figure 6-5A to F), the minimum E_T is higher than the one of Approach 1 for any scenario, but at the same time the Lack of Resilience is lower than for Approach 1. The recommendation would then be to use Approach 2 to obtain a more resilient network, or to use Approach 1 to reduce energy consumption.

Similarly to Approach 1, AMGA2 shows a tendency to reach a lower magnitude of minimum energy than NSGA-II. It is also evident that the use of Real decision variables in the optimization (Figure 6-5B and C) provides lower E_T than Binary variables (Figure 6-5E and F). In fact, the use of VSP's is expected to have better performance than ON/OFF pumps. So this does not come as a surprise.

Comparing Approach 1 and Approach 2 solutions, it is evident that Approach 1 converges faster to lower E_T than Approach 2. This presents a second disadvantage for Approach 2 because its convergence is slower. It is also evident that the final Pareto fronts contain only 50% of the feasible solutions in Approach 2. This indicates that the algorithms are still evolving after 2,000 function evaluations.

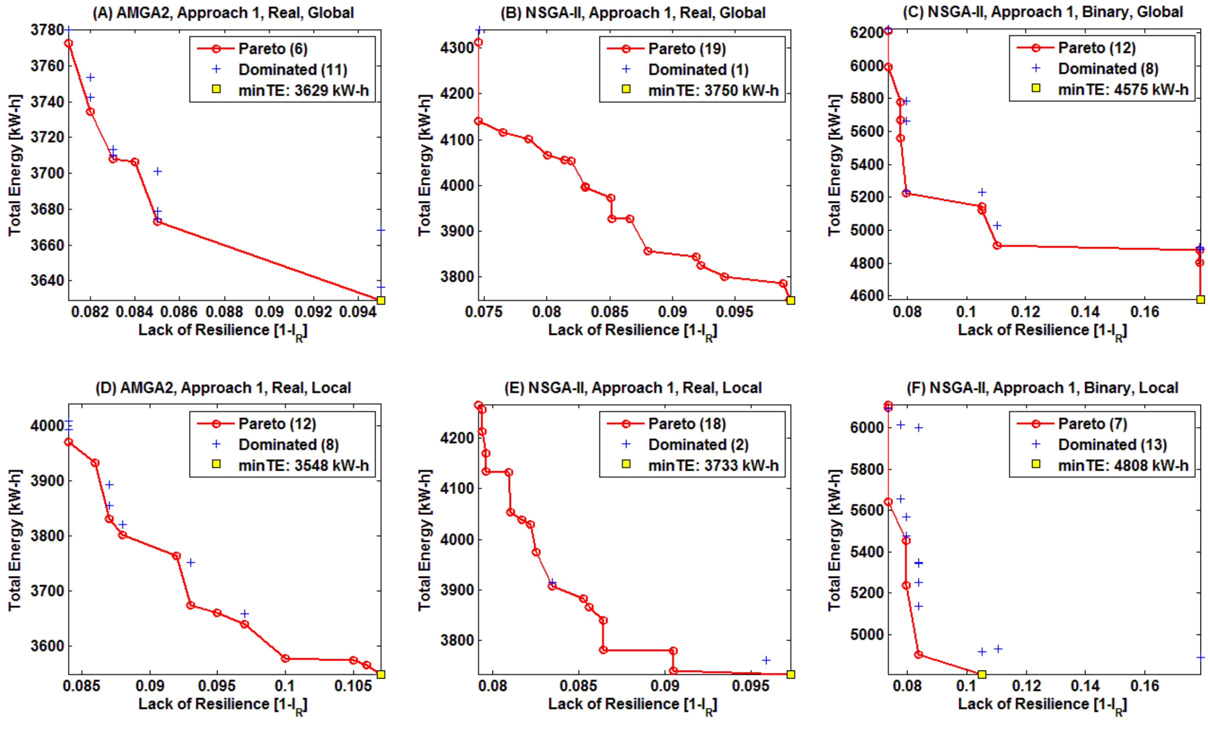


Figure 6-4. Pareto fronts of last generation from pump scheduling obtained for Approach 1.

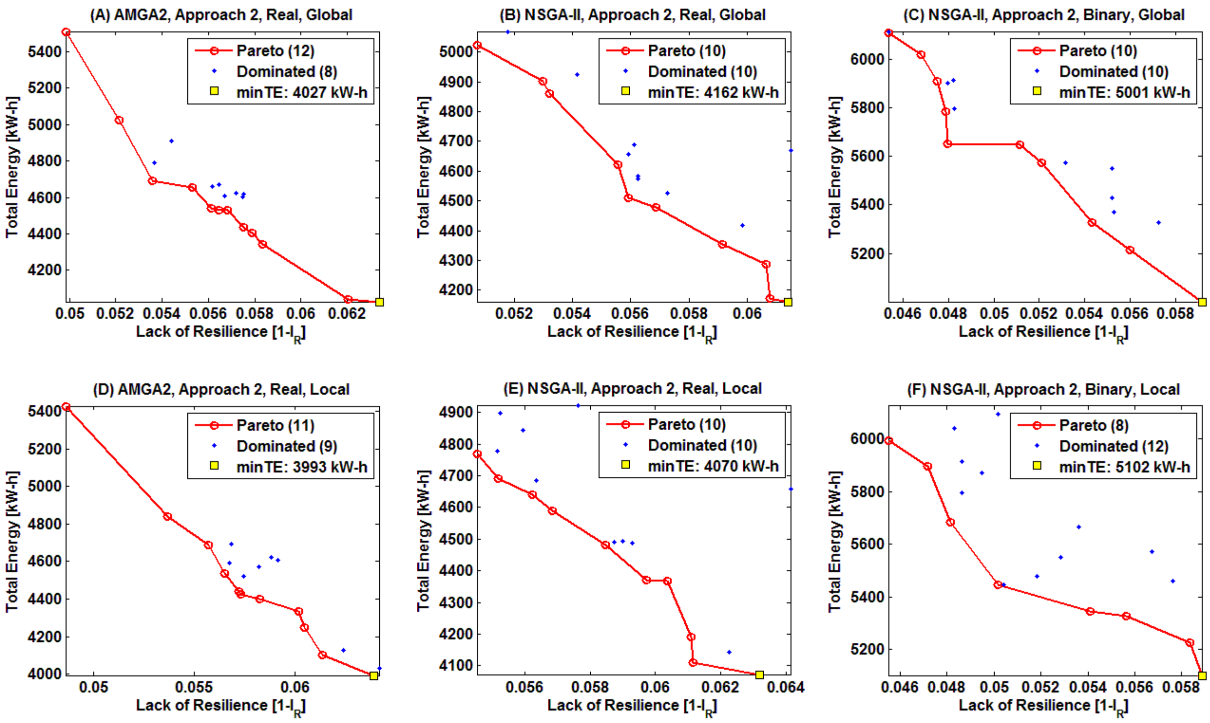


Figure 6-5. Pareto fronts of last generation from pump scheduling obtained for Approach 2.

In general, it was found that the variation of the $1\text{-}I_R$ is not as significant as an objective function as the variation of E_T in the optimization problem, independent of the Approach used. The values of Lack of Resilience are low for all scenarios, showing a system with a hydraulic resilience of around 90% or more. Basically, for the case of Abbiategrasso WDN, what matters for the operators is the minimization of E_T, given that the range of variation of $1\text{-}I_R$ is low. In other systems, the range of $1\text{-}I_R$ may be different so the applicability of the approaches presented becomes general but must be adapted accordingly to each particular case.

An analysis of E_T savings is possible as a 'before' and 'after' comparison. Operation of the system prior to the WDN interventions that took place in 2014, using the results with Binary decision variables for PS is called 'before'. System operation using Real decision variables for PS is called 'after'. This comparison reveals that E_T savings in the order of 20% can be achieved by the implementation of different pumps and pump scheduling optimization between 'before' and 'after'. To extend the explanation on the matter, applying Global constraints in Approach 1, a saving of E_T of 18.1% can be achieved with NSGA-II and 20.7% using AMGA2. If Local constraints are used in Approach 1, E_T savings of 22.4% and 26.4% are achieved for NSGA-II and AMGA2, respectively. By applying Global constraints in Approach 2, AMGA2 achieves an E_T saving of 19.5% and NSGA-II achieves 16.8% E_T savings. In the case of Local constraints, in Approach 2, E_T savings are 21.7% with AMGA2 and 20.2% with NSGA-II. In fact, this serves as proof of concept for using VSP for the case of Abbiategrasso and their further use by the utility.

- Pressure distribution in the system

Of hydraulic relevance are the pressure distributions in the PMZ under any of the optimization scenarios. A total of 8 pressure sensors were located in the PMZ (see Figure 5-3). The sensors are: one pressure sensor at the exit of the pumping station (P_{exit}), two pressure sensors (P_{crit1} and P_{crit2}) which should measure the critical pressure in the PMZ (used as well for the Local constraints), two pressure sensors for each Pressure Regulating Valve (PRV) which connects the PMZ with the whole system in case of being required (PRV_1 *and* PRV_2) and three additional sensors required to have an estimate of the average pressure in the WDN ($Av.P_1$, $Av.P_2$ and $Av.P_3$).

In order to be able to compare the pressures in the system under different algorithms, three solutions of minimum E_T are selected.

First, the solution of minimum E_T for NSGA-II under Approach 1, with Global constraints and Binary decision variables is used to represent the optimal scenario of the 'before' system (Figure 6-6A). Second, given that AMGA2 under Approach 1, with Real variables, shows the lowest E_T, pressures in the PMZ, these results are presented for Global (Figure 6-6B) and Local (Figure 6-6C) constraints together.

When using Binary variables the range of pressure is 18.3-55.2 m (Figure 6-6A). With AMGA2, the pressures in the system are in the range between 20.1-46.8 m for Global (Figure 6-6B) and 18.9-45.8 m for Local (Figure 6-6C), although the minimum pressures in all cases are located at the PRVs not at the critical pressure nodes. This implies that using VSP pumps in the PMZ will reduce the pressures during the day. For the three scenarios during the time of 07:00-08:00 am, when the largest demand in the system occurs, using the VSP (Real variables) the system is able to deliver both demand and pressure, while by contrast the old system (Binary variables) presents the lowest pressures during the same hour of the day.

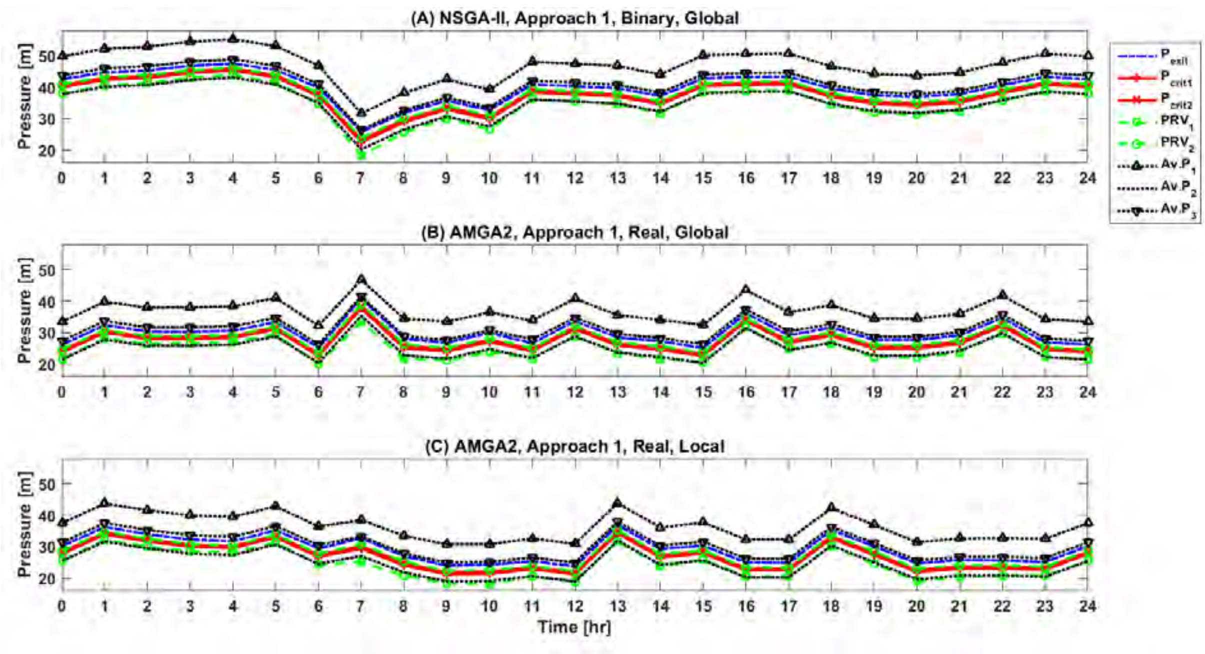


Figure 6-6. Daily pressure distribution in sensor locations for the three cases analysed.

The variation of pressures in the system during low consumption (02:00-05:00 am) also shows that the old system (Binary variables) operates at a high pressure, while the use of VSP (Real variables) allows the operators of MM to reduce pressure when it is not required.

The minimum pressures in the system are not obtained in the critical nodes selected by the utility, but rather on the locations of the PRV's for the three scenarios. This is explained by the combination of the configuration of the WDN and the topography (High elevation in the North to low elevations in the South as presented in Figure 3-2 and Figure 3-3), making these nodes the most susceptible to pressure variations by being located at the North boundary of the PMZ and far from the pumping station.

- Daily pump schedules and energy consumption

Using Binary variables the minimum E_T is obtained with only one pump in operation (Figure 6-7A), while the minimum E_T obtained using Real variables presents a saving even if two pumps are operated all day long (Figure 6-7B and Figure 6-7C). These results demonstrate theoretically the advantages of the interventions performed in the PMZ, and of the use of VSP to reduce energy consumption.

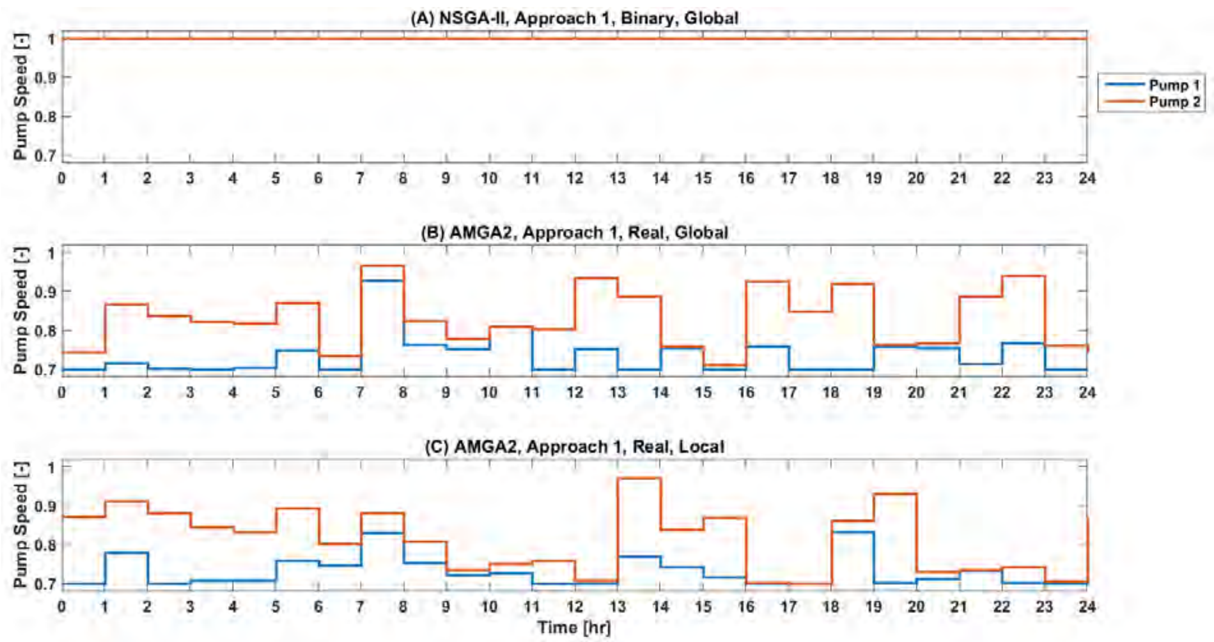


Figure 6-7. Daily pump speeds (schedule) for the three cases analysed.

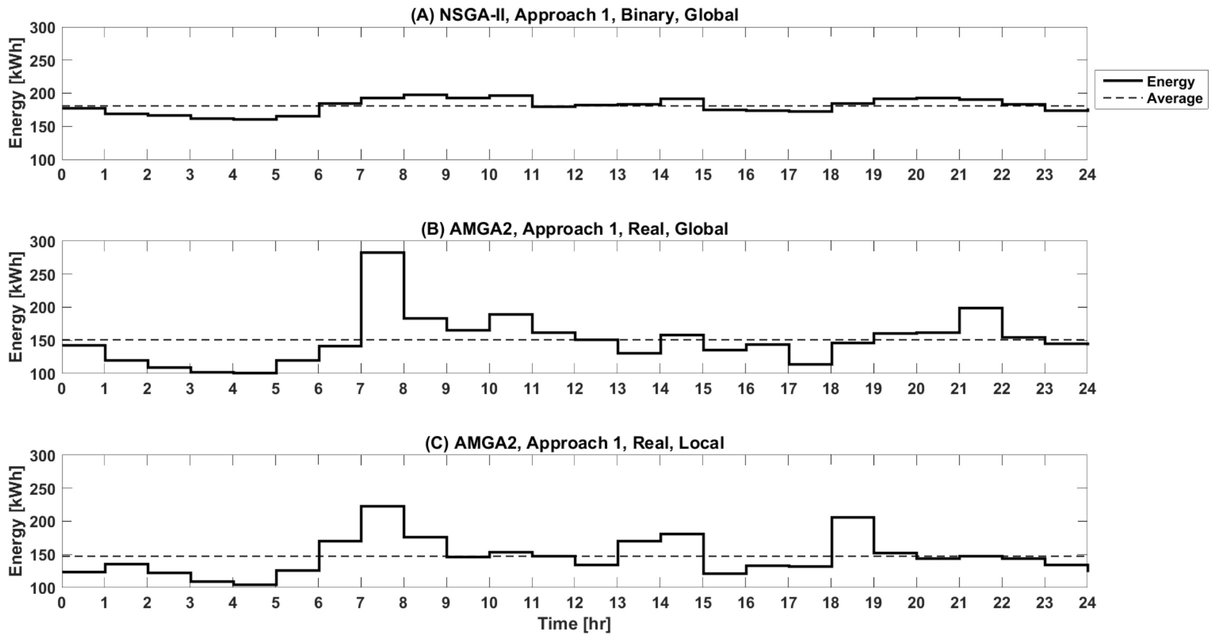


Figure 6-8. Daily energy consumption for the three cases analysed. Dotted lines show the average energy consumption.

In general, the daily energy consumption presents a uniform behaviour for Binary variables (Figure 6-8A). By contrast, the optimal pump schedule using Real variables shows a peak at time of critical demand (Figure 6-8B and Figure 6-8C), but throughout the day the energy consumptions are lower than for Binary variables. The use of the Local constraints reduced also the peak value of E_T between 07:00-08:00 compared to Global constraints. The average energy consumption, also presented in Figure 6-8, shows a reduction due to the application of VSP in the system, when comparing ON/OFF pumps and VSP pumps.

- PS for variable demand and required pressure

After performing the simulations with all the algorithms, it was noted that there was a need to simulate the behavior of the system for variable demand and variable required pressure. In this way, it is possible to cover several operational scenarios for water supply. In this case, it is important to know the proper pump schedules for daily operations under special conditions.

This analysis was carried out to cover large landscape of demands and minimum pressure. To do this multiple MOO PS problems where performed, with pump speed results presented in Figure 6-9.

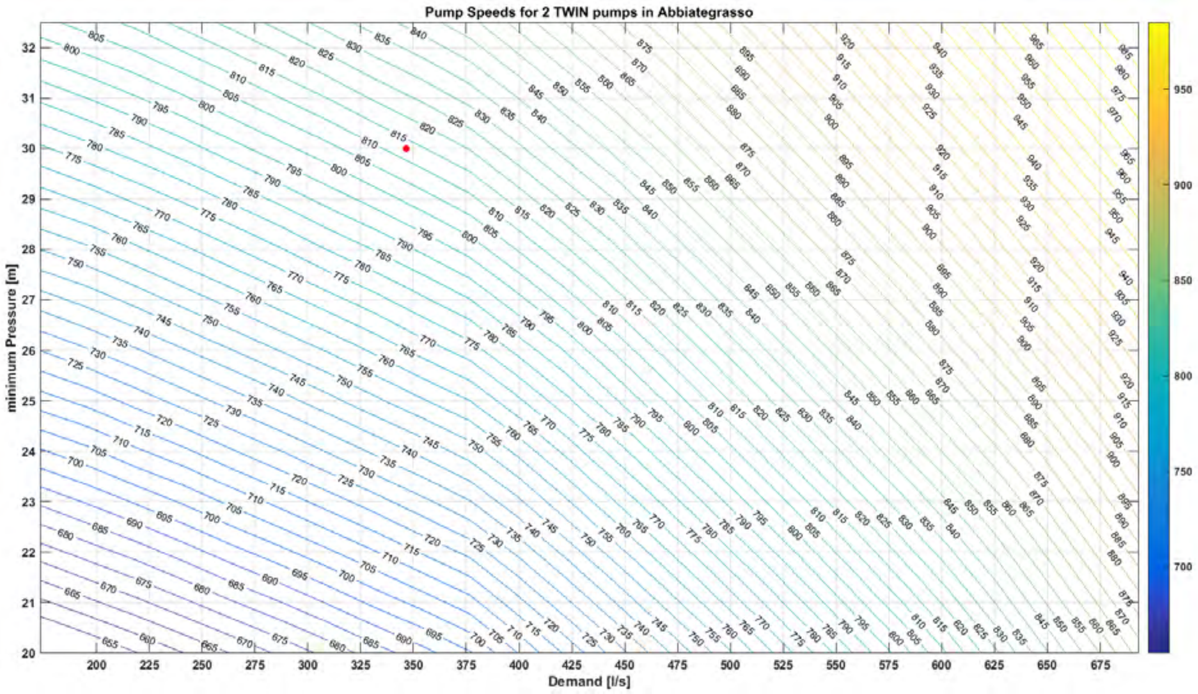


Figure 6-9. Pump speeds in revolutions per minute (RPM) required to satisfy the demand in Abbiategrasso with 2 twin pumps as a function of Demand [l/s] and minimum Pressure [m]. Red dot presents the obtained results for two twin VSP pumps with current demand and pressure management.

All problems have a set up in which both pumps in Abbiategrasso are set as twin pumps, meaning that they operate at the same pump speed simultaneously. In this case, the number of decision variables was only 24 variables. In the end, it was possible to generate the pump speed for each of the two pumps of the system of Abbiategrasso. The results are summarized in Figure 6-9, where the red dot contains the data of the current demand and pressure requirement in Abbiategrasso. The pump speeds are presented as RPM values instead of multipliers as in EPANET, because the operator requires such values as input to the SCADA system rather than MOO formulation results.

As an additional result, the same analysis was performed with variation of pressure and demand in the system, but now with the possibility to supply water to Abbiategrasso with only 1 pump. The results of such analysis are presented in Figure 6-10. It should be noted that the operation of one pump is allowed to have over-throttle during optimization up to 10%. The current installed pump operates at 980 RPM, so values above this threshold correspond to such condition. With only 1 pump it is possible to satisfy a demand from 350 l/s in the district up to a maximum of 447 l/s. This implies that the results obtained using Binary decision variables are confirmed and only 1 pump may be enough to supply Abbiategrasso.

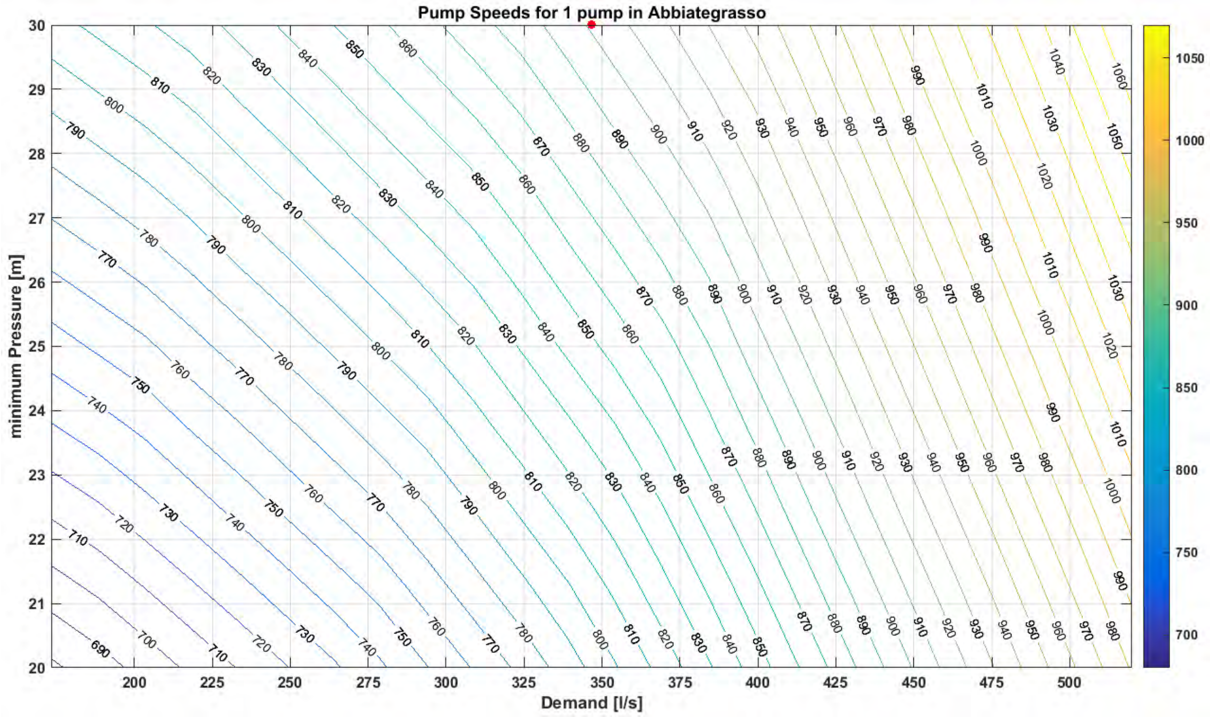


Figure 6-10. Pump speeds in revolutions per minute (RPM) required to satisfy the demand in Abbiategrasso with 1 pump as a function of Demand [l/s] and minimum Pressure [m]. Red dot shows the current required operation in Abbiategrasso.

6.7.2 Field test in Abbiategrasso

An experiment was performed with operators of MM, with the idea of applying the results obtained with MOO to the real system of Abbiategrasso. Such activity was performed in June 2015. It needs to be remembered that there was no direct link between the developed DSS services of the ICeWater project and the SCADA system as presented in Figure 1-3. For that reason, a pump schedule was supplied to MM (by email) and the job of the operators at MM was to update the pump speeds accordingly, throughout the day in the SCADA system.

For comparison purposes the day of June 19th 2015 was used as Base Case (BC), while the day of June 25th 2015 was the day for the Optimised Case (OC). Optimised case, means when the pump schedule provided by the optimization algorithm with Approach 1 for VSP and global constraint was applied by MM.

The resulting energy recorded in the SCADA system is presented in Figure 6-11. It is evident that the OC presents lower energy consumption throughout the day with respect of the BC. The only exceptions are 09:00, 20:00 & 21:00 where the energy consumption is practically the same.

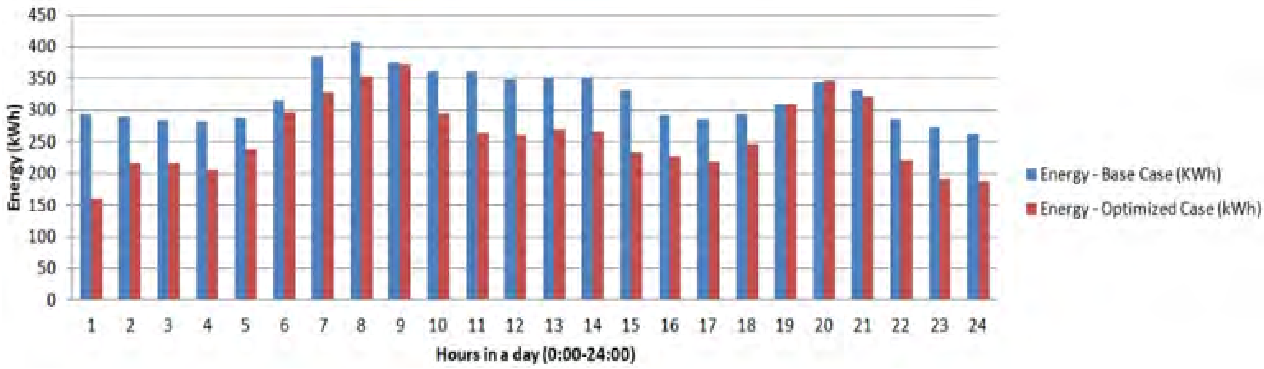


Figure 6-11. Comparison of Energy consumption in Abbiategrasso. Base Case (BC) and Optimised Case (OC).

In addition, the pressure at the outlet from the pumping station for both BC and OC is presented in Figure 6-12. It is evident that there is an additional gain as the pressure in the system is significantly reduced for most of the day (~900 minutes or ~ 15 hr) with around 10 m column of water reduction. In the last hours of the day the OC presents marginal pressure reduction.

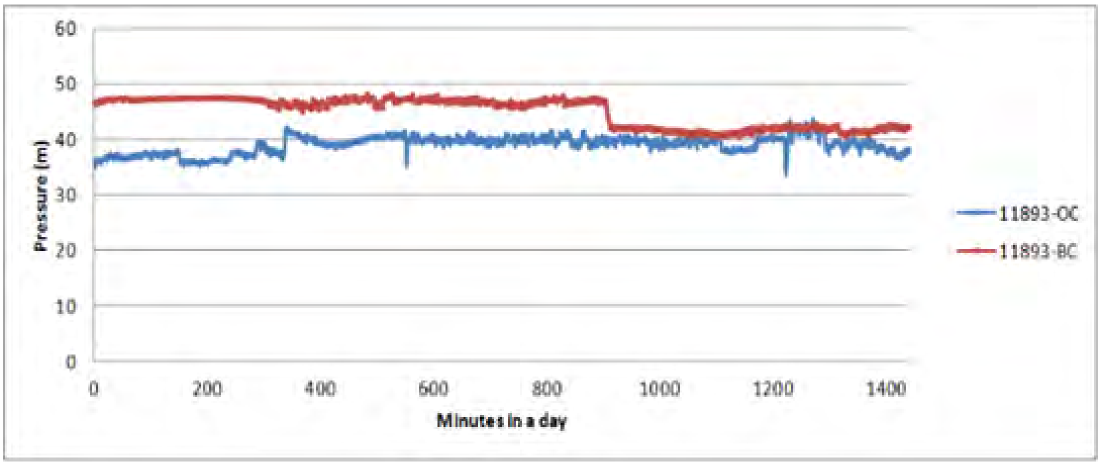


Figure 6-12. Comparison of pressures of Base Case and Optimized Case in Abbiategrasso at the outlet of pumping station (sensor id: 11893 in Figure 5-3).

Table 6-2. Pump scheduling and pressure management business case results

Key Performance Indicator	Units	Value
Reduction in avg. system pressure	M	5.50 (~10 for 1st 15 hours)
Corresponding reduction in energy required for pumping	kWh/day	1454.5
Unit Cost of Energy (average over 3 tariffs for the different periods in the day)	€/kWh	0.15
Energy Cost Saving	€/day	~218
Reduction in MNF	l/s or m^3/day	50 or 4320
Marginal Cost of water	€/m^3	0.070

Key Performance Indicator	Units	Value
Reduction in leakage related cost	€/day	~ 302

MNF: Minimum Night Flow.

Summary of some common performance indicators after the application of the pump schedule is presented in Table 6-2 were obtained from MM. In general, the average pressure is reduced by 5.5 m, the energy required for pumping by 19% and the Minimum Night Flow (MNF) by 50 l/s. This represents a reduction of pumping costs of 218 €/day, while a reduction of water cost of 302 €/day. The return of investment of the application of pump scheduling and pressure management is in the order 528 days or 1.44 yr. Basically MM, has already recovered the investment (~€390,000) made in the implementation of the new VSP and installation of the PRV's and inverters.

6.7.3 Optimization results of Full WDN of Milan

Given that the correct/optimal operation of the system of Milan was still unknown, it was decided to proceed and perform a MOO of the whole network of Milan. Two restrictions are the computational time to execute each time step of the whole network and the large number of possible demand patterns that can be supplied to the system for a daily operation. For those reasons it was decided that necessary MOO would be set up in such a way that a MOO scenario was run for a single time period with the demands in the system affected by a single demand multiplier. Although this process breaks the continuity in the operation of the system, it was known since early runs that it would be too complex to run the whole WDN as an EPS providing the pattern for each pump and at the same time preserve the stability of the MOO.

The MOO was set then for the current operation of the system of Milan with pumps operating as ON/OFF pumps (Binary decision variables). A total of 103 decision variables were used corresponding to each of the booster pumps. The constraint was set to Global in the whole network, to guarantee that the minimum pressure of 30 m, a requirement of the utility, is maintained.

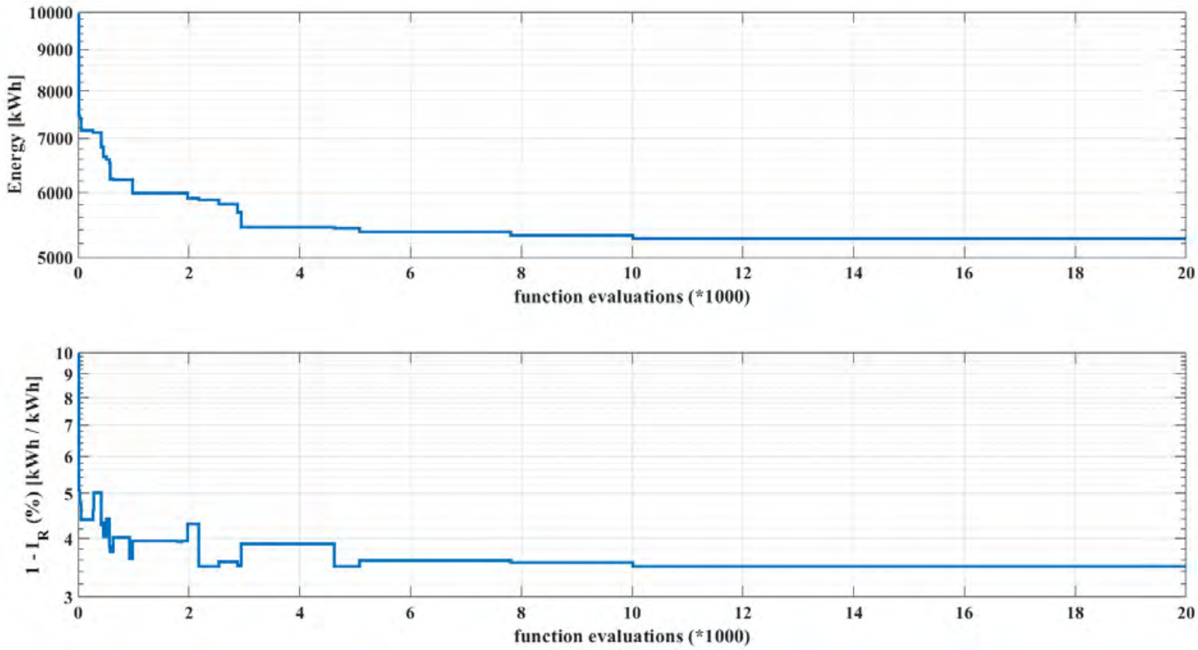


Figure 6-13. Evolution of the objective functions as number of function evaluations increase. (top) ET (kWh), (bottom) Lack of Resilience (%).

Finally, the same two objectives Lack of Resilience and E_T were used, as it was in the case of Abbiategrasso. Furthermore, three additional performance indicators of the system were used, minimum pressure (P_{min}), maximum pressure (P_{max}) and average pressure (P_{ave}). Each scenario was run for a total of 20,000 function evaluations taking in average a total of 20 days as time of computation. A total of 22 scenarios were simulated. In early runs of the algorithm it was perceived that the convergence was achieved when the number of function evaluations was close to 10,000 (see for example Figure 6-13). Nonetheless, the runs were left to continue until completing the 20,000 function evaluations.

All the scenarios run are presented in Table 6-3, where the demand multiplier corresponds to the factor applied to the base demands in EPANET model for the city of Milan. Only results for the solution corresponding to the operation with minimum energy obtained for each MOO scenario are presented. The column *Idx. sol* corresponds to the index of the function evaluation of a particular optimization run that was selected.

In general, there is an expected trend for the increase in energy consumption as the total demand increases (Figure 6-14). Although near the average demand (Demand multiplier ~ 1.0) there is a valley in the E_T consumption obtained. For the lack of Resilience there is a reduction of this objective as the demand multiplier increases. This result is expected due to the change in energy losses in the system as part of the calculation of resilience.

Considering the pressures in the system, the minimum value obtained by all possible scenarios of this pump schedule setup is close to the required value of 30 m.

Table 6-3. MOO results of pump scheduling for the Full WDN. Solution presented corresponds to the operation with minimum energy.

		Objectives		Additional Performance Indicators		
		Lack of Resilience	Energy	Pressure maximum	Pressure minimum	Pressure average
Demand Multiplier	Idx. sol	$1\text{-}I_R$ [%]	E_T [kWh]	P_{max} [m]	P_{min} [m]	P_{ave} [m]
0.300	15,352	6.44	1,361	79.19	37.90	60.22
0.375	19,794	5.69	1,522	73.09	30.54	52.95
0.400	11,052	5.63	1,652	72.52	31.27	53.26
0.500	11,641	5.62	2,133	73.35	31.95	54.31
0.600	8,224	5.57	2,507	72.85	30.18	53.42
0.675	13,436	5.18	2,752	71.15	32.09	51.01
0.700	10,757	4.80	2,816	69.03	30.75	49.05
0.750	3,759	5.10	2,908	68.48	30.23	49.30
0.800	17,056	4.69	3,026	69.28	30.18	47.07
0.875	12,801	4.72	3,235	66.02	30.09	46.67
0.900	14,590	4.61	3,291	66.71	30.02	46.05
1.000	4,240	4.90	3,970	69.47	30.15	49.23
1.100	4,153	4.19	3,977	60.75	30.04	44.44
1.140	11,140	3.42	3,963	57.10	30.36	41.07
1.200	19,164	3.92	4,452	59.87	30.12	44.00
1.280	7,537	3.68	4,789	59.44	30.96	43.24
1.300	14,318	3.36	4,658	61.55	30.05	41.45
1.400	11,492	3.64	4,909	57.26	30.04	42.08
1.420	8,433	3.22	5,248	60.01	30.06	41.52
1.500	4,799	3.30	5,419	56.15	30.16	41.48
1.560	10,001	3.48	5,274	52.49	30.03	41.14
1.600	14,301	3.84	5,544	54.26	30.09	42.68

For the indicator of average pressure it is evident that as, demand increases there is a reduction in the average pressure (see Figure 6-15). This may sound counterintuitive, however the same result is obtained for the maximum pressure. In both cases, this can be explained because an increase of demand will increase the number of pumps in operation and, as soon as this occurs, a balance in the whole system is reached. Water will travel less distance between pumping stations to satisfy the demand. This being the case, less nodes with high pressure will be obtained in the southern part of the network.

The pump schedule which should be provided during the day can be seen in Figure 6-16. It displays the variation of demand multiplier and each of the active pumps in the whole. The pump schedule presented (each row) represents the one with the lowest energy consumption for a particular value of demand multiplier ran in each scenario. The values in yellow represent active pump (ON), while the blue ones represent pumps which are inactive (OFF).

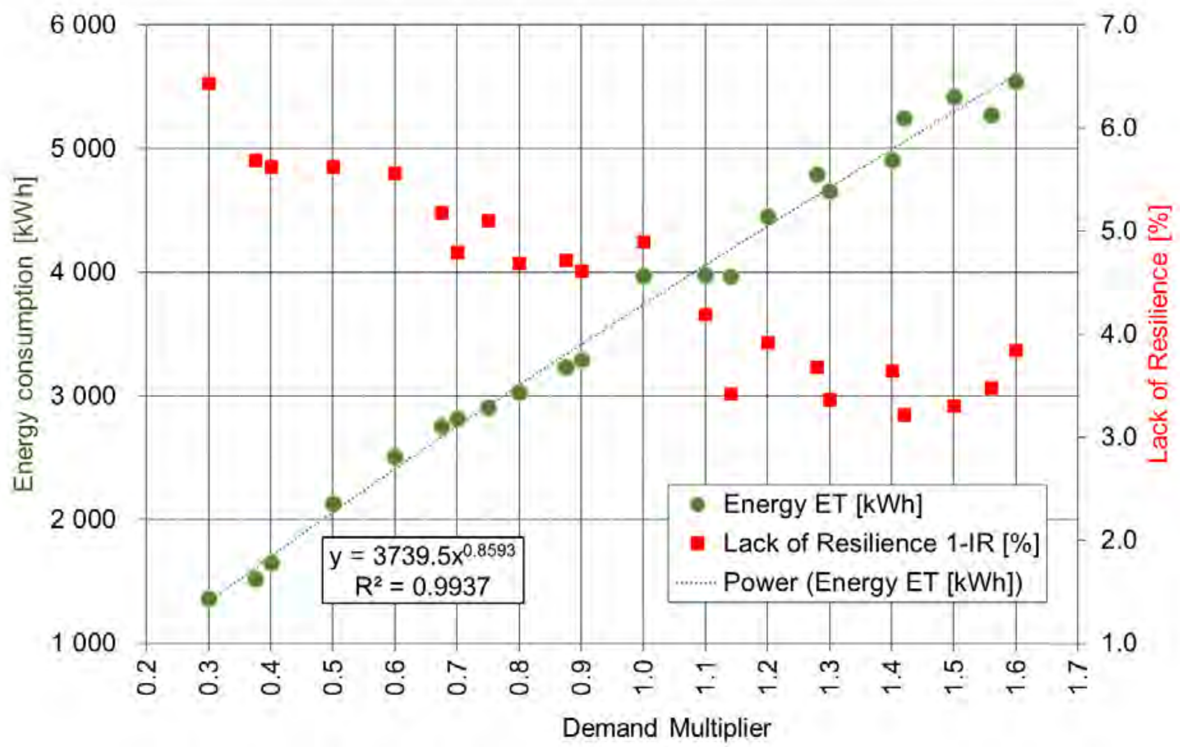


Figure 6-14. Energy and lack of resilience as a function of demand multiplier for optimal solutions obtained with MOO.

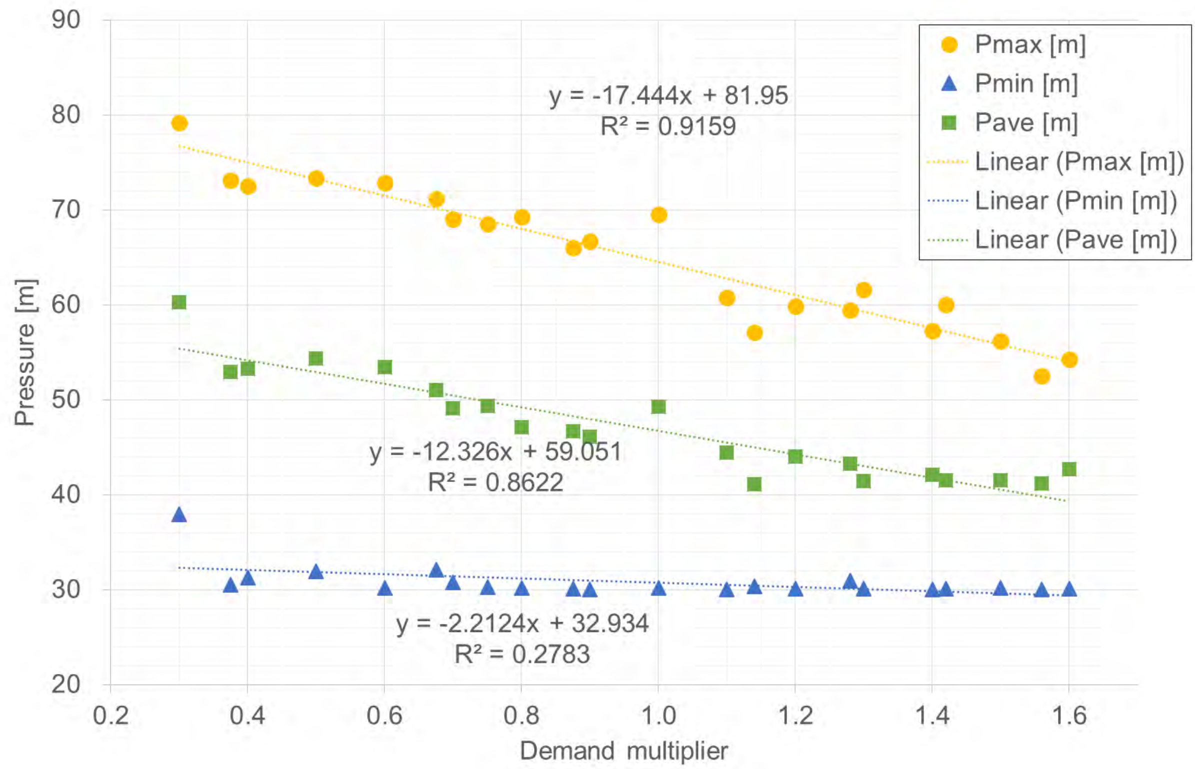


Figure 6-15. Pressure variation in the whole network as a function of the demand multiplier for optimal solutions obtained with MOO.

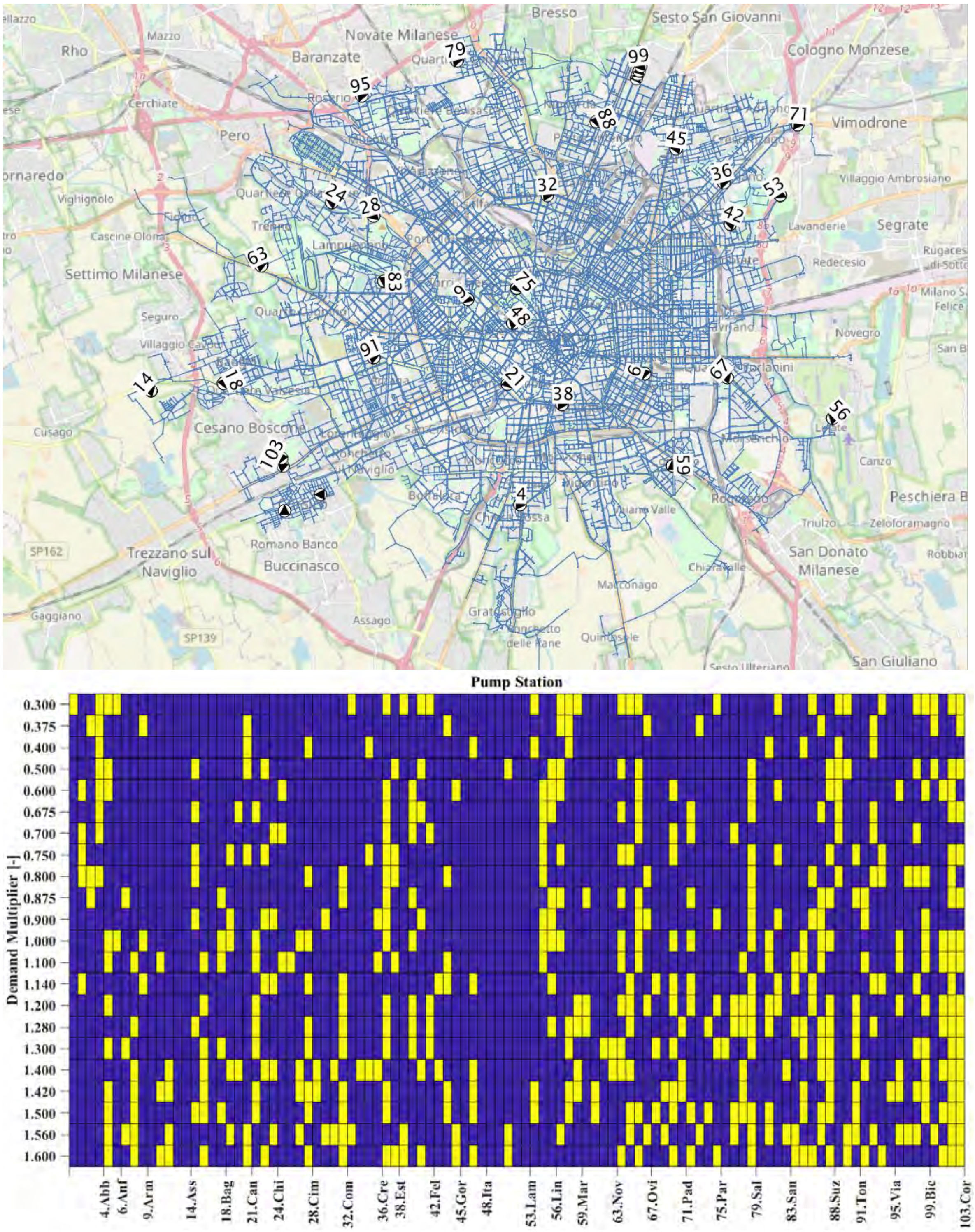


Figure 6-16. (top) location of each of the pumping stations in the city of Milan. See Table 5-2. (Below) Pump schedule for the whole network of Milan as a function of the demand multiplier (vertical axis), and the pumping station (horizontal axis) applied to Full WDN model. Yellow color means the pump is ON, while blue color means the pump is OFF.

There is no real trend in the behavior of the optimal pump schedule obtained as the demand increases. As each of the rows was obtained from a different optimization run, there is no connection between these independent runs. Besides that, the boundary conditions (levels in the tanks and demands) are kept similar for all the 22 scenarios of demand multipliers. It is evident that there is an exchange of active pumps in the south of the system. Abbiategrasso (#4) and Linate (#56) appear active as there is a need for a low consumption of water, while once the demand becomes around 90% of the average demand, these pumping stations become inactive for the operation of the whole system. Another aspect to take into account is that the two pumping stations of Biccoca (#103) and Corsico (#99) tend to be active for most of the optimization runs. In fact, in the real system operation these two pumping stations were barely used.

- Pressure management

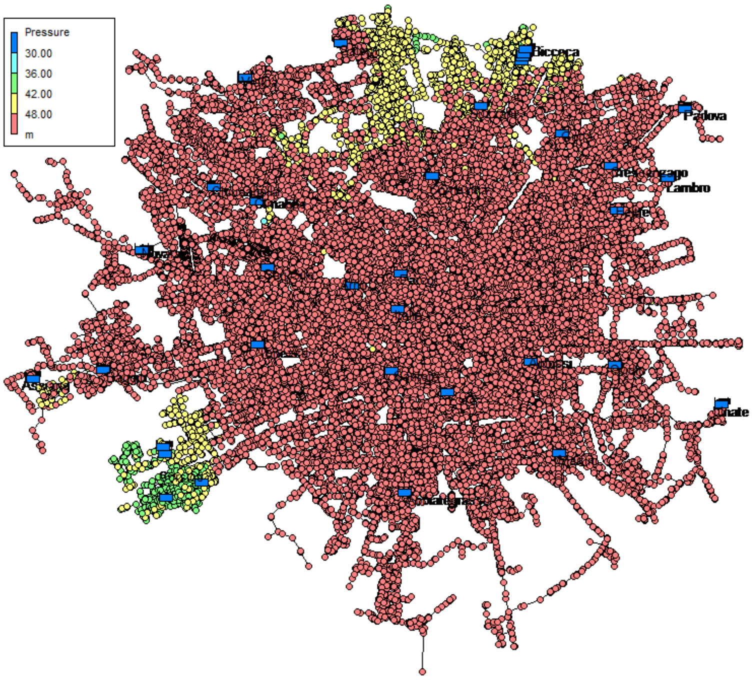
Figure 6-17, also shows an additional criterion that is of relevance for the utility regarding the need to apply VSP throughout the system. This would be needed at locations with high pressure, even after optimization. Such locations are only in the south (already done within the ICeWater project) in Abbiategrasso (#4), and on the pumping stations of Martini (#59), Linate (#56) and Ovidio (#67) on the southeast and Novara (#63) on the west. This is very important as can highlight the prioritization of further investments by the utility, if their objective is to operate their water supply more efficiently from an energy perspective.

6.8 Summary

It can be concluded that the optimal PS is proven to be efficient measure for E_T reduction and better pressure management of the system. In general, savings in the order of 20% of energy consumption were demonstrated by both theoretical results and by application of proposed optimal PS solutions in the field. Two algorithms were tested and their advantages and disadvantages from a computational perspective were discussed. The application of the pump schedule for the Full WDN of Milan displays additional gains in energy saving that can be made just using ON/OFF pumps with an improved, optimized pump scheduling. It is interesting also that one of the conclusions of the application of PS is the identification and prioritization of pumping stations to be transformed (if wanted) into VSP operation.

In the case of Milan, there is abundance of water availability. This is not commonly the case in many parts of the world. The point to be made here is the fact that all simulations are run using a Demand Driven Approach (DDA) instead of a Pressure Driven Approach (PDA), however, the number of booster and well pumps guarantee that the tanks have enough water to be pumped on a daily basis independent of the season or time of the year, and that the pressure basically never drops below 30 m.

(A)
Base Case, showing that most pressures in the system are above 48 m.



(B)
Optimised Case, shows that the pressures in the system contain a reduction of pressure for around 70% of the system. Pressure drops between 12-18 m.

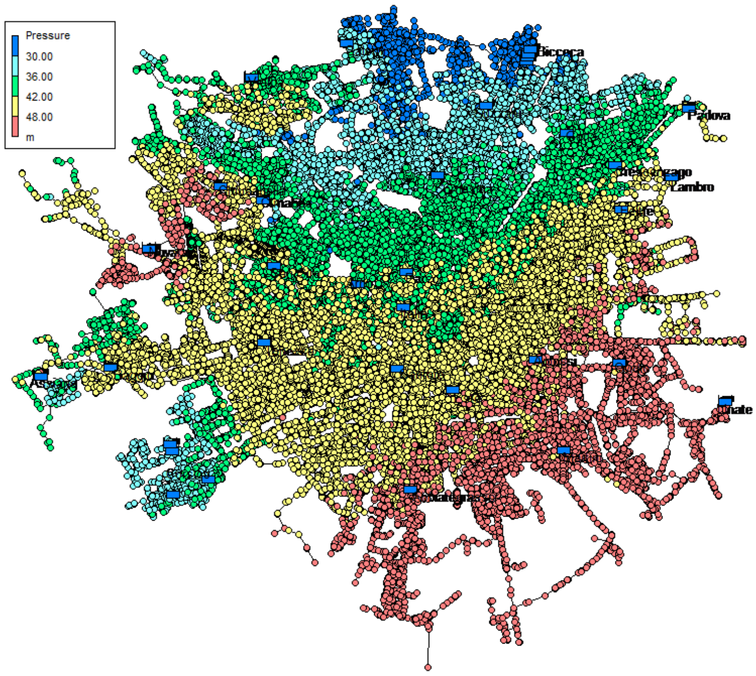


Figure 6-17. Comparison of pressures for Full WDN Milan at 08:12 or peak daily demand.

Additional analysis were not required for added demand, as the population is not expected to increase, but rather to decrease in the coming years. This points to the implementation of pressure management as one of the main needs of the utility for foreseeable future. Also, asset management and active leakage control as part of the operational strategies of the utility (not explicitly considered here), can benefit from pressure management in the Full WDN. In fact, pump scheduling and pressure management in Abbiategrasso showed that the gains can be in the order of 50 l/s in MNF.

7 OPTIMIZED SECTORIZATION OF LARGE WATER DISTRIBUTION NETWORKS – CASE OF FULL WDN OF MILAN

This chapter presents the formulation of WDNs as graphs and shows some definitions of relevance. These basic concepts are required for the understanding of the application of sectorization for energy minimization applied to the full WDN of Milan. Two different Approaches are used for sectorization. The formulations are presented in detail. In section 7.3 the results and discussion are presented, followed in section 7.4 by a further discussion of the limitations. The chapter ends with a summary of the obtained results.
This chapter is based on the following publications:

- Castro-Gama, M., Lanfranchi, E.A., Marelli, F., and Jonoski, A. (2017) Avoiding Myopic Decision Making In Water Supply Operation. Servizi a Rete 2017(3)47-48. ISSN 2499-6688. (In Italian)
- Castro-Gama, M., Pan, Q., Jonoski, A., Solomatine, D. (2016) A Graph Theoretical Sectorization Approach for Energy Reduction in Water Distribution Networks. Procedia Engineering. Special Issue of the 12th International Conference on Hydroinformatics (HIC 2016) – Smart Water for the Future. 154, 19-26. DOI: 10.1016/j.proeng.2016.07.414.
- Pan, Q., Castro-Gama, M.E., Jonoski, A., and Popescu, I. (2016) Decision Support System for Daily and Long Term Operations of the System of Milan, Italy. Procedia Engineering. Special Issue of the 12th International Conference on Hydroinformatics (HIC 2016) – Smart Water for the Future. 154, 58-61. DOI: 10.1016/j.proeng.2016.07.419.
- Castro Gama, M., Pan, Q., Jonoski, A., and Chiesa, C. (2015) Model-Based Sectorization Of Water Distribution Networks For Increased Energy Efficiency. Proceedings of the HIC2014. Paper 233.

7.1 Graph theory-based Representation of WDN

7.1.1 Graph theory definitions used

The main algorithm for hydraulic simulations of WDN is known as the Global Gradient Algorithm (GGA), as it is implemented in EPANET2.0 (Rossman, 2000). Inside this algorithm, a definition for a topological incidence matrix is elaborated. This matrix, known as incidence matrix $\boldsymbol{A_{pn}}$ has dimensions of [$\boldsymbol{n_p}$ x $\boldsymbol{n_n}$], where $\boldsymbol{n_p}$ is the number of links (including pipes, valves and pumps) and $\boldsymbol{n_n}$ is the number of nodes in the network (including demand nodes and water sources such as tanks and reservoirs). Each row contains only two non-zero values which correspond to the initial and ending node of the pipe. The values are {1,-1} depending on the positive direction of the assumed flow in the pipe.
By analogy, this matrix can be interpreted as a graph incidence matrix where nodes are graph vertices ($\boldsymbol{V_1}$) and pipes (valves and pumps) are graph edges ($\boldsymbol{E_1}$). By definition, a graph $\boldsymbol{G_1}$ contains a set of $\boldsymbol{G_1}(\boldsymbol{V_1},\boldsymbol{E_1})$ elements, so it is possible to analyse WDN using the same principles of graph theory (Yazdani & Jeffrey (2011) (2012).

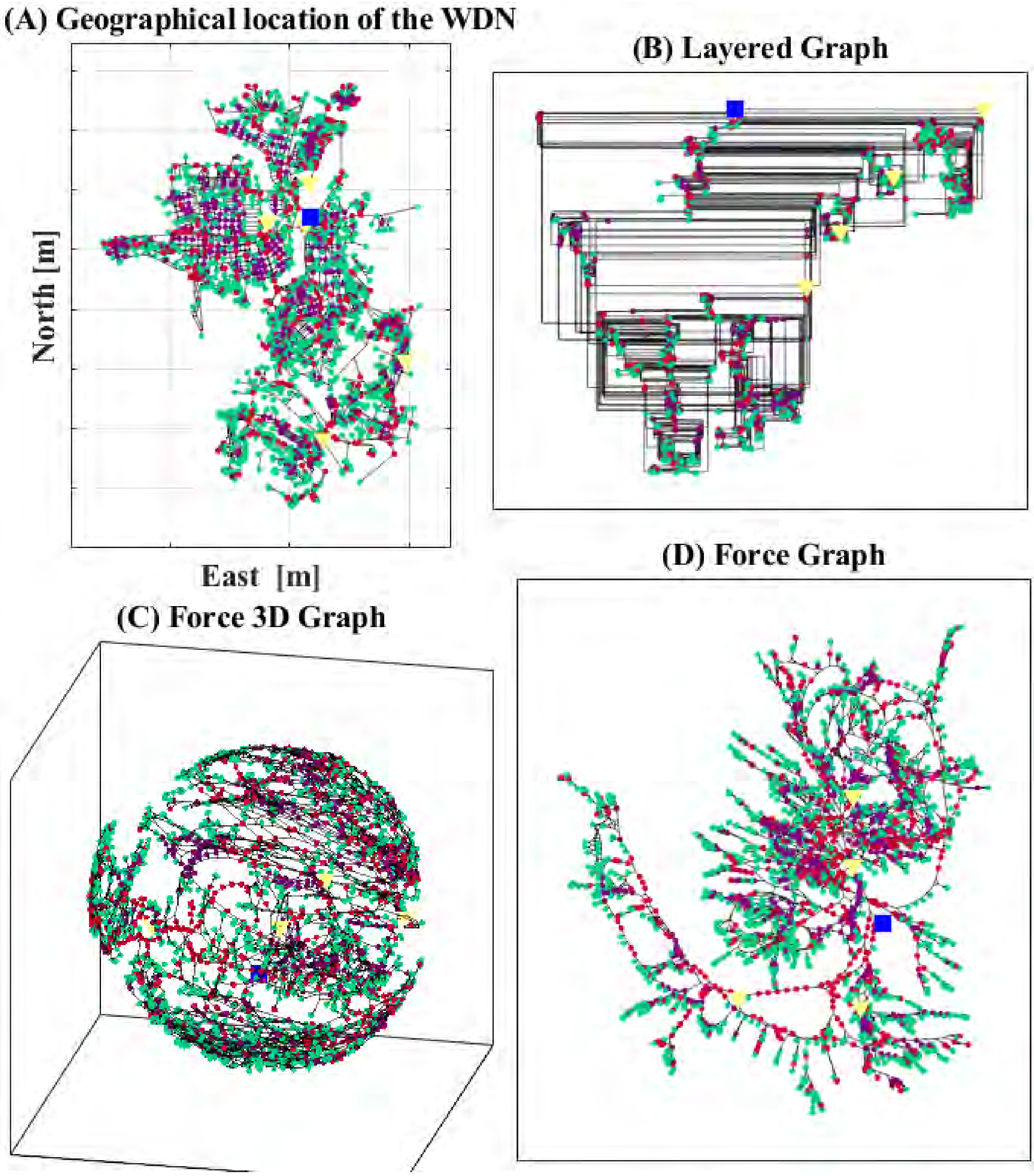


Figure 7-1. Representation of a WDN as a graph. The colors represent the degree of each vertex (node), Degree = Number of edges connected to each vertex. Degree = 1, green; Degree = 2, red; Degree ≥ 3, purple. Blue square is the reservoir, while yellow triangles are the tanks. (A) Representation given by coordinates, (B) Layered graph representation (C) sphere/force 3D graph representation (D) Force 2D graph representation.

As an example, a visualization of a WDN as a graph is presented in Figure 7-1. This WDN corresponds to the supply system of a city in Colombia[10] and can be represented in multiple ways as a graph. Layers graph (Barth, et al., 2004) (Brandes & Koepf, 2002) plots nodes into a set of layers, revealing a hierarchical structure. Circles graph (Gansner, et al., 1993) are a

[10] This network was selected as it was smaller and facilitated the analysis presented for graph theory in comparison to the models used for pump scheduling and sectorization of the Full WND which are much larger.

good way to represent small world networks (Watts & Strogatz, 1998) (Milgram, 1967) and random networks (Barabasi, 1999) (Erdos & Renyi, 1960). Force graphs (Fruchterman & Reingold, 1991), uses artificial attractive forces between adjacent nodes and artificial repulsive forces between distant nodes to create a representation of the system. A WDN can be expressed as a planar graph, because all of its elements are located in two dimensions (Barthelemy, 2011), and its connectivity and layout allows for its study differently than complex networks (Yazdani & Jeffrey, 2011).

Given this property, some graph theoretical indicators may be used to demonstrate different properties of a WDN. In this case, we present 2 different indicators: Closeness centrality and Betweenness centrality. The closeness centrality uses the inverse sum of the distance from a node to all other nodes in the graph. If not, all nodes are reachable, then the centrality of node i is:

$$C(i) = \left(\frac{A_i}{N-1}\right)\frac{1}{C_i}$$

Equation 7-1. Closeness centrality formulation of a graph.

Where A_i is the number of reachable nodes from node i (not counting i), N is the number of nodes in the graph G, and C_i is the sum of distances from node i to all reachable nodes. If no nodes are reachable from node i, then $C(i)$ is close to zero (and its logarithm is negative).

The Betweenness centrality measures how often each graph node appears on a shortest path between two nodes in the graph. Since there can be several shortest paths between two graph nodes i and j, the centrality of node k is:

$$C(k) = \sum_{i,j \neq k} \frac{n_{ij}(k)}{N_{ij}}$$

Equation 7-2. Betweenness centrality formulation of a graph.

Where $n_{ij}(k)$, is the number of shortest paths from nodes i to j that pass through node k, and N_{ij} is the total number of shortest paths from nodes i to j.

To demonstrate the principle of both indicators of graphs, these were applied to the same WDN. The results are presented in Figure 7-2. Closeness centrality shows that this system has a large variation, while many nodes are difficult to reach, depicted as dark blue. This is caused by the fact that these are located far away to its surroundings, there are also nodes which are reachable from many different locations (dark red), meaning that water can reach theses nodes of the WDN from different surrounding vertices.

In the case of the Betweenness centrality, the number paths for which nodes can be reached, also presents large variability. Remarkably nodes which are located in extreme vertices of paths of the graph have a value close to zero (dark blue), while nodes which are internal to the WDN present a higher value (dark red) close to one.

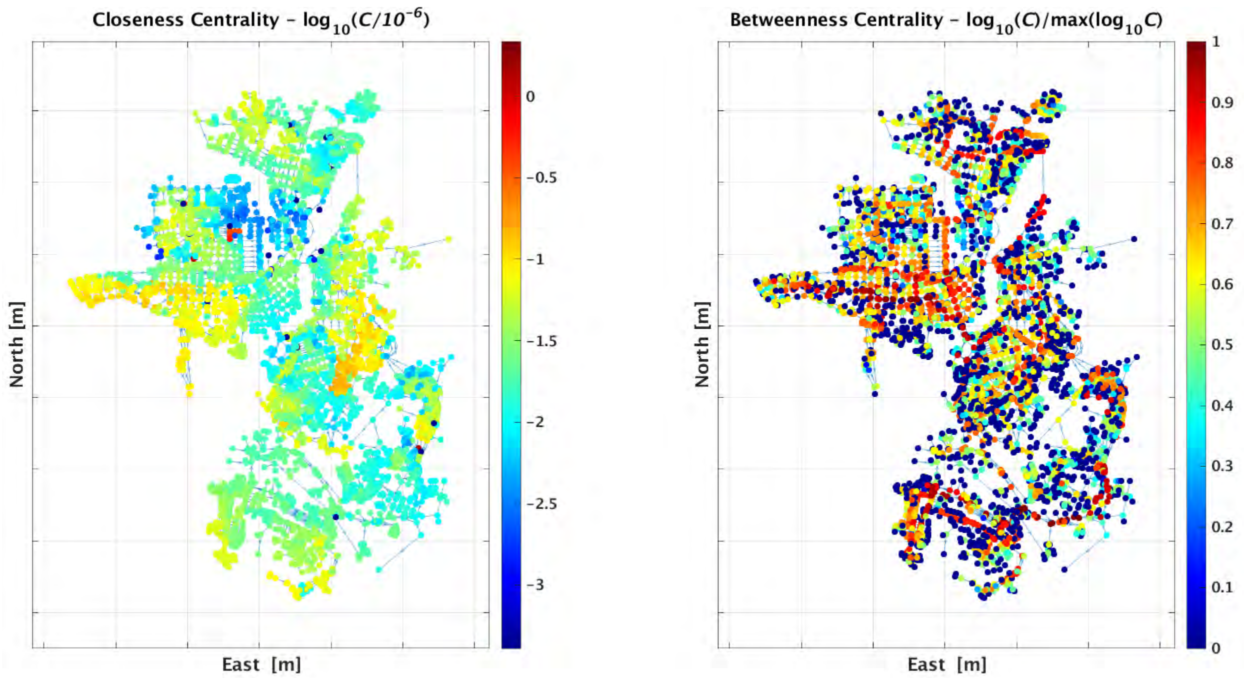


Figure 7-2. (left) Closeness centrality and (right) Betweenness centrality of the example WDN in Colombia.

7.1.2 Shortest dissipated power path

The algorithm for sectorization of a WDN is composed of two different steps. This first step is initialization and the second one is sectorization. Initialization deals with the identification of elements of the WDN which may isolate smaller subsystems supplied by source(s). As a result of initialization, smaller subsectors are identified. The number of subsectors is established as the maximum number of sectors for a given WDN. If all subsectors are connected, then a WDN operates as a single sector, while if all subsectors are isolated, the maximum isolation has been reached (and the largest possible number of sectors). As mentioned earlier, currently the WDN of Milan operates as a single connected system.

It is also possible to create larger sectors from the subsectors depending on their neighbours. This allows for the possibility to create a diverse number of sectors of different size (that we call ‘sectorization configurations’), where each sector can be supplied with single or multiple sources. This process of splitting a graph is known as a *k-way* graph partitioning (Kernighan & Lin, 1970) (Karypis & Kumar, 1998).

Previously, Castro-Gama et al. (2015), presented an algorithm for initialization based on graph theory using Shortest Dissipated Power Path – SDPP based on previous work of Di Nardo and Di Natale (2011). It corresponds to a shortest path analysis of a WDN, in which the distance measured along each vertex is the head loss from a hydraulic simulation. This algorithm was presented in of Di Nardo and Di Natale (2011) only for use when the sources of each subsector are gravity sources. In the case of gravity sources, the energy supplied, or the maximum distance reached from any source, is the result of the head losses of pipes connected to a certain source. In the case of pumping stations as sources, the limitation is not only the head loss of the pipes added to each source, but also the maximum available discharge which may be

supplied by the pumping station. This is overcome by taking into account the maximum extent or SDPP to which a pumping station can provide flow to satisfy the demands.
Given that the sources are pumps, an equivalent pump curve can be constructed as presented in Figure 7-3. Each time a new link is added to a source there is an increase in demand and a reduction on the available head from the pumping station. For this reason, the supply of each pumping station is limited not only by the friction losses between a source and adjacent nodes, but with the total demand that needs to be quantified. The shortest path algorithm (Dijkstra, 1959), deals only with distances along the edges of a graph. The calculation of the SDPP here is performed by affecting the dissipated distance by a factor depending on the total demand which a pumping station can supply.

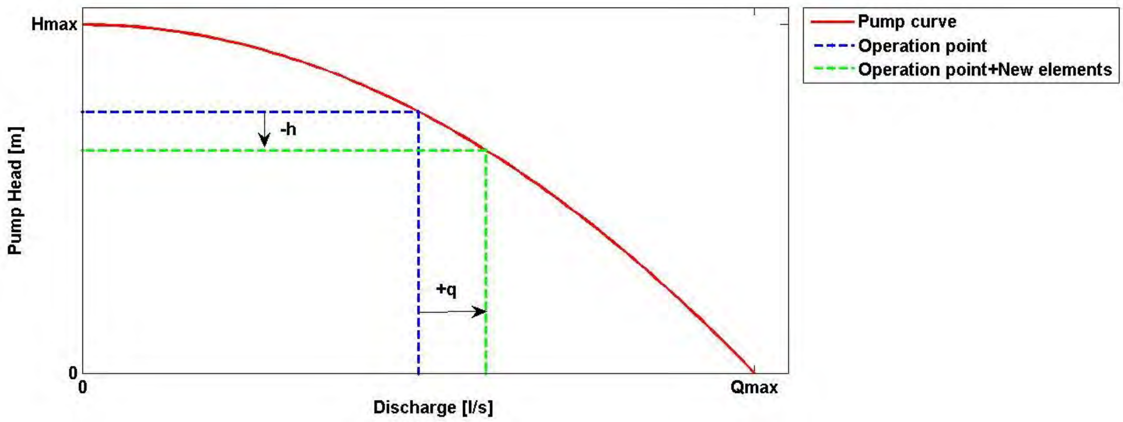


Figure 7-3. Increase of demand by adding new elements and reduction of available head in pump curve.

The representation of the adjacency matrix for the Milano Full WDN is presented in Figure 7-4, where two different representations are made while comparing with the sparse adjacency matrix (Figure 7-4c).

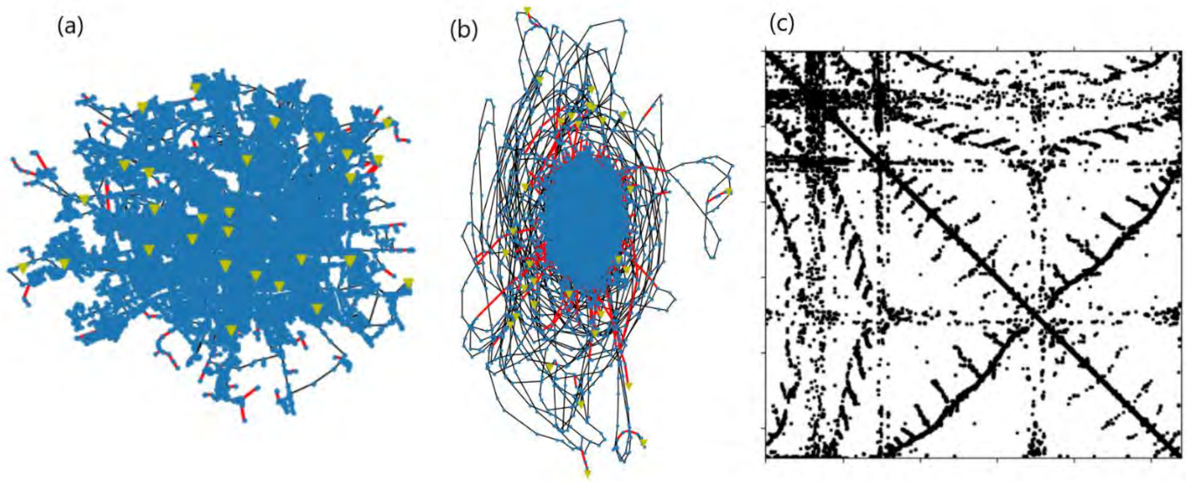


Figure 7-4. (a) Milano Full WDN, (b) force graph, (c) visualization of sparsity of adjacency matrix of graph.

Based on the graph of Milano Full WDN, it was possible to estimate the SDPP from different pumping stations. Such result is presented in Figure 7-5. Colors represent SDPP distances from the pumping stations. Blue color means nearby the pumping stations, while red color represents locations where customers are further away. A similar treatment is made for all pumping stations, although not all are presented here. The intersections of such SDPP from all pumping stations allows the identification of valves which isolate the system in subsectors.

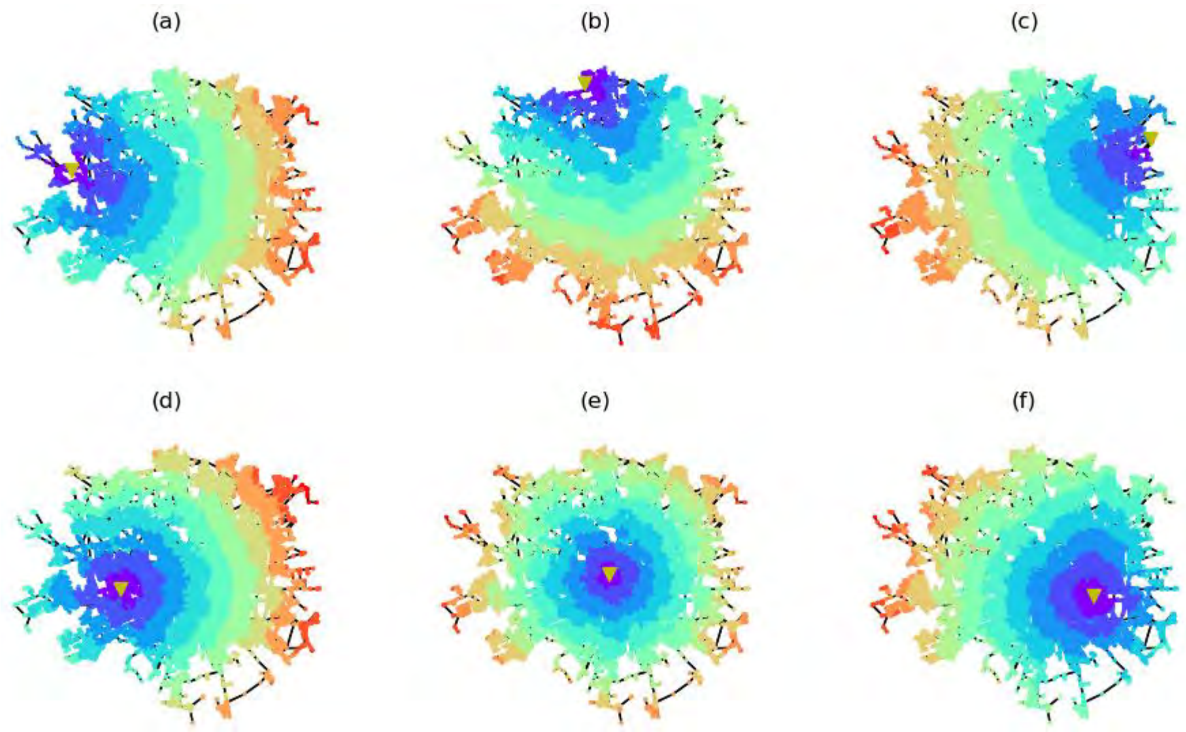


Figure 7-5. SDPP as a result of the graph of Milano Full WDN. Results from six different pumping stations.

7.2 Problem formulations

The initialization algorithm presented in Castro-Gama et al., (2014) identified the boundaries between subsectors, named *cut-sets* (sets of isolation valves). However, in that approach, once the isolation valves were identified, these *cut-sets* were included as decision variables in a MOO problem formulation. Given that the opening or closing of cut-sets was driven only by the MOO, it was not possible to fix the number of sectors during optimization. This is presented here as Formulation 1. That formulation presented some drawbacks and because of that, a second formulation was developed to minimize the hurdles obtained with the first one (see Figure 7-6).

When evaluating the MOO formulations, a computational consideration is made not to include more than two objectives (same ones used in PS optimization). In some cases, it has been tried to perform some simulations including indicators of pressure as objectives, but it was shown that this restricts the evolution, creating more effort for the optimization algorithm.

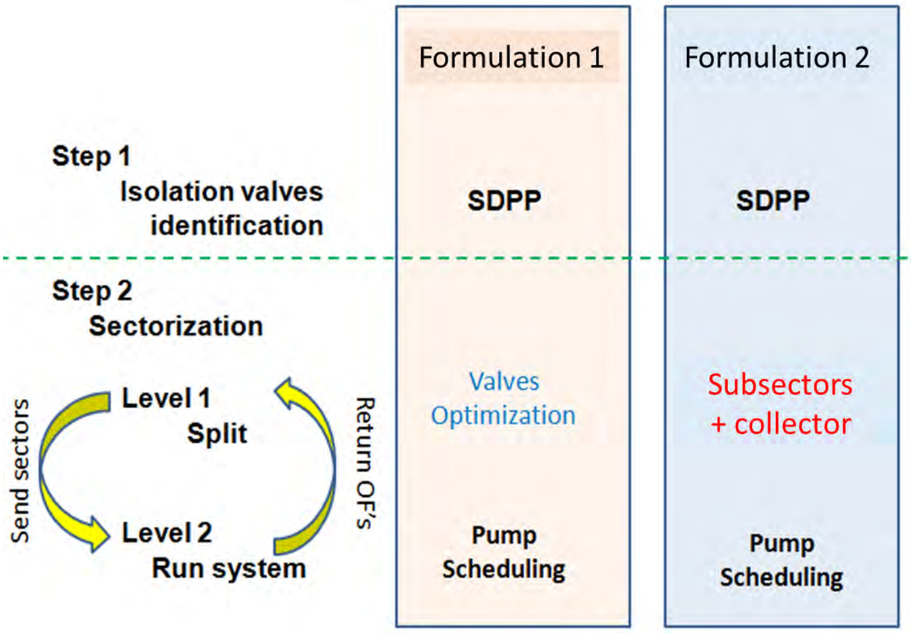


Figure 7-6. Two different approaches used for sectorization. Formulation 1 takes into account the valves as individual decision variables. Formulation 2 considers creating larger sectors from a predefined subset.

After estimating the SDPP from each source to all the elements, the valves which contain nodes belonging to two sources are marked as the splitting elements. As mentioned in Chapter 5, the Full WDN contains 26 pumping stations and 2 sources from neighbouring cities (Biccoca and Corsico). Some pumping stations share pipelines which cannot be completely isolated and some larger initial subsectors had to be formed. That is the case of Tonezza, Baggio and Assiano, located in the southwest of the city; Armi, Italia and Parco located in the center; Feltre, Crescenzago, Lambro and Padova located in the east, and Ovidio and Linate located in the southeast. After the application of this approach a total of 346 valves were identified, distributed in 38 boundaries. The system of Milan can be split into a total of 18 subsectors (s_1 to s_{18}) identified in Table 7-1, and in Figure 7-7. It is also possible to identify that each subsector contains a different number of pumping stations (sources) (also Table 7-1). Of particular notice is the fact that the vertex of the graph presented in Figure 7-7 correspond in this case to a set of cut-valves and not to individual valves. In the following sections the two formulations indicated in Figure 7-6 will be presented.

Table 7-1. Subsectors created with SDPP for Full WDN Milan. It includes the names of pumping stations and how many pumps in total belong to the subsectors.

Subsector	s_1	s_2	s_3	s_4	s_5	s_6
P. Stations	Salemi	Vialba	Suzzani	Gorla	Chusabella	Cimabue
n-pumps	4	4	5	3	3	4
Subsector	s_7	s_8	s_9	s_{13}	s_{14}	s_{15}
P. Stations	Comasina	Novara	San Siro	Cantore	Este	Anfossi
n-pumps	4	4	4	3	2	2

Subsector	*S10*	*S11*	*S12*	*S16*	*S17*	*S18*
P. Stations	Armi Italia Parco	Feltre Crescenzago Lambro Padova	Tonnezza Baggio Assiano	Ovidio Linate	Abbiategrasso	Martini
n-pumps	10	17	12	7	4	3

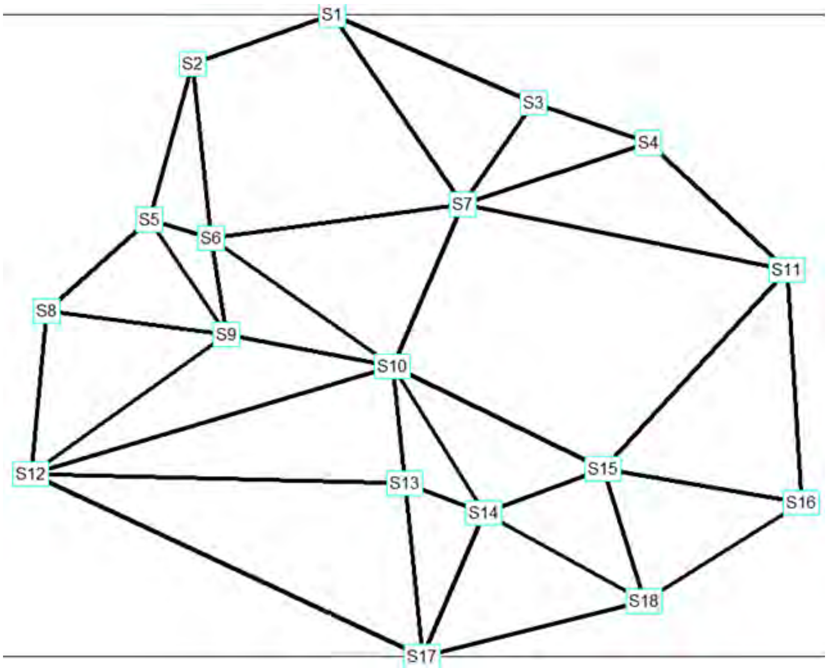


Figure 7-7. Graph of the 18 subsectors for the WDN of Milan.

7.2.1 Formulation 1 – Automatic sectorization evolution

- Algorithms

This is a single level MOO with NSGA-II. This algorithm was selected because it has the possibility to use binary variables. In the case of AMGA2 the evolution is made through differential evolution and binary variables pose a problem for its convergence.

- Decision Variables

The decision variables in this case are Boolean for ON/OFF (closed or opened cut-set valves and pumps). This formulation provides the valves to be closed and the pump schedule to be supplied. This means that a total of 141 decision variables are considered (38 isolation cut-set valves or vertex in Figure 7-7, plus 103 booster pumps). As it will be presented in the results section, this originated two additional issues as some large *idle* sectors start to appear. In some cases even some *idle* boundaries exist in the system.

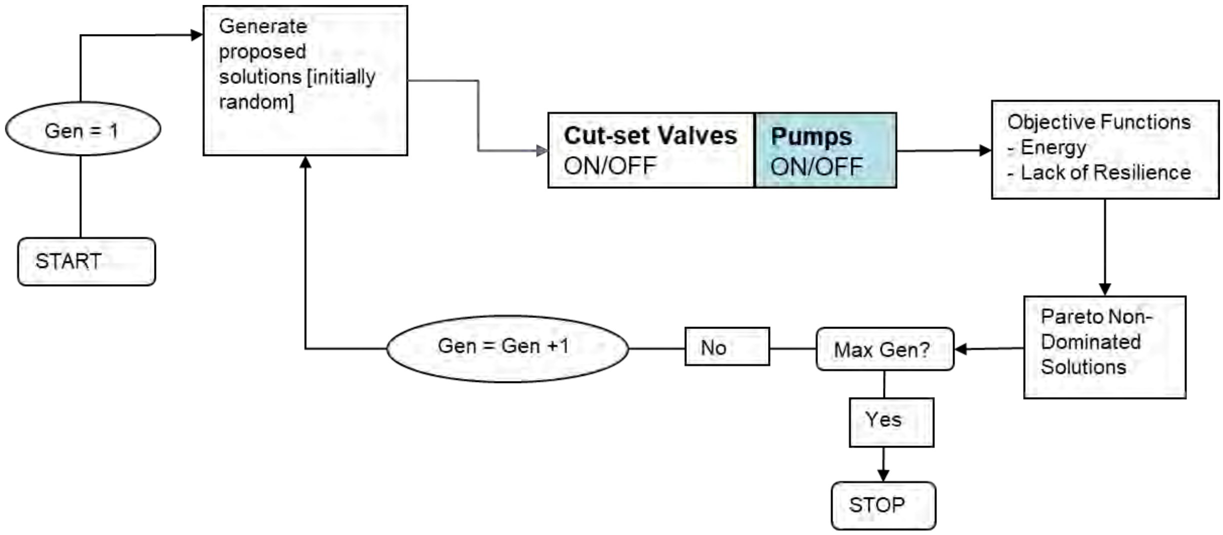


Figure 7-8. Flowchart of MOO for Formulation 1

- Objective Functions

Here the implementation takes into account the same two objectives used during pump scheduling: minimization of total energy consumption and lack of resilience.

- Constraints

Global pressure constraint approach was used with value of 30 m for all function evaluations. If there were negative pressures due to idle sectors, then the solution was assigned a hard penalty.

7.2.2 Formulation 2 – User driven sectorization

- Algorithms

The algorithm starts from the same basis as the first formulation. The goal here is to guarantee that there is possibility to create larger sectors from the set of subsectors defined using SDPP. Here an algorithm known as *card collector* is applied. For the purposes of illustration, consider a WDN composed of 14 subsectors *s* that needs to be split into 4 larger sectors *LS* (see Figure 7-9). The pseudocode of the algorithm follows the steps presented in Table 7-2.

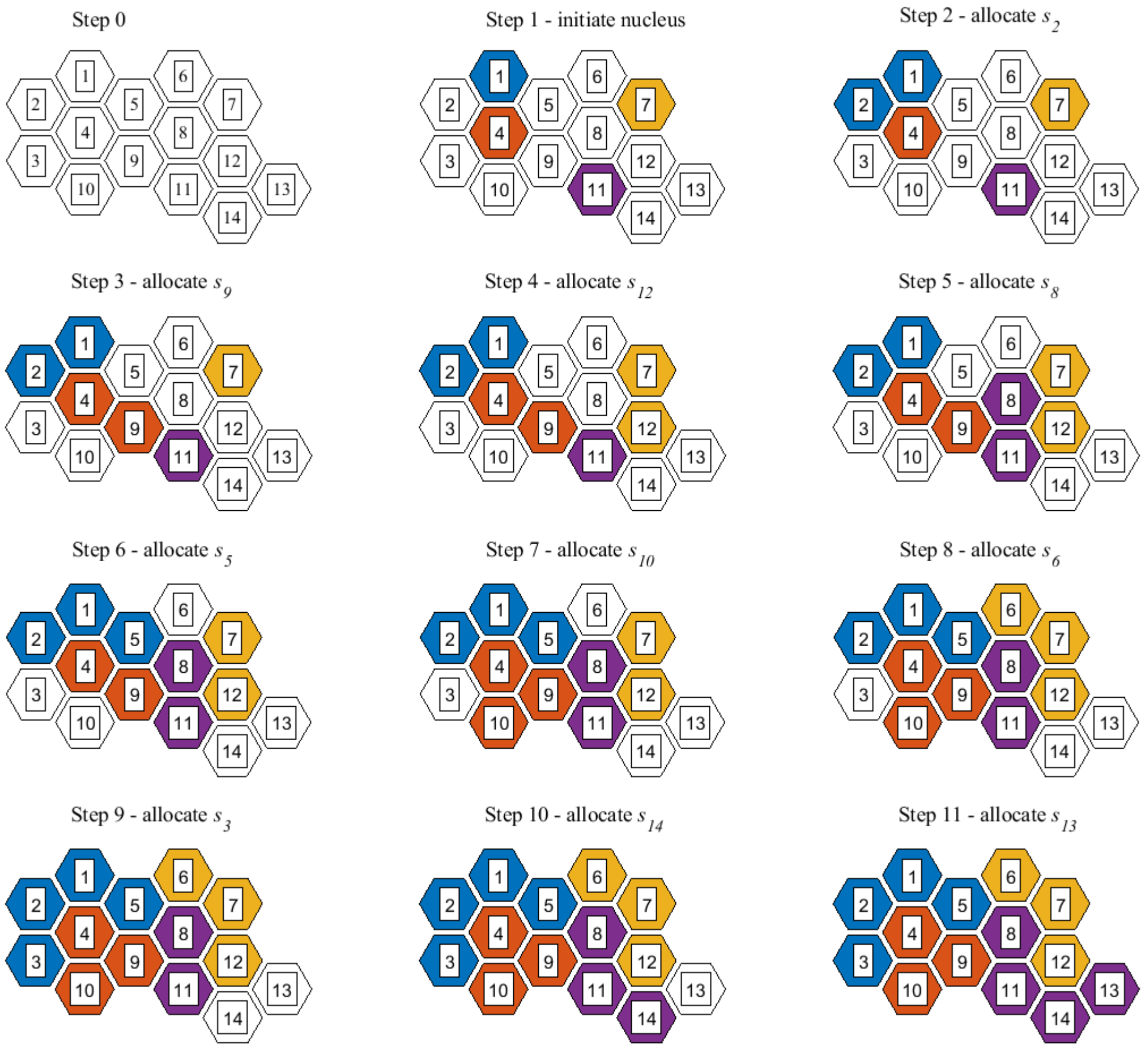


Figure 7-9. Step by step allocation of subsectors of Formulation 2 for sectorization. Here a conceptual WDN which can be split using SDPP into 14 subsectors is allocated iteratively into 4 larger sectors. In this case the maximum number of neighbours for any subsector is six.

Table 7-2. pseudocode for allocation of subsectors in Formulation 2.

Step 0, corresponds to the identification of all subsectors *s* and their neighbours *n*. For example s_1 is neighbour of {s_2, s_4, s_5} while for example s_{11} is neighbour of {s_8, s_9, s_{12}, s_{14}}. A total of 4 larger sectors *LS* are required.

Step 1 initializes randomly the so-called 'nucleus of allocation'. In this particular case the nucleus is composed of *LS1* ={s_1}, *LS2* = {s_4}, *LS3* = {s_7}, *LS4* = {s_{11}}. During this step the subsectors are removed from the list of available subsectors (*AS*) or subsectors yet to be allocated (a total of 10 of them) *AS* = {s_2, s_3, s_5, s_6, s_8, s_9, s_{10}, s_{12}, s_{13}, s_{14}}. Notice that after Step 1, s_4 is not a neighbour subsector of s_1 and vice-versa. In that case their neighbourhood must be removed.
The neighbourhood of *LS1-neighbours* corresponds to {s_2, s_5}, while *LS2-neighbours* = {s_2, s_3, s_5, s_9, s_{10}}.

Step 2, a sector *LS* is selected at random. Let's say *LS1*. Then s_2 is randomly selected as neighbour of *LS1* (the other only possible alternative is s_5). Then *LS1*={s_1, s_2} and *LS1-neighbours* = {s_3, s_5}. After allocation of s_2, the neighbourhood is updated for the other three

LS. Subsequently *LS2-neighbours* = {s_3, s_5, s_9, s_{10}}. An additional update of the remaining subsectors to be allocated shows that *AS* = {s_3, s_5, s_6, s_8, s_9, s_{10}, s_{12}, s_{13}, s_{14}}. If a *LS* has no more neighbour subsectors ***s***, then it is finalised.

Step 3-12, the procedure of **Step 2** is iteratively followed until *AS* is empty.

The big picture of the algorithm is presented as final solution for all possible number of large sectors with all possible number of initial subsectors. In the case of Milano, the total number of subsectors is 18 and the number of subsectors can vary between 2 and 17. Only a small set of scenarios can be run in real life, as the total number of combinations is exponential. On top of that, after performing the allocation of subsectors into larger sectors, each larger sector contains a group of pumps. In order to guarantee that the sectorization is feasible an optimal pump schedule of the system configuration is run.
The selected configurations were obtained in consultation with MM, and in the end, it was of their best interest to obtain either 2, 3 or 9 sectors. On average, a computer simulation of the whole WDN takes around 200 s (> 3min). So, an initial set up of the system was performed identifying that a MOO becomes almost stagnant after around 20,000 function evaluations. A single run under these conditions, may take around 1.5 months. Given the total number of scenarios employed for each configuration of sectorization (10 in average), it was estimated that a total computational power equivalent to 6 years was necessary on a single machine with a couple of cores.
Set up of this optimization was made using a cloud computing service known as SURFSARA. In this case, all the selected configurations were obtained and then the system was subjected to PS optimization.

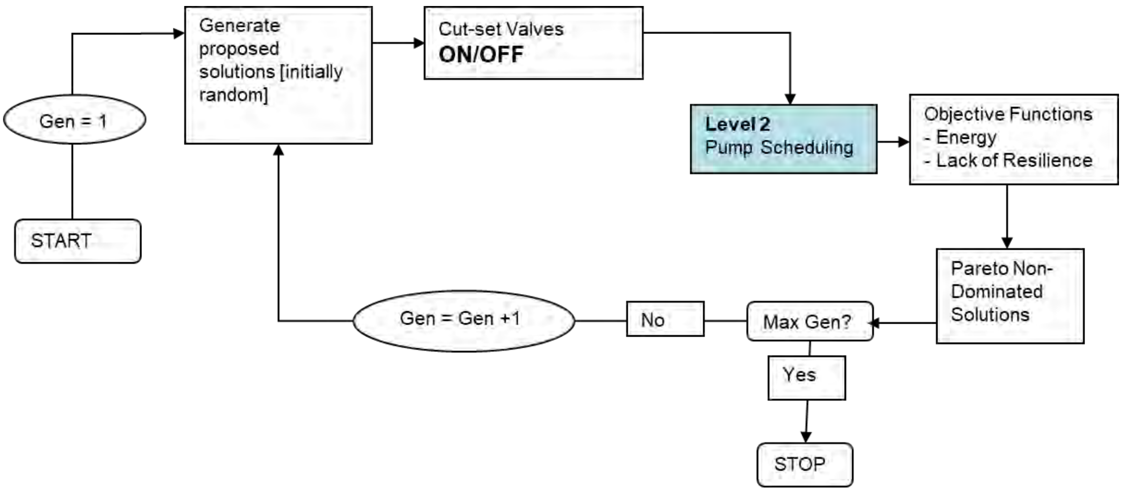


Figure 7-10. Flowchart of MOO for Formulation 2 of sectorization.

To circumvent this computation time issue an executable for the simulation of the WDN was developed in C/C++ and was called as objective function(s) from MATLAB. At the time the computational efficiency on the use of an EPANET wrapper developed in MATLAB was rather low compared with running EPANET directly from C/C++. Given that the maximum number of function evaluations obtained in precooked runs was of around 20,000, a population of 100

(similar to the number of decision variables = 103 pumps) and a maximum number of generations of 200 was set up in the enhanced NSGA-II algorithm implemented in the Global Optimization package of MATLAB. In 2016, the total computation time was of the order of 2 weeks for 20,000 function evaluations. A new test of the same code performed in 2019, showed that the computational time can be reduced by half.
The optimization is run in such a way that minimization of E_T and $1\text{-}I_R$ are the key objectives for the whole system. This means that a MOO was still in use as presented in Chapter 6. At the same time, results are constrained in such way that a minimum pressure in the whole network was obtained.

- Objective Functions

Same objectives of minimization of E_T and lack of resilience were used, as it was the case for pump scheduling. In some cases, when mentioned, an additional setup as single objective in which only the E_T was taken into account with a hard constraint on the minimum pressure.
Other performance indicators were stored as well in order to have a clear view of the behaviour of the WDN as a whole. These include minimum pressure (P_{min}), maximum pressure (P_{max}) and average pressure (P_{ave}), as already introduced in PS optimization of full WDN in Chapter 6.

- Decision Variables

Decision variables are binary variables, which correspond to the pump status as ON/OFF pumps. In fact, the sectorization input files for EPANET are created in advance so the boundaries remain in the same status during the whole pump scheduling optimization.

- Constraints

Majority of the cases simulated were set with a minimum pressure of 30. This corresponds to the utility's requirement with the municipality. Some cases were simulated with a setup for a required pressure of 20 m for comparison. In case that minimum pressure was not obtained in the demand nodes the simulation was thrown by using a hard penalty constraint as it was the case for Abbiategrasso's Pump Scheduling and Full WDN Sectorization.

- Extended analysis

The analysis of solutions of each MOO run is based on exploratory analysis. The goal is not only to find the optimal solution, but rather to develop understanding of behavioural patterns of the system under different configurations. As in the words of Hamming: "*The purpose of computing is insight, not numbers.*" (1973). This information is valuable for the utility, as at the moment this research was conducted it was unknown to them what would be the outcome of sectorization of the whole system.
In the case of this formulation, expert knowledge was used to include the dominated solutions in the additional analysis, which is performed to obtain the best unbiased solutions of MOO. For this reason, pressure indicators are included in the analysis as a factor to consider. Just looking at the energy and resilience of the system can blindly indicate a configuration with large pressures in some part of the network. This happens due to the nature of the sectorization analysis, when some solutions with low energy consumption may create nodes with high pressure.
The number of solutions obtained for each Pareto front (and set) is limited in each run (less than 30 solutions). For that reason, analysis are performed in what may be understood as

enlarged Pareto front. Such solutions correspond to the 2,000 function evaluations which are closer to the Pareto front in terms of dominated and non-dominated solutions. In that case, solutions closer to the Pareto front can reveal interesting aspects of the operation of the system for the utility, even if these are suboptimal. An additional brushing of solutions was performed by limiting the average pressure of the system to a maximum of 45 m. An utility can perform the interventions on WSS only one time. The selection of the best possible configuration (and its associated pump schedule) is made performing unbiased selection based on the methods of data visualization (see Table 4-1). Several data visualization methods have been developed during the years, such as Scatter 2D and 3D (Miettinen, 2014) (Tukey & Tukey, 1981a) (Tukey & Tukey, 1981b), Parallel Plot (Parallel Plot) (Inselberg, 1985), level diagram (LD) (Blasco, et al., 2008); and Hyper-Radial Visualization (HRV) (Chiu & Bloebaum, 2008) and trade-off index (Unal, et al., 2016). These are applied for each enlarged Pareto front.

In a first stage the PS was performed trying to obtain the pumps which must be active during the regular operation of the system, similar to ON/OFF pumps (Binary decision variables). Then, after obtaining the number of pumps which are required for each configuration, a selection of a single PS solution is made based either on the minimum E_T [kWh] and lack of resilience.

Additionally, for the objectives and the pressure performance indicators, a classification of all the solutions is performed with Self Organizing Maps (SOM) (Kohonen, 2001). In this way, it is possible to see that the solutions of the extended Pareto front tend to be clustered into different groups of solutions.

Finally, a dendrogram (Morse, 1980) of the pump schedules is performed to visualize how different the obtained pump schedules of the Pareto front are from each other. In this case, the distance used for the dendrogram is Hamming distance (Hamming, 1950).

7.3 Results and discussion

7.3.1 Results for Formulation 1

In Figure 7-11, the corresponding sectorization for Approach 1, with IDLE boundaries is presented. IDLE boundaries refers to a problem in which an additional boundary is set between two sectors or as an internal division in a sector, but in reality there is no added value to its implementation as the sector does not become either split or isolated. This particular issue is highlighted more in section 7.4. The total energy consumption of the system is 5,216 kWh, which is a significant reduction with respect to the base case (of about 30%). It can be observed that the optimization algorithm has a tendency to reduce the number of sectors, creating a large sector in the middle of the network.

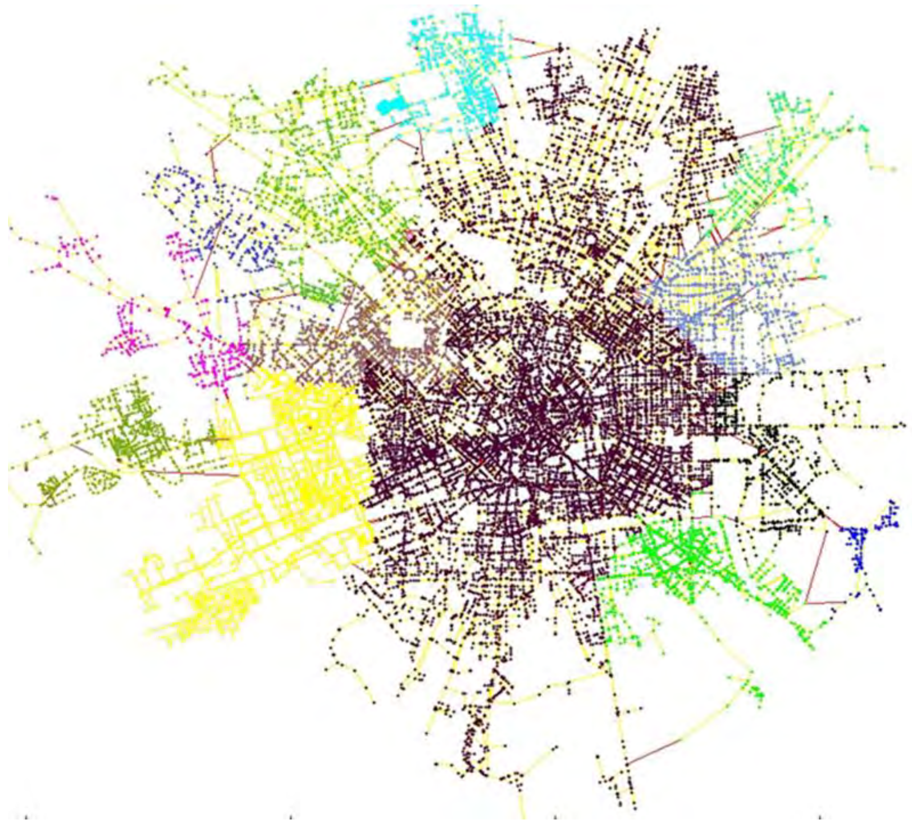


Figure 7-11. Sectorization for Formulation 1, with idle boundaries.

For that reason it was required to force the formulation to remove the idle boundaries during the optimization stages. This task was performed by forcing idle boundaries to be removed from the set of decisions of the optimization. The final results present a scenario opposite to what was expected as final sectorization of the WDN of Milano with non-idle boundaries are presented in Figure 7-12. The final energy consumption is 3,601 kWh, which is a further reduction from the previous result. The results show that Formulation 1 forces the optimization to create a single sector of the whole network, with couple of small sectors in the periphery of the city. In other words, *no sectorization* seems to be the optimal sectorization.

Regarding the pressures of the system it was discovered that the algorithm indeed reduces the pressure in the network, but it created two additional issues during evolution: 1) the pressure range of operation was still high, 2) there were areas which became isolated sectors with no supply. One example result of pressures obtained in a particular simulation run are shown in Figure 7-13. In general, such solutions get disposed by the optimization algorithm in the evolutionary process of several generations, however this delayed the convergence to good solutions to some extent.

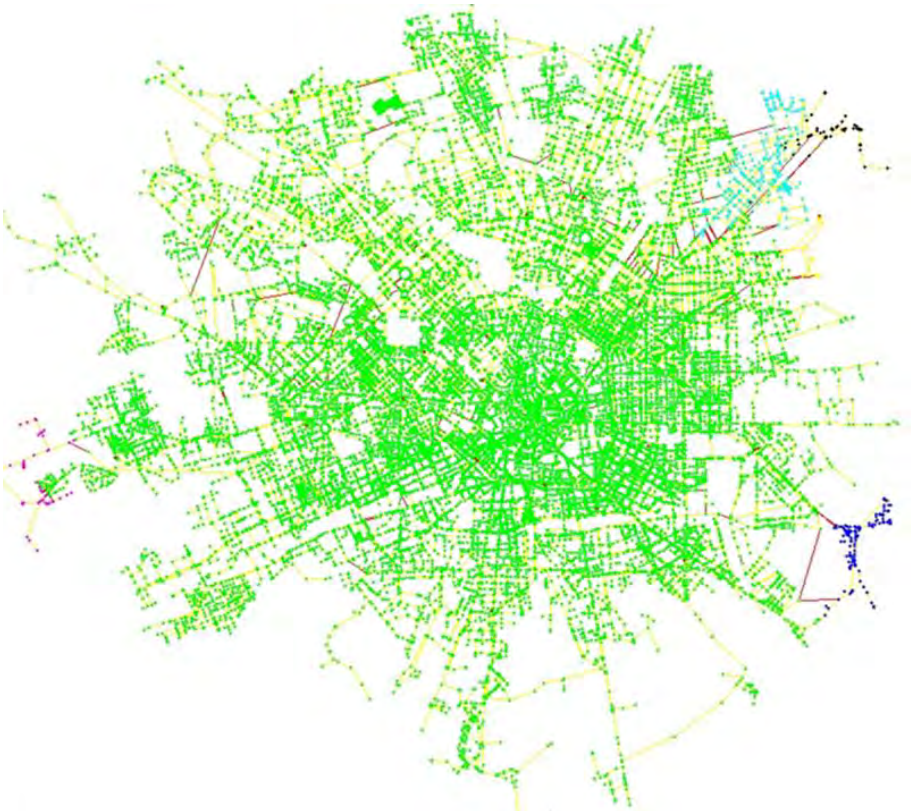


Figure 7-12. Sectorization for Formulation 1, with Non-idle boundaries.

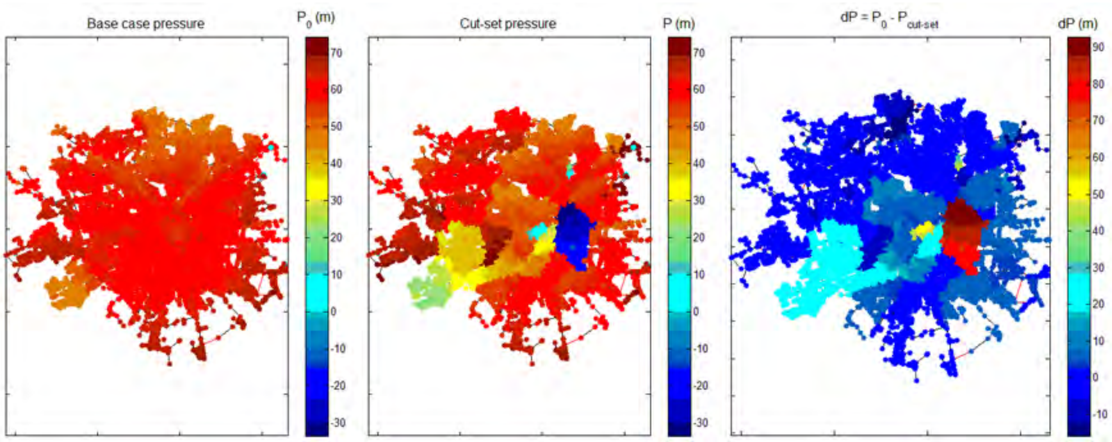


Figure 7-13. Pressure variation in one sectorization attempt with Non-IDLE boundaries.

It is evident that some areas can be completely isolated from the system (with negative pressures) and still develop lower energy consumptions compared to no sectorization. Due to the dubious nature of this result it was decided to implement Formulation 2.

7.3.2 Results for Formulation 2

For the second formulation of sectorization problem, it was necessary to perform a large number of sectorization scenarios.

The first scenario was the existing situation of the WDN without sectorization as a single PMZ. This scenario of WDN configuration was named 01 sector. In this configuration all elements of the system are connected and the only way to modify the energy consumption is through PS.

The second scenario of interest was the simulation of the system completely split into the maximum number of 18 sectors. This scenario of WDN configuration was named 18 sectors. In this configuration of the system there is a variation in operation both by use of the sectorization and PS.
The third scenario that was planned was to perform the partitioning of the WDN in two sectors. There are 11 cases of sectorization in two sectors that were studied.
Due to a specific request by the utility (MM) to operate the system as a three-sector PMZ's network, there was the additional need to investigate the possible outcome of such configuration for system operation. In this case a total of nine different possible configurations were run.
The final scenario that was planned, corresponds to split the system in nine sectors. For such a scenario 10 different possible configurations have been explored.
Detailed results will be presented here for the scenarios with one and with 18 sectors. Results for scenarios with 2, 3 and 9 sectors are included in the Appendix.
It is interesting that for most of the scenarios and configurations the optimal PS contains around ~30 active pumps (out of 103 pumps), independent of the configuration.

- Scenario with one sector

There is only one possible configuration for the operation of the system as a single sector. For that reason, several cases were ran for a configuration of 01 sector, which differ in the PS optimization setup, as presented in Table 7-3. A total of 4 configurations were ran and will be contrasted versus the *Base case* which corresponds to the current operation of the system.

Table 7-3. Scenario with 01 sector, all configurations analysed.

Parameter		Base Case	Config. 1-1	Config.1-2	Config.1-3	Config.1-4
	Unit	**Current Status**	**01 Sector**	**01 Sector**	**01 Sector**	**01 Sector**
Optimization	type	-	SO	MO	MO	MO
n-objectives	global	-	1	2	2	2
Var. type	type	-	Binary	Binary	Binary	Binary
n-variables	global	103	103	103	103	95
n-constraints	global	-	1	1	1	1
P required	m	-	20.0	20.0	30.0	30.0
n-pumps	-	40	29	30	35	31
Lack of resilience	%	7.14	6.80	4.99	3.48	3.33
Total Energy (E_T)	kWh	7 379	5 447	4 509	***5 274***	5 669
P min	m	41.1	26.6	20.2	30.0	30.0
P max	m	69.9	60.0	54.6	52.5	54.8
P ave	m	56.4	43.1	32.9	41.1	42.6

Although, only 2 objectives are used for most of the cases, Configuration 1-1 was run as a SOO with a minimum pressure of 20 m. Configuration 1-1 differs from Configuration 1-2 only due to the setup as SO and MO respectively. Configuration 1-2 and Configuration 1-3 differ only in the minimum required pressure in the WDN (20 for the former, 30 for the latter). Configuration 1-3 and Configuration 1-4 differ only by the fact that the pumps of Bicocca and Corsico are turned OFF in the latter (95 pumps), while they are part of the MOO in the former (103 pumps). In addition to the results in terms of values obtained for objective functions, other performance criteria such as number of active pumps (n-pumps), minimum pressure (P_{min}), maximum pressure (P_{max}) and average pressure (P_{ave}) are presented as well. These other performance criteria correspond to the solution with the minimum energy obtained for each case. As a general conclusion, all the cases show an improvement with respect to the *Base case* for energy, pressure and resilience. Detailed analysis of results for Configuration 1-3 is presented below.

- Analysis of solutions for Configuration 1-3

A visualization of the evolution of the function evaluations for the different objectives and other performance criteria is presented. Figure 7-14, shows the different 2D scatter plots possible with the two considered objectives (E_T and $1\text{-}I_R$) and three additional performance criteria (P_{max}, P_{min}, P_{ave}) for all function evaluations. Such diagrams are known as generalized draughtsman's view (Miettinen, 2014) (Tukey & Tukey, 1981a) (Tukey & Tukey, 1981b). The figure shows a classification by colour for the average pressure (P_{ave}), and a classification by marker size for minimum pressure. This follows a similar classification as implemented for solutions of diverse engineering problems with MOO (Woodruff, et al., 2013) (Shah, et al., 2011) (Fu, et al., 2013). Solutions which are more likely for selection must present a red colour with a large triangle. Solutions in the set with an average pressure higher than 45 m are shown as brushed solutions. In typical optimization analysis of results the ideal point is the one that would hit 0 for all objective functions (if all are set to minimization). However, we use here an slightly loose definition as it is not possible to reach zero for any of the objectives. Here ideal point refers to the point with coordinates corresponding to the minimum value obtain for a particular optimization run. Figure 7-14 upper left, corresponds to the real optimization which was run (trade-off of objectives), while the other two plots correspond to the simultaneous responses of the additional performance criteria. It is interesting that both the sizes of the markers and red colour triangles approach the ideal point in all plots. This shows that there is a progressive evolution towards an optimal solution. The minimum energy obtained is 5,274 kWh for a lack of resilience of 3.48%, a minimum pressure of 30 m, a maximum pressure of 52.5 m and average pressure of 41.1 m.

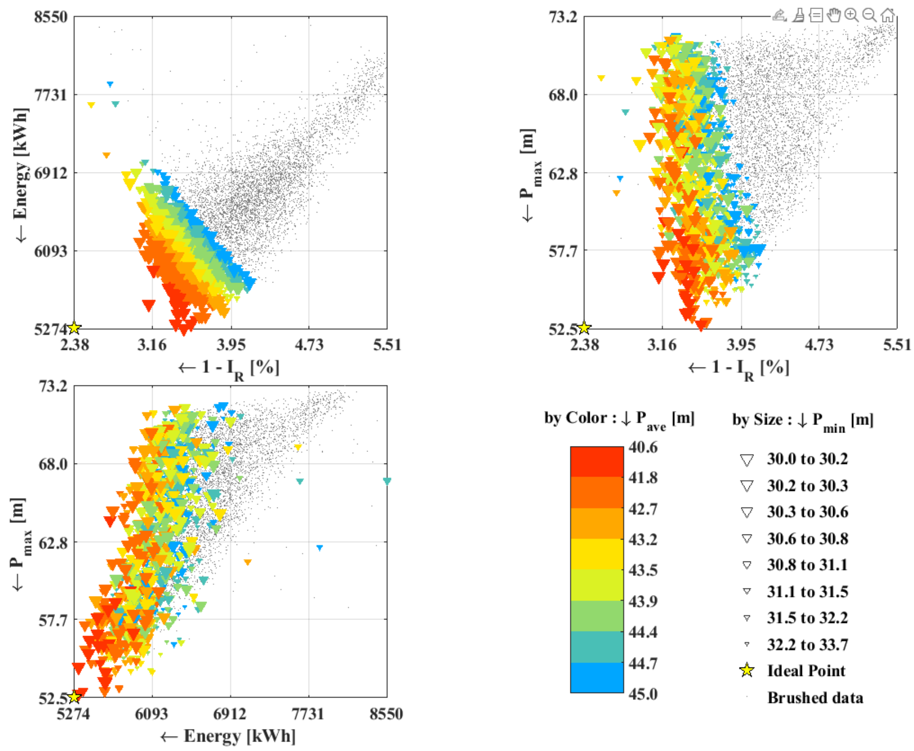


Figure 7-14. Scatter of all possible solutions as 2D plots (Configuration 1-3: 01 sector).

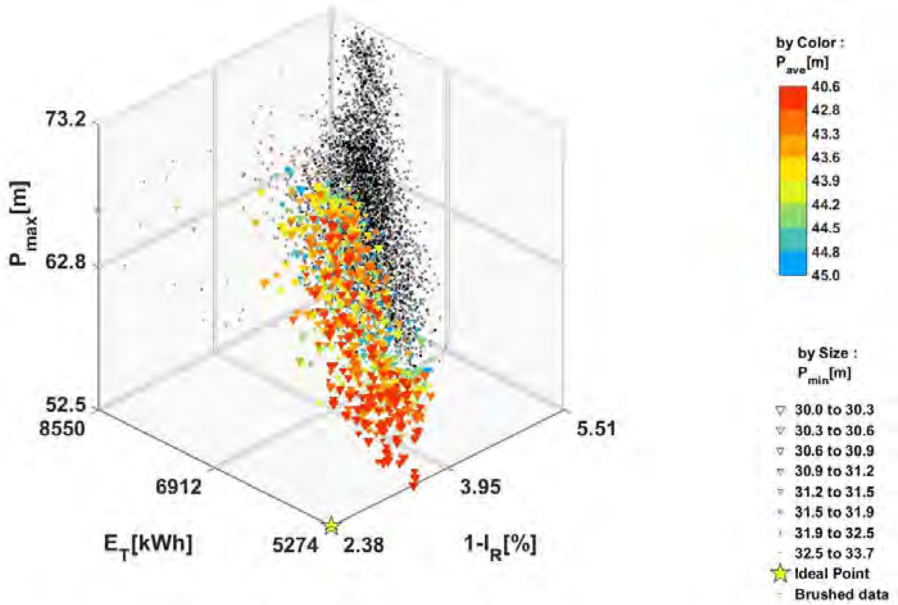


Figure 7-15. Scatter of possible solutions as 3D plots (Configuration 1-3: 01 sector).

A different visualization of the same set of solutions is presented in Figure 7-15. In this case a 3D scatter plot is presented where the same criteria are applied for both colouring and sizes of triangles. The z-axis corresponds to the maximum pressure criteria. It is easy for example to visualize how some solutions which belong to the Pareto front in Figure 7-14 also display a higher maximum pressure.

An additional visualization of the results for this case is performed by using a Parallel Coordinates plot (Figure 7-16) (Inselberg, 1985). In this case the range of each variable is standardized between [0, 1] and then each solution corresponds to a line which connects objectives (and other performance criteria). In this case, the colours are kept same as in the previous scatter plots related to average pressure, to be able to discern differences in the solutions. In total, to visualize all trade-offs one may require a total of $n_{obj}/2$ parallel plots, or 3 in this case. To reduce the number of figures only the first parallel plot is presented.

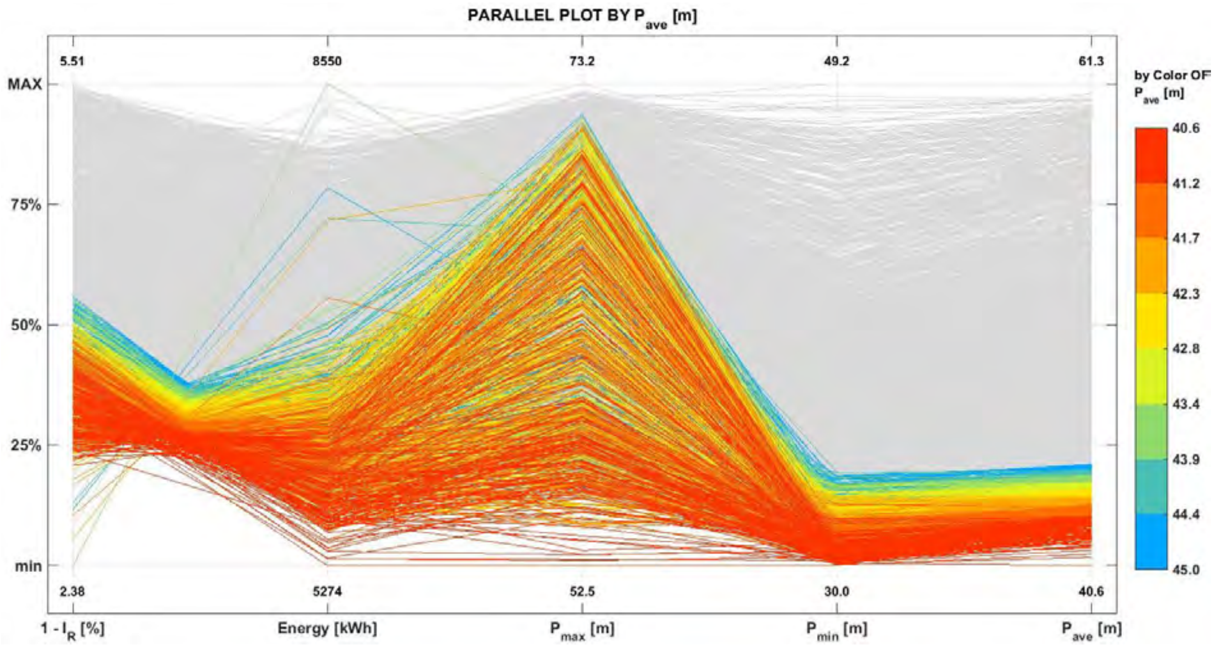


Figure 7-16. Parallel plot of the objective for Configuration 1-3. Vertical axis presents the percentage of the range between minimum and maximum for each objective or performance criteria.

Solutions present an average pressure below 45 m. The bulk of solutions present a low average pressure, but, at the same time there is a large variation of maximum pressure. It is also of interest to see that given low values of average pressure, the minimum pressure of the system is also low. Minimum values of average pressure are also related to the minimization of energy. This is also observed in the scatter plots previously presented.

In order to be able to identify trade-offs among solutions, the last 2,000 function evaluations are selected and the Trade-off Index (λ) (Unal, et al., 2016) is estimated as presented in Figure 7-17. The trade-off index is a measure of the percentage of trade-offs among individual solutions in MOO. A large value of λ (close to 1.0) indicates that the solutions between 2 criteria display a significant trade-off. Otherwise, low λ values indicate that the two objectives are significantly correlated. Each large square represents a trade-off between 2 criteria, where OF_1: $1 - I_R$, OF_2: E_T, PC_1: P_{max}, PC_2: P_{min}, PC_3: P_{ave}. Inside each square the small squares represent the average trade-off index of a particular solution vs all other solutions between those two objectives.

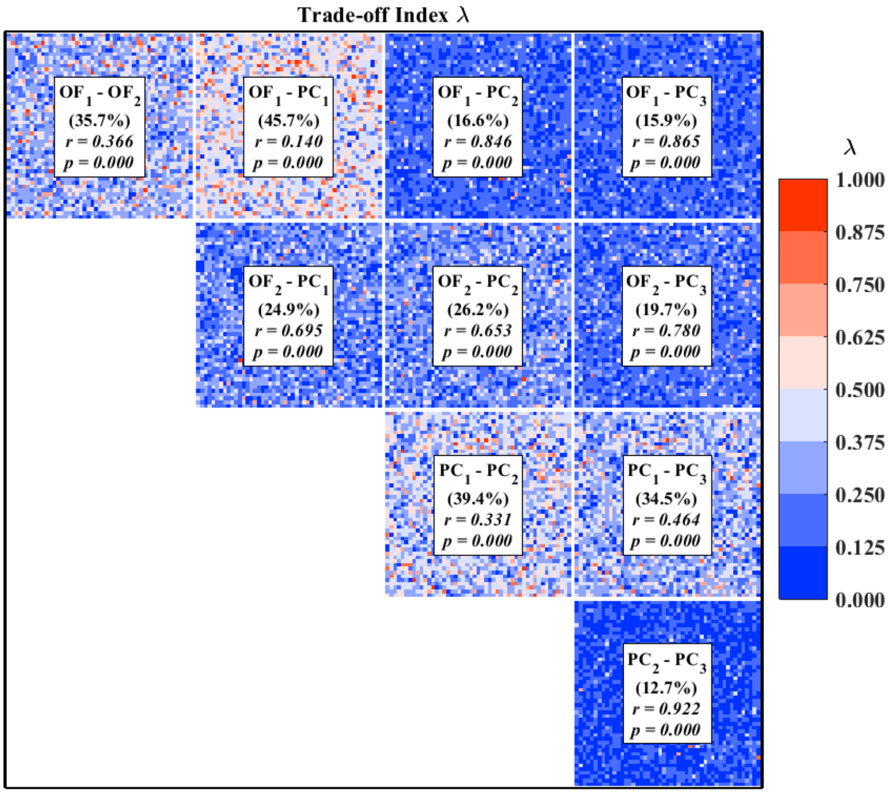


Figure 7-17. Trade-off index for last 2,000 solutions of Configuration 1-3. OF_1: *1 - I_R*, OF_2: *Energy*, PC_1: P_{max}, PC_2: P_{min}, PC_3: P_{ave}.

If a simple correlation analysis is performed between the objectives, the correlation (***r***) is not able to identify whether or not there is significant correlation among objectives and performance criteria, because the *p*-values tend to be very close to zero. This is presented for each trade-off in Figure 7-17. The trade-off index is able to identify for example that there is a significant trade-off between resilience and maximum pressure (OF_1-PC_1), maximum pressure and average pressure (PC_1-PC_3), and an intermediate trade-off for the 2 objectives (OF_1-OF_2); while at the same time it confirms that minimum pressure and average pressure (PC_2-PC_3) are highly correlated.

In order to perform an unbiased selection for the best possible solutions among all solutions, two different methods have been applied. The first one is the level diagram method (Blasco, et al., 2008) where exploration and visualization of high dimensional objective spaces is made using an algorithm that selects a *single* optimal solution based on criteria specified a priori such as 1-norm or Euclidian norm. The word single is highlighted because it presents its major drawback. Decision makers may be interested in different options, this implies giving more importance to certain objectives. For this, one must apply weighting schemes on the criteria. Some authors have used weighting to each objective or performance criteria in selection, however this would imply that the selected solution is biased, which in principle is what a modeller wants to avoid. A second drawback of level diagram selection is that the Euclidean norm of solutions is made with respect to the origin, although this is not a problem in the current setup.

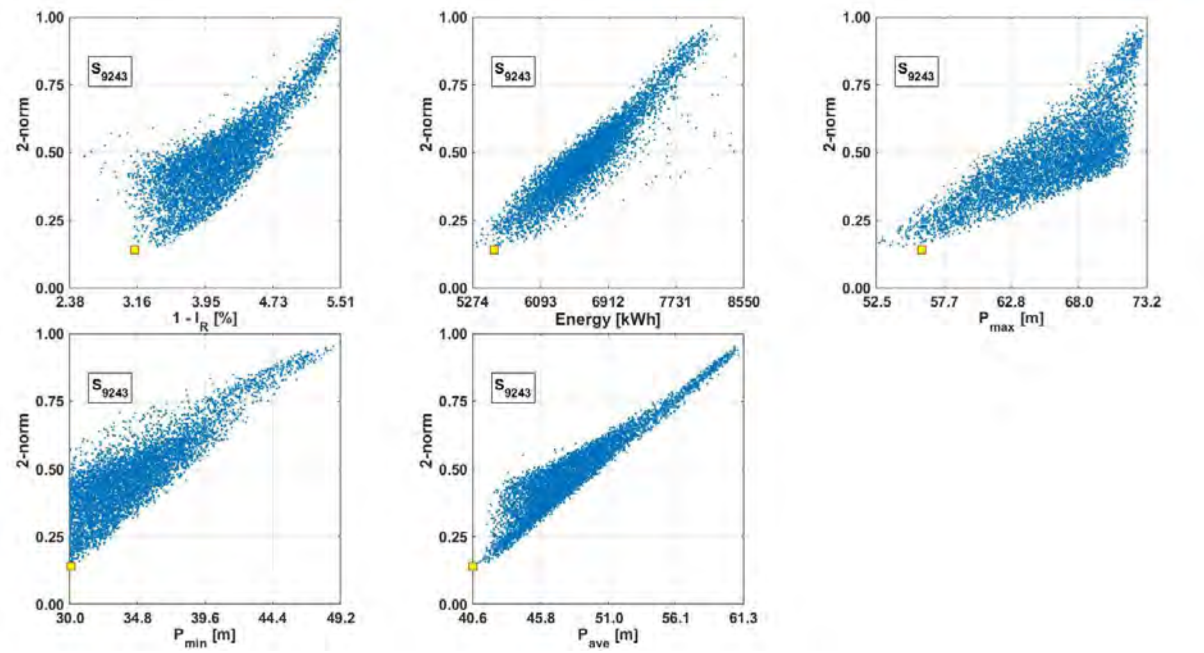


Figure 7-18. Level diagram Configuration 1-3.

Figure 7-18 shows the level diagram for Configuration 1-3, showing the best solution (yellow square) obtained, being $\boldsymbol{S_{9243}}$ (read as solution 9,243 of all solutions). This solution presents a Lack of Resilience of 3.13%, E_T consumption of 5530 kWh, maximum pressure of 55.96 m, minimum pressure of 30.1 m, and average pressure of 40.64 m. It is evident than by selecting this solution there will be an increase in energy consumption and maximum pressure but there will be improvement in all other criteria for the utility. Even though these criteria related to pressure were not included in the MOO of Configuration 1-3, the analysis shows unequivocally that this solution is of importance.

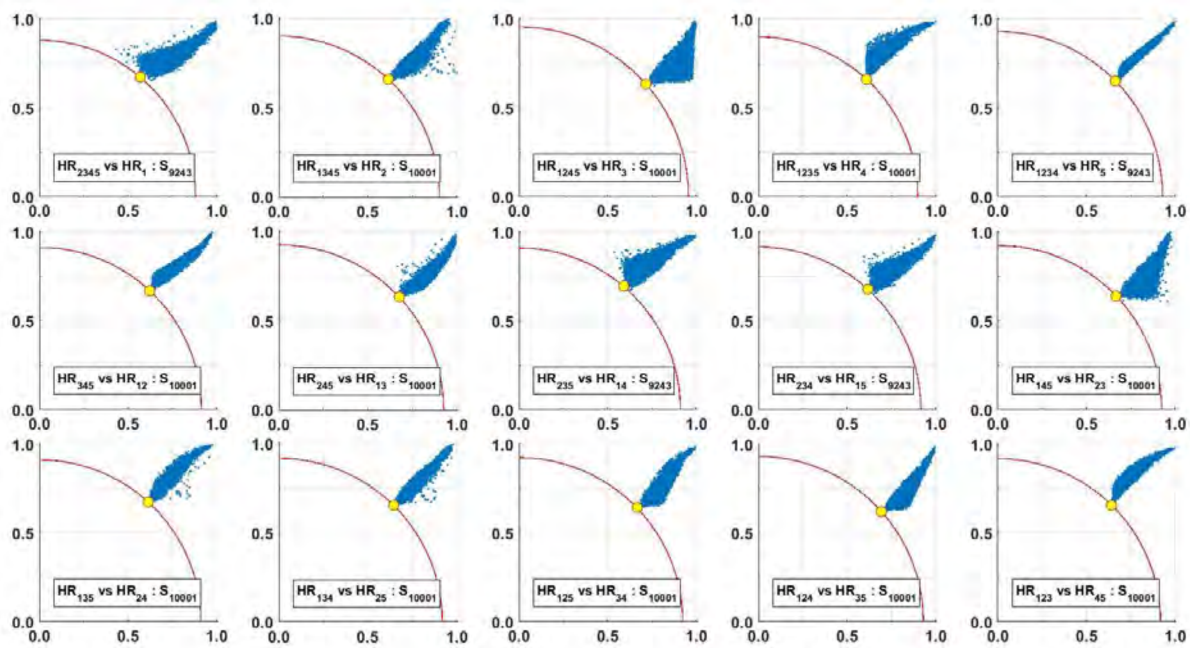


Figure 7-19. Hyper-Radial Visualization of objectives for Configuration 1-3.

A second method to perform unbiased selection of solutions is Hyper-Radial Visualization (HRV) (Chiu & Bloebaum, 2008). This corresponds to a full comparison of possible Euclidean norms of subsets of objectives (or criteria). In this case the objective space is composed of all solutions and a split is made among performance criteria. In our case, 2 objectives and 3 additional performance criteria are taken into account.

A single objective can be compared with the set of the other 4 in 5 ways (e.g. HR_{2345} vs HR_1, reads comparison of hyper-radius of objectives 2, 3, 4 and 5 vs hyper-radius of objective 1), 2 objectives can be compared with the other 3 in 10 ways (e.g. HR_{345} vs HR_{12}, reads comparison of hyper-radius of objectives 3, 4 and 5 vs hyper-radius of objectives 1 and 2). This gives a total of 15 different comparisons. In order to display information in the same ranges, all objectives are normalized and their Euclidean norms are standardized, by the number of objectives. This guarantees that all hyper-radii are measured between 0 and 1. The solution which is closer to the coordinate {0, 0} in each hyper-radial visualization is the best possible solution for that comparison of objectives and criteria.

Figure 7-19 shows the HRV applied to the solutions obtained for Configuration 1-3. In this case two different solutions are identified as the most relevant by this method ($\boldsymbol{S_{9243}}$ and $\boldsymbol{S_{10001}}$). The former has been identified also by the level diagram of the solutions, the latter corresponds exactly to the solution with the lowest energy consumption of the system as presented in Table 7-3. This implies that both solutions are viable for the operation of the WDN as a single sector. Even more, the selection is unbiased.

As a final form of visualization of results, a classification of the objective space solutions was performed using Self Organizing Maps (SOM) (Kohonen, 2001) for a total number of 9 clusters arranged in a 3x3 topology. After several trials, it was identified that 1,000 iterations were enough for convergence.

Figure 7-20 shows the SOM for solutions of Configuration 1-3. In this case all objectives and criteria trade-offs are presented, while the colour scheme represents the cluster to which each solution belongs to. This visualization is able to present different clusters of solutions which show similar characteristics. Cluster 2 for example presents a set of solutions which present low lack of resilience and intermediate energy consumption but rather high maximum pressures. Cluster 6 corresponds to solutions with intermediate Lack of Resilience but low energy consumption. Cluster 7 isolates solutions which belong to highly dominated solutions for all objectives. Cluster 9 corresponds to solutions which present intermediate energy consumption, lack of resilience and pressures. Although not presented here each of the clusters of the Pareto front represents also particular sets of operations in the Pareto set of pump schedule.

The resulting Pareto front of Configuration 1-3 is presented in Figure 7-21 left, where the solutions have been ranked in order of minimum energy consumption. The solution with minimum energy is ranked as 1 and corresponds to $\boldsymbol{S_{10001}}$. A total of only 11 solutions belong to the Pareto front. This is due to the complex operation of the system and the selection of binary decision variables. Although the Pareto front is composed of a size equal to the population (100), most of the solutions start appearing to have multiplicity (up to 20 in some cases). This means that several solutions in the Pareto front are in reality the same solution.

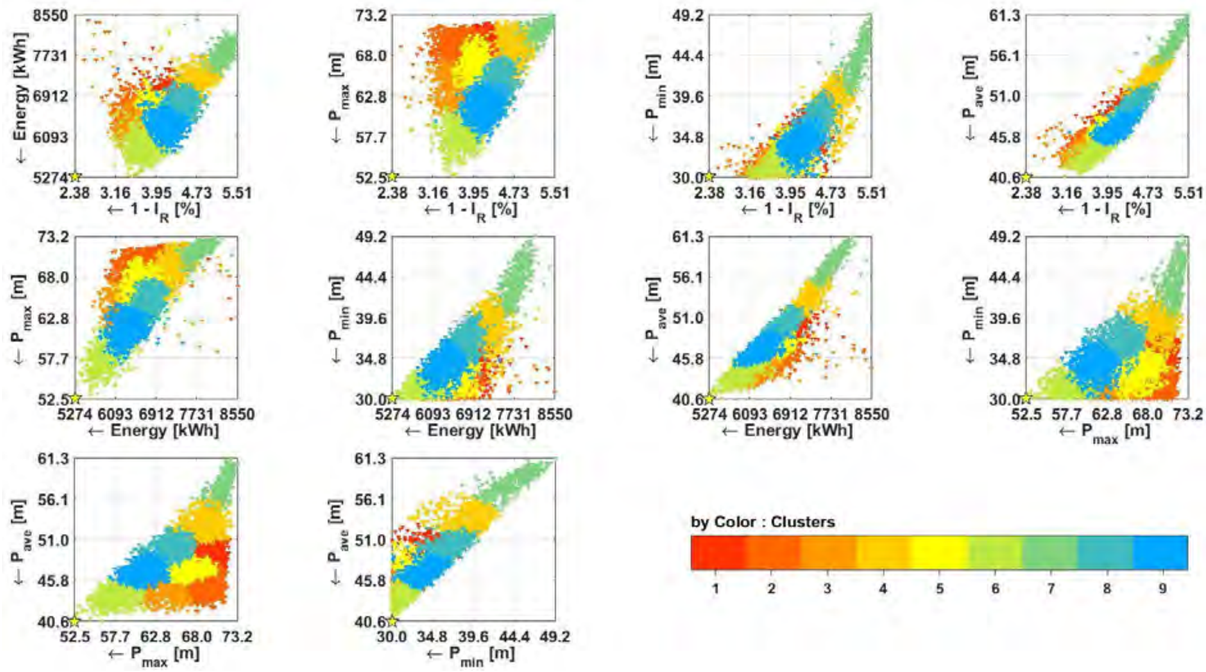


Figure 7-20. Self Organizing Map into 9 clusters for objective space of Configuration 1-3.

This presents a limitation of the use of Binary variables in the MOO implementation for PS. In order to estimate the difference in pump schedules between the different solutions obtained in the Pareto front, a dendrogram (Morse, 1980) is calculated between the pump schedules of each solution. The dendrogram was calculated based on a distance between elements of the pump schedules using Hamming distance (Hamming, 1950). If a pump is either active or inactive simultaneously in 2 solutions (in the Pareto Set) there is no increase in the Hamming distance, however if one pump is active in one solution and inactive in another the Hamming distance increases. In that way, it is possible to see for example that the number of different pumps in operation between ranked solutions 4 and 9 of the Pareto front is just six pumps (ON/OFF). This displays how complex the operation of such large system can be just changing a small set of pumps.

Finally, a comparison among the pump schedules (Pareto set) is presented in Figure 7-21 center, rearranged accordingly with the dendrogram. In this case for example the decision maker at MM can identify which pumps are to be operated during the maximum demand period (around 8am). In Figure 7-21 right, it is also indicated that some pumps remain active in all solutions (ON_{ALL}) (see Table 7-4).

Table 7-4. Pump schedule of Configuration 1-3. Pumps which remain ON for all solutions and OFF for all solutions.

ON_{ALL}	Cimabue (3), Gorla (3), Salemi (2), San Siro (2), Suzzani (1), Bicocca (1) and Corsico (1)
OFF_{ALL}	Abbiategrasso (all), Assiano (1,2 and 5), Baggio (1, 2 and 4), Cimabue (4), Comasina (1), Este (all), Feltre (3), Gorla (2), Italia (1), Linate (1), Ovidio (1), Padova (4), Parco (1, 3 and 4), Salemi (3), San Siro (1), Suzzani (5), Vialba (1 and 3), Bicocca (4)

One interesting comparison to perform with the cases for 01 sector is when the pumps at Corsico and Bicocca are turned OFF for optimization purposes (Configuration 1-4). In that case the Pareto front and the Pareto set are presented in Figure 7-22. Only 8 solutions are obtained in the Pareto front (Figure 7-22 left).

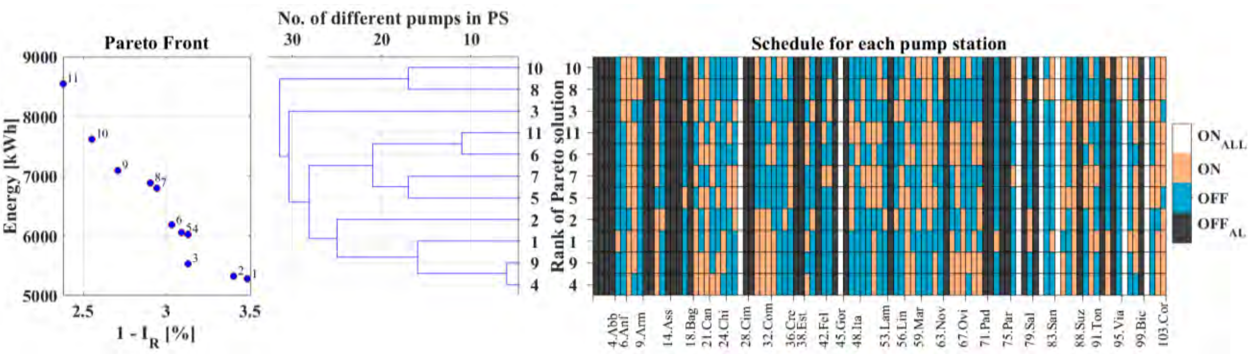


Figure 7-21. Pareto front and set of Configuration 1-3. (left) Pareto front, (center) dendrogram of Hamming distance of pump schedules among solutions and (right) resulting pump schedule or Pareto Set.

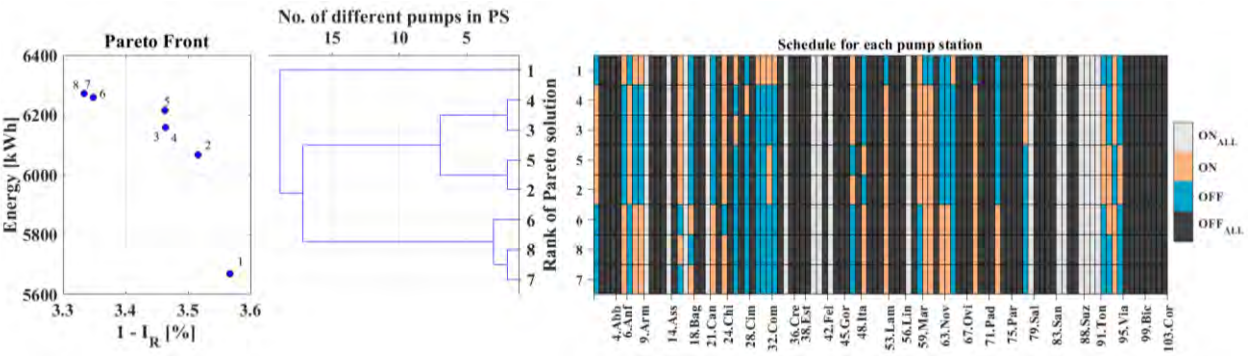


Figure 7-22. Pareto front and set of Configuration 1-4. (left) Pareto front, (center) dendrogram of Hamming distance of pump schedules among solutions and (right) resulting pump schedule or Pareto Set.

When looking at the differences between pump schedules (Figure 7-22 center), ranked solutions 7-8, 2-5 and 3-4 have difference of only two pumps operating. The best ranked solution presents a difference of 18 pumps with respect to its most similar schedule respectively. This represents a singular solution but highlights also another aspect of the system of Milan, namely that it is not feasible to have significantly lower energy consumption by simple operation of the system with ON/OFF pumps. It is evident also in Figure 7-22 right, that good operational practices for the utility as a single sector would not include pumps in Abbiategrasso (2, 3 and 4), Anfossi (3), Assiano (2, 3 and 4), Baggio (1), Cantore (1 and 2), Chiusabella (2), Cimabue (1 and 3) , Comasina (1), Crescenzago (2 and 4), Este (1 and 2), Feltre (1 and 4), Gorla (2 and 3), Italia (1 and 3), Lambro (2, 3 and 4), Linate (1, 2 and 3), Martini (2), Novara (3), Ovidio (3 and 4), Padova (1, 3, and 4), Parco (1, 3 and 4), Salemi (1 and 2), San Siro (1 to 4) and Suzzani (3 and 4). On the other hand pumps which are operated for all Pareto solutions are Assiano (1 and 5), Bagio (3), Cantore (3), Crescenzago (3), Feltre (2 and 3), Gorla (1), Martini (1), Salemi (4), Suzzani (1, 2 and 5), Tonezza (1, 2 and 3).
Even more, solution 1 of Configuration 1-4 indicates that Abbiategrasso pumping station should not operate at all. This is a similar solution as obtained by Configuration 1-3 where all solutions of the Pareto front display all pumps of Abbiategrasso as inactive (see Figure 7-21

right). This is an unexpected result, given the investment made by the utility with the goal to perform an isolation of a PMZ in that specific area for the implementation of VSP.

- Scenario with 18 sectors

There is only one possible configuration for the operation of the system into 18 sectors. For that reason other cases were ran for a configuration of 18 sectors as presented in Table 7-5. A total of three cases were ran and have been contrasted versus the *Base case* which corresponds to the current operation of the system.

Although only two objectives are used for most of the cases, Configuration 18-1 was run as a SOO with a minimum pressure of 20 m. Configuration 18-1 differs from Configuration 18-2 only due to the setup as SO and MO respectively. Configuration 18-2 and Configuration 18-3 differ only in the minimum required pressure in the WDN (20 m for the former, and 30 m for the latter). All cases are run for 103 pumps. In addition to the results in terms of values obtained for objective functions, other performance criteria such as number of operating pumps (n-pumps), minimum pressure (*Pmin*), maximum pressure (*Pmax*) and average pressure (P average) are presented for the best solution. These other performance criteria correspond to the solution with the minimum energy obtained for each case. As a general conclusion, all three cases show an improvement with respect to the *Base case* for energy, pressure and resilience. Detailed analysis of results for Configuration 18-3 is presented below.

Table 7-5. Scenario with 18 sectors, all configurations analysed.

Parameter	**Unit**	**Base**	**Config. 18-1**	**Config. 18-2**	**Config. 18-3**
		Current Status	**18 Sectors**	**18 Sectors**	**18 Sectors**
Optimization	type	-	SO	MO	MO
n-objectives	global	-	1	2	2
Var. type	type	-	Binary	Binary	Binary
n-variables	global	103	103	103	103
n-constraints	global	-	1	1	1
P required	m	-	20.0	20.0	30.0
n-pumps	global	40	29	31	38
Lack of resilience	%	7.14	5.88	5.37	3.30
Total Energy (E_T)	kWh	7 379	5 077	5 336	***5 825***
P min	m	41.1	20.3	20.1	30.0
P max	m	69.9	67.7	66.3	66.8
P ave	m	56.4	37.9	37.6	41.9

- Analysis of solutions for Configuration 18-3

A visualization of the evolution of the function evaluations for the different objectives and other performance criteria is presented. Figure 7-23 shows the different 2D scatter plots possible with the two considered objectives (*TE* and Lack of Resilience) and three additional performance criteria (P_{max}, P_{min}, P_{ave}) for all function evaluations. The figure shows a classification by colour for the average pressure (P_{ave}), and a classification by marker size for minimum pressure. Solutions which are more likely for selection must present a red colour with a large triangle. Solutions in the set with an average pressure higher than 45 m are shown as brushed solutions. The ideal point would be obtained if all objectives were met as minimization simultaneously, as minimum value for all objectives. Figure 7-23, upper left corresponds to the real optimization which was run (trade-off of objectives), while the other two plots correspond to the simultaneous responses of the other performance criteria (not used as objectives in the optimization). It is interesting that both the sizes of the markers and red colours approach the ideal point in all plots. This shows that there is a progressive evolution towards an optimal solution. The minimum energy obtained is 5,825 kWh for a lack of resilience of 3.29%, a minimum pressure of 30 m, a maximum pressure of 66.7 m and average pressure of 41.9 m. It is interesting that the evolution of solutions as the MOO progressed tends to create two different clusters of solutions as displayed in the second scatter (upper right). This implies that after performing the sectorization into 18 sectors, if some pumps are operated this increases dramatically the maximum pressure of the system. If one were to look only for solutions in the Pareto front without verifying the overall behaviour of the system - a myopic decision would be made. It needs to be clarified that once a particular sectorization is actually implemented it would be very costly to return to the old system as a single PMZ. That being the case, having solutions with a maximum pressure above 69 m would not be good, as it would certainly cause pipe breaks across the system. For that reason, additional visualizations of the solutions obtained highlight the avoidance of such possibility.

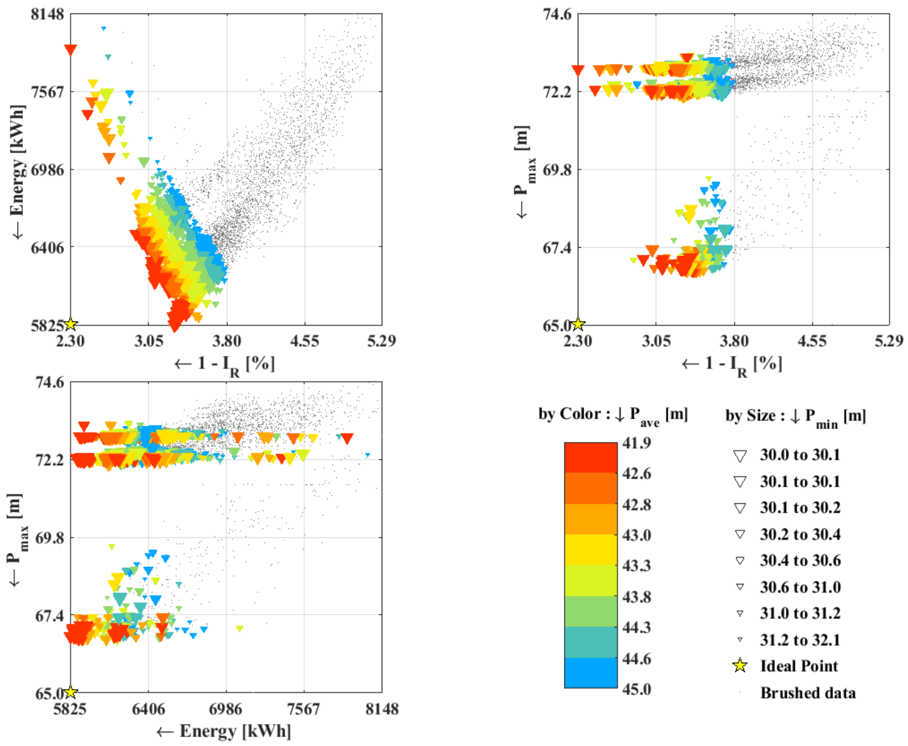


Figure 7-23. Scatter of all possible solutions as 2D plots (Configuration 18-3: 18 sector).

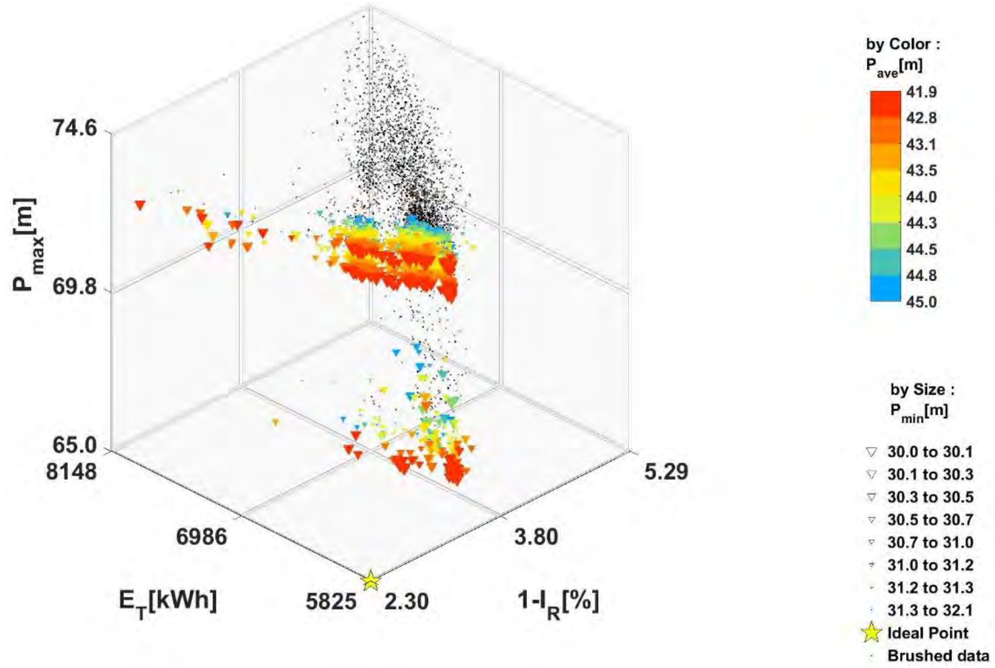


Figure 7-24. Scatter of possible solutions as 3D plots (Configuration 18-3: 18 sectors).

A different visualization of the same set of solutions is presented in Figure 7-24. In this case, a 3D scatter plot is presented where the same criteria are applied for both colouring and sizes of triangles. The z-axis corresponds to the maximum pressure criteria. It is easy for example to visualize how some solutions which belong to the Pareto front in Figure 7-24 also display a higher maximum pressure above 69 m.

An additional visualization of the results for this case is performed by using a Parallel Coordinates plot (Figure 7-25). In this case the range of each variable is standardized between [0, 1] and then each solution corresponds to a line which connects objectives (and other performance criteria). In this case the colouring was kept same as in the previous scatter plots related to average pressure, to be able to discern differences in the solutions.

Solutions present average pressure below 45 m. Most solutions present a low average pressure, but at the same time there is a large variation of maximum pressure. There is a large variation in the possible energy consumption among solutions.

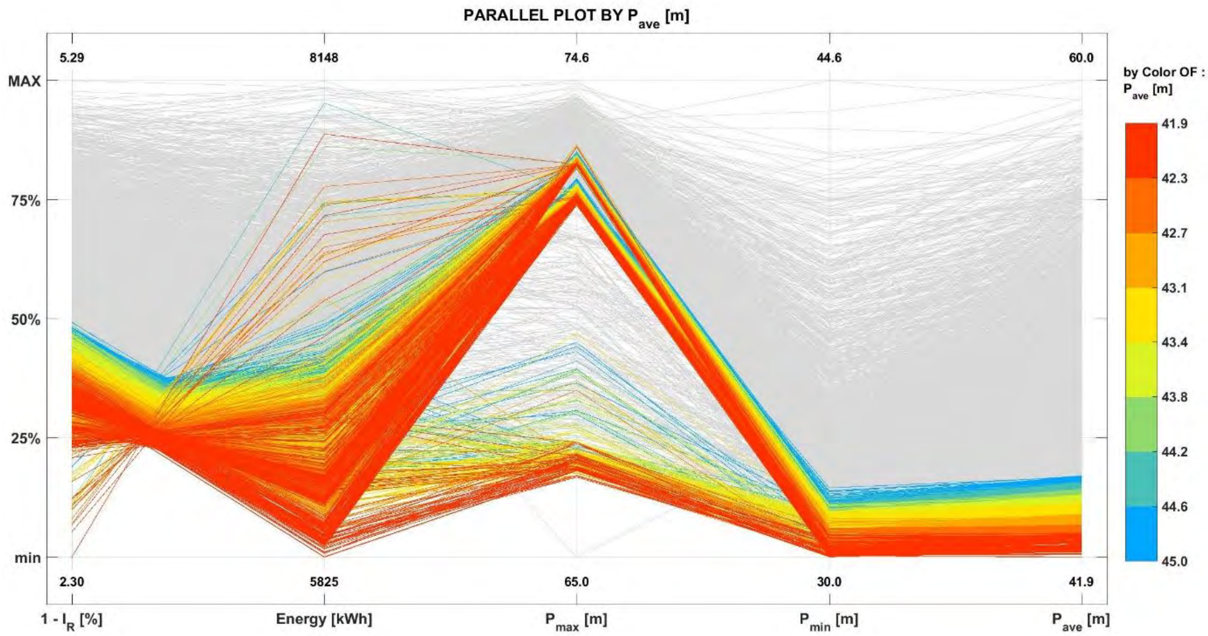


Figure 7-25. Parallel plot of the objective for Configuration 18-3.

In order to be able to identify trade-offs among solutions, the last 2,000 function evaluations are selected and the trade-off Index (λ) is estimated as presented in Figure 7-26, where OF_1: 1 - I_R, OF_2: E_T, PC_1: P_{max}, PC_2: P_{min}, PC_3: P_{ave}. The trade-off index is able to identify for example that although there seems to be no statistical significance for the correlation, there is a significant trade-off between resilience and maximum pressure (OF_1-PC_1). An analysis of Lack of resilience and energy consumption (OF_1-OF_2) also reveals that there is no significant correlation between the two objectives, however, there is a 46.2% of trade-offs among the solutions.

In order to perform an unbiased selection for the best possible solutions among all solutions level method and HRV are performed as well to the set of solutions of Configuration 18-3.

Figure 7-27 shows the level diagram for Configuration 18-3, presenting the best solution (yellow square) obtained being $\boldsymbol{S_{12322}}$ (read as solution 12,322 of all solutions). This solution presents a Lack of Resilience of 3.11%, E_T of 6150 kWh, maximum pressure of 66.78 m, minimum pressure of 30.01 m and average pressure of 42.11 m. Even though these criteria related to pressure were not included in the MOO of Configuration 18-3, the analysis shows unequivocally that this solution is of importance.

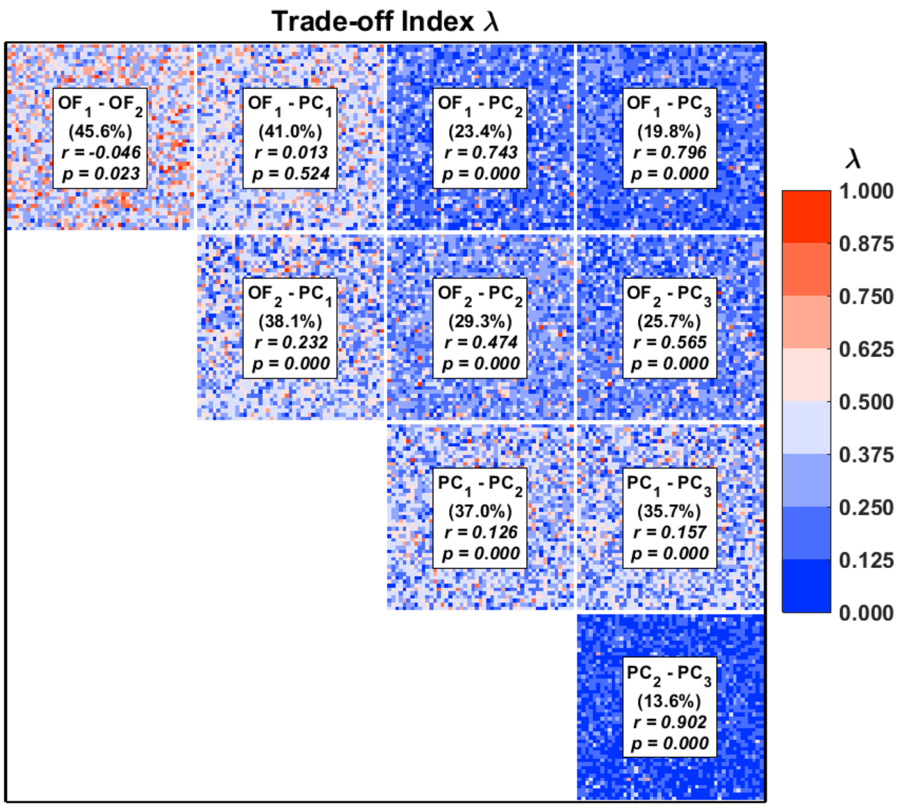


Figure 7-26. Trade-off index for last 2,000 solutions of Configuration 18-3. OF_1: 1 - I_R, OF_2: Energy, PC_1: P_{max}, PC_2: P_{min}, PC_3: P_{ave}.

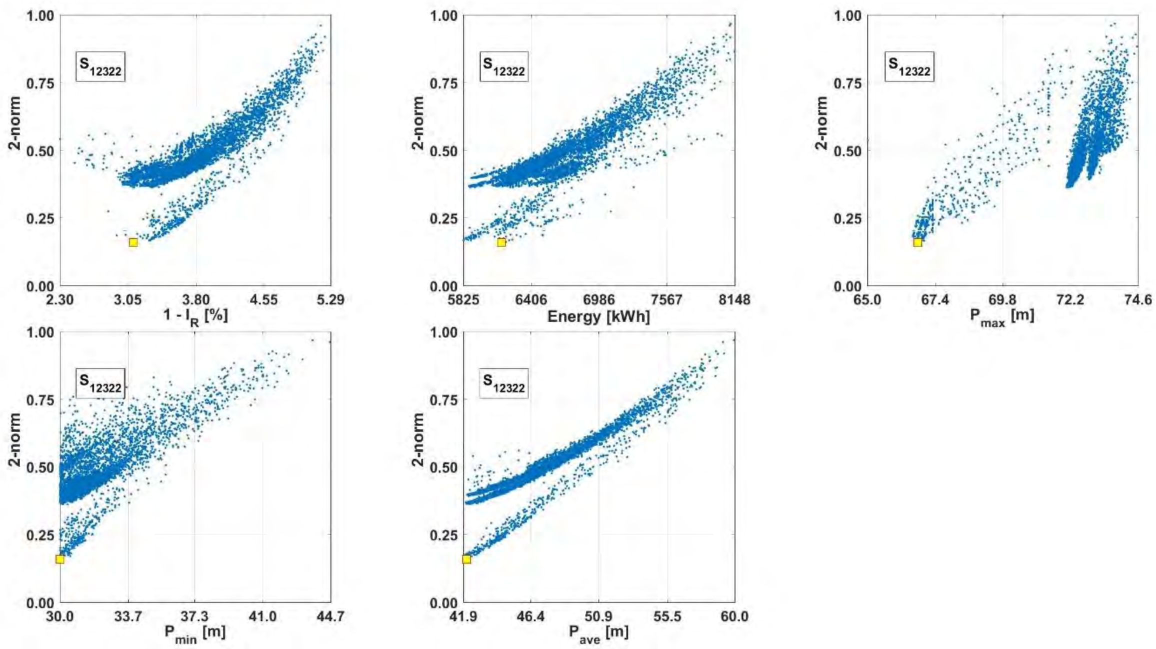


Figure 7-27. Level diagram Configuration 18-3.

The second method for unbiased selection of solutions is Hyper-Radial Visualization (HRV). Figure 7-28, shows the HRV after applied to the solutions obtained for Configuration 18-3. In this case three different solutions are identified as the most relevant by this method. $\boldsymbol{S_{15648}}$, $\boldsymbol{S_{12322}}$ and $\boldsymbol{S_{13841}}$. $\boldsymbol{S_{12322}}$ have been identified also by the level diagram of the solutions. $\boldsymbol{S_{15648}}$, corresponds to the solution with the lowest energy consumption of the system as presented in Table 7-3. Finally, S_{13841}, is identified as a third possible solution, although this one is only of importance by looking at the lack of resilience (2.46%) while the energy consumption is quite high (7398 kWh).

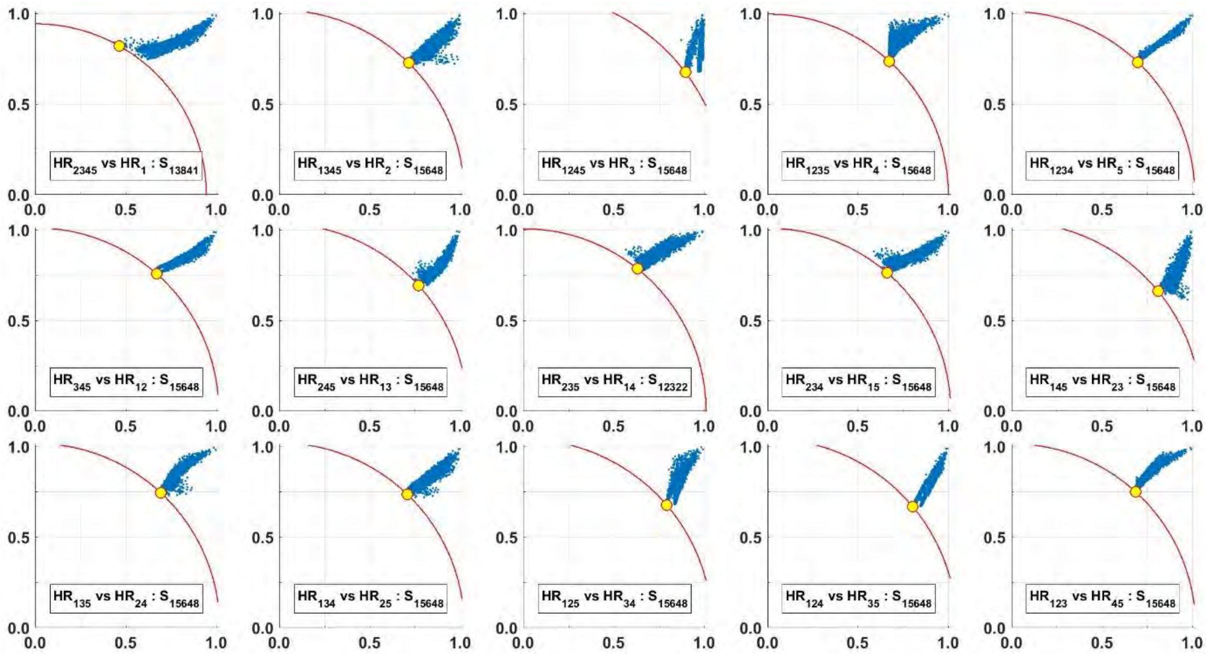


Figure 7-28. Hyper-Radial Visualization of objectives for Configuration 18-3.

As a final form of visualization of results, a classification of the objective space solutions was performed using Self Organizing Maps (SOM) for a total number of 9 clusters arranged in a 3x3 topology. Again results are shown after 1,000 iterations, when convergence is met.
Figure 7-29, shows the SOM for solutions of Configuration 18-3. In this case all objectives and criteria trade-offs are presented, while the colouring scheme represents the cluster to which each solution belongs to. This visualization is able to present different clusters of solutions which display similar characteristics. Cluster 9 contains the set of best feasible solutions available in terms of lower maximum pressure. Solutions corresponding to Cluster 6 appear to be close to the Pareto front but when looking at their maximum pressure, all of these solutions possess a maximum pressure higher than 70 m. Other cluster of interest is Cluster 7, which basically corresponds to fully dominated solutions.

The resulting Pareto front of Configuration 18-3 is presented in Figure 7-30 left, where the solutions have been ranked in order of minimum energy consumption, with rank 1 being the solution in the Pareto front with the lowest energy. The solution with minimum energy is S_{15648}. A total of only 22 function evaluations belong to the Pareto front. This is due to the complex operation of the system and the selection of binary decision variables. Although the Pareto front is composed of a size equal to the population (100), most of the solutions are overlapping as it was for Configuration 1-3 as well.

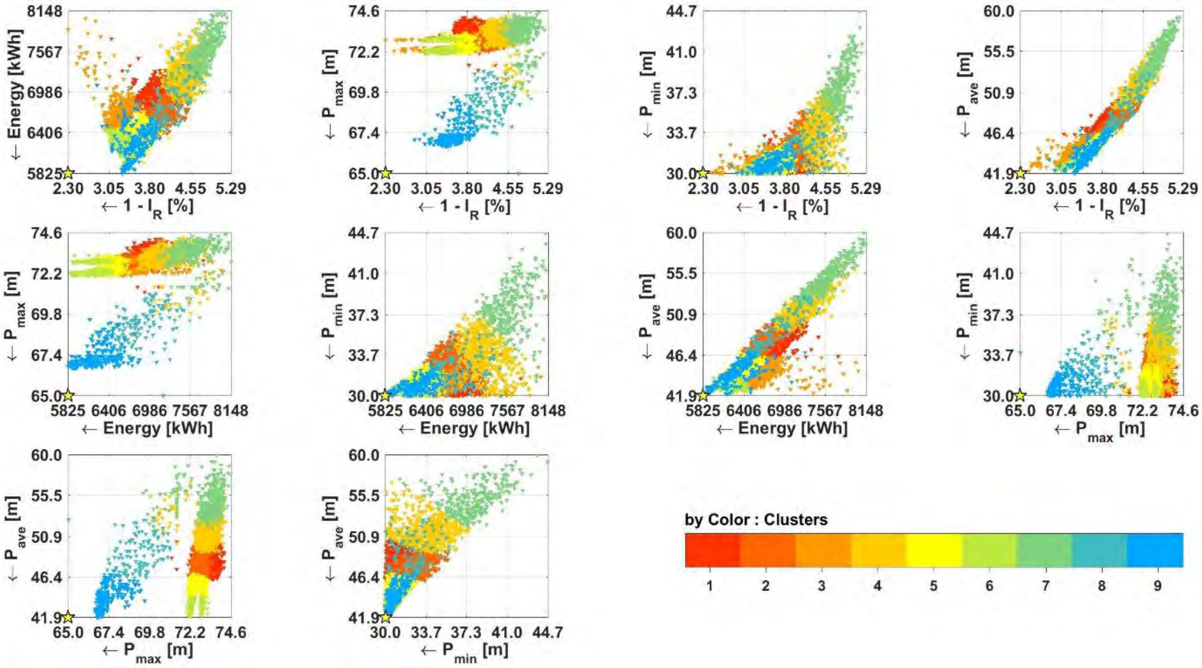


Figure 7-29. Self organizing Map into 9 clusters for objective space of Configuration 18-3.

A dendrogram of hamming distance among pump schedules is presented in Figure 7-30 center. In that way, it is possible to see, for example, that the number of different pumps in operation between ranked solutions 6 and 21, 9 and 13 and 17 and 22 of the Pareto front is just one pump (ON/OFF). Solutions 1 and 2, 4 and 15 differ only in two pumps. This displays how complex the operation of the system can be with 18 sectors.

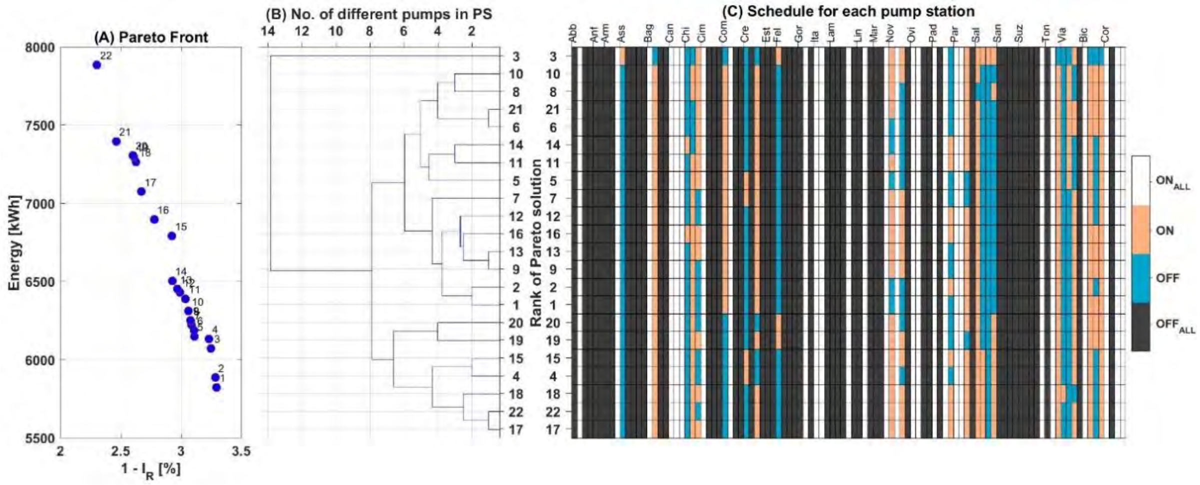


Figure 7-30. Pareto front and set of Configuration 18-3. (left) Pareto front, (center) dendrogram of Hamming distance of pump schedules among solutions and (right) resulting pump schedule or Pareto Set.

Finally, a comparison among the pump schedules (Pareto set) is presented in Figure 7-30 right, rearranged accordingly with the rank and position in the dendrogram. In Figure 7-30 right, it is shown that some pumps remain active in all solutions (ON_{ALL}) (see Table 7-6).

Table 7-6. Pump schedule of Configuration 18-3. Pumps which remain ON for all solutions and OFF for all solutions.

ON_{ALL}	Abbiategrasso (2), Armi (3), Baggio (1), Cantore (1, 2 and 3), Cimabue (1), Comasina (2), Gorla (2), Italia (1 and 2), Lambro (4), Linate (2), Martini (3), Novara (2), Ovidio (1 and 2), Padova (1 and 3), Parco (1 and 2), Suzzani (5), Tonezza (2), Bicocca (1) and Corsico (1, 3 and 4)
OFF_{ALL}	Abbiategrasso (1, 3 and 4), Anfossi (3 and 4), Armi (1 and 2), Assiano (2, 3, 4 and 5), Baggio (3 and 4), Cimabue (2, 3 and 4), Comasina (3 and 4), Crescenzago (2 and 4), Este (1 and 2), Feltre (2, 3 and 4), Gorla (1 and 3), Italia (3), Lambro (1, 2, 3 and 5), Linate (1 and 3), Martini (1 and 2), Novara (4), Ovidio (3 and 4), Padova (2), Parco (4), San Siro (all), Suzzani (1, 2, 3 and 4), Tonezza (1), Vialba (4) and Corsico (2)

- Comparison of pump schedules and pressures for other sectorization scenarios

Scenarios for 2, 3 and 9 sectors where run as well (see Appendix). The corresponding pump schedules of the last generation of each algorithm run for the best cases are presented in Figure 7-31. It should be noticed that some pumps are set on or off all the time depending on the configuration.

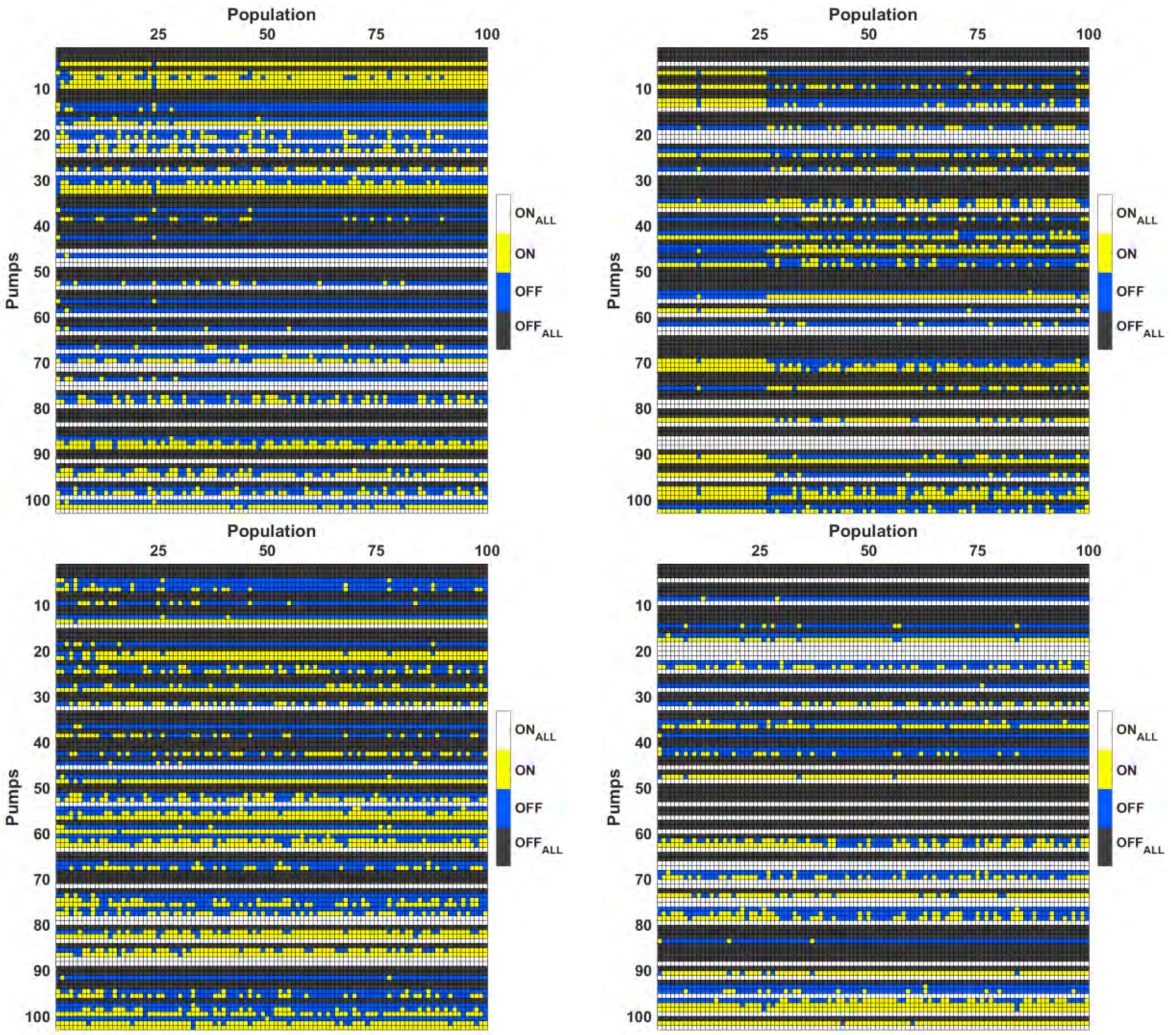


Figure 7-31. Pump schedules obtained for population of last generation of configurations (top-left) 02

sectors, (top right) 03 sectors, (bottom-left) 09 sectors, (bottom-right) 18 sectors.

Finally the pressures for the best solution of each configuration are presented in Figure 7-32. Notice how the pressure distribution for 09 sectors (bottom-left) provides a more uniform pressure management, while at the same time presenting lower average pressure than for the case of 18 sectors (bottom-right). The utility made the request to investigate the cases of 02 sectors (top-left) and 03 sectors (top-right), however these two configurations present higher pressures than for the 09 sectors configuration. In fact the 09 sectors configuration (bottom-left) shows less likelihood of having nodes with pressure higher than 50 m.

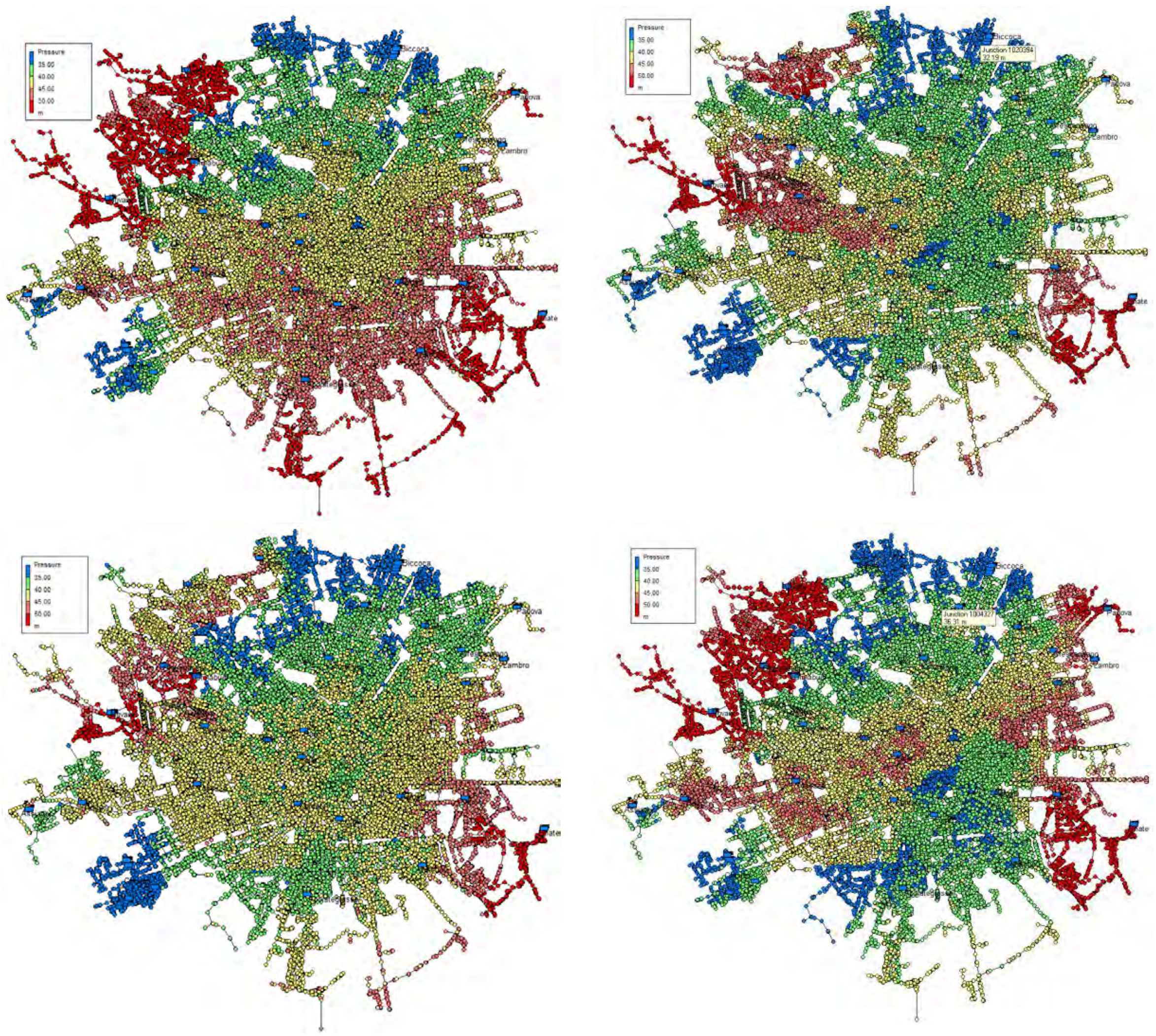


Figure 7-32. Pressures in the WDN for the different configurations. (top-left) 02 sectors, (top-right) 03 sectors, (bottom-left) 09 sectors, (bottom-right) 18 sectors. Ranges of pressure are the same for comparison.

7.4 Limitations related to considered formulations

7.4.1 Formulation 1

The main drawback of this formulation is that the boundaries between subsectors are included as decision variables during the evolution of the GA. In most cases, this implies that even if some pre-set configurations are provided to the optimization as initial population, the final outcome shows that there is no fixed number of sectors in the final population. Usually, what a utility would like to have is a system split into different PMZ or even into smaller DMA's. This formulation would not allow this. In fact, this creates what we call *Idle* and *non-Idle* boundaries (Figure 7-33). Sometimes, two particular population members can have conflicting decision variables. In those cases an area is isolated by closing the valves on one side while leaving another area in connection with other sector(s). Although this may be overcome by performing additional check-ups, it becomes computationally inefficient, mainly because this needs to be done for every solution at every generation of optimization prior to even running the hydraulic simulation.

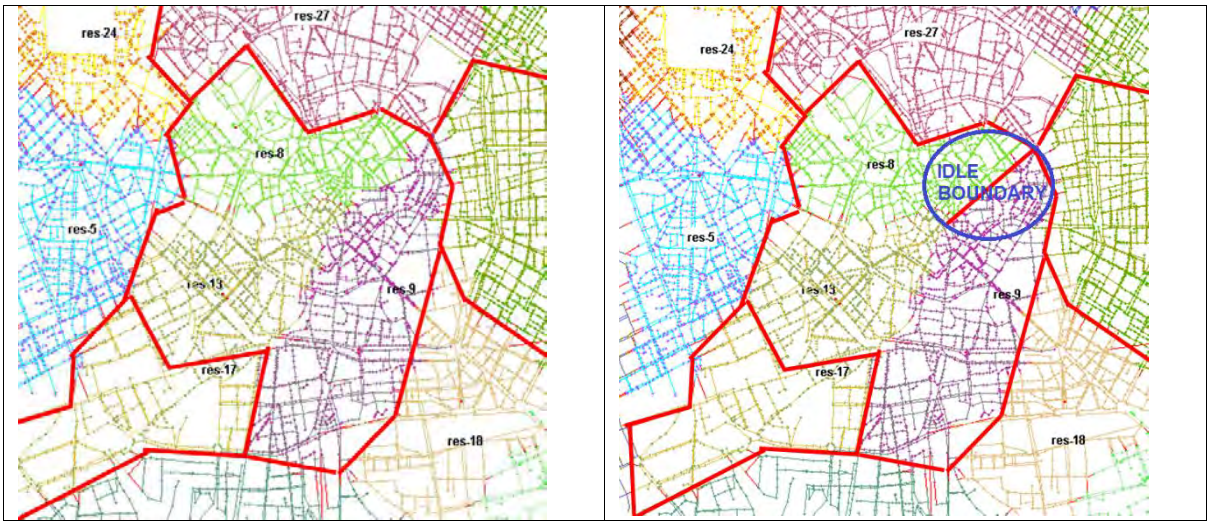


Figure 7-33. Representation of idle boundaries for the sectorization formulation 1.

Given the inclusion of the boundaries as decision variables in the evolution, sometimes a particular solution can in fact isolate a sector (or collection of subsectors). Also, given that an intrinsic pump schedule is performed simultaneously, it is possible to have an isolated area with no pumps in operation. This creates a problem for EPANET, giving a solution that will be rejected by the optimization algorithm, but only after simulation is performed. The demand cannot be satisfied if there are no operating pumps in an isolated area, as the case of Milan contains no alternative gravity sources (Figure 7-34).

Finally, it was perceived that it has the tendency of creating as a final outcome a single sector with some idle boundaries. This needs to be further implemented as a constraint in the number of boundaries to be deployed in the WDN in future research.

Because of such inefficiencies of the Fomulation 1, it will be presented that such are overcome through the application of Formulation 2, it seems that the best possible scenario for the utility is to operate the system as a single PMZ with an optimal Pump Schedule.

7.4.1 Formulation 2

The main drawback of this formulation is the fact that there is no possibility to remove a subsector from a larger sector and make the system evolve accordingly during optimization. This means that the decision on the number of sectors must be made beforehand. That was the main reason to use a card-collector method (see Table 7-2) to generate different sectorization configurations for different numbers of required sectors (2, 3 and 9) and then afterwards perform pump schedule in each configuration of sectorization.

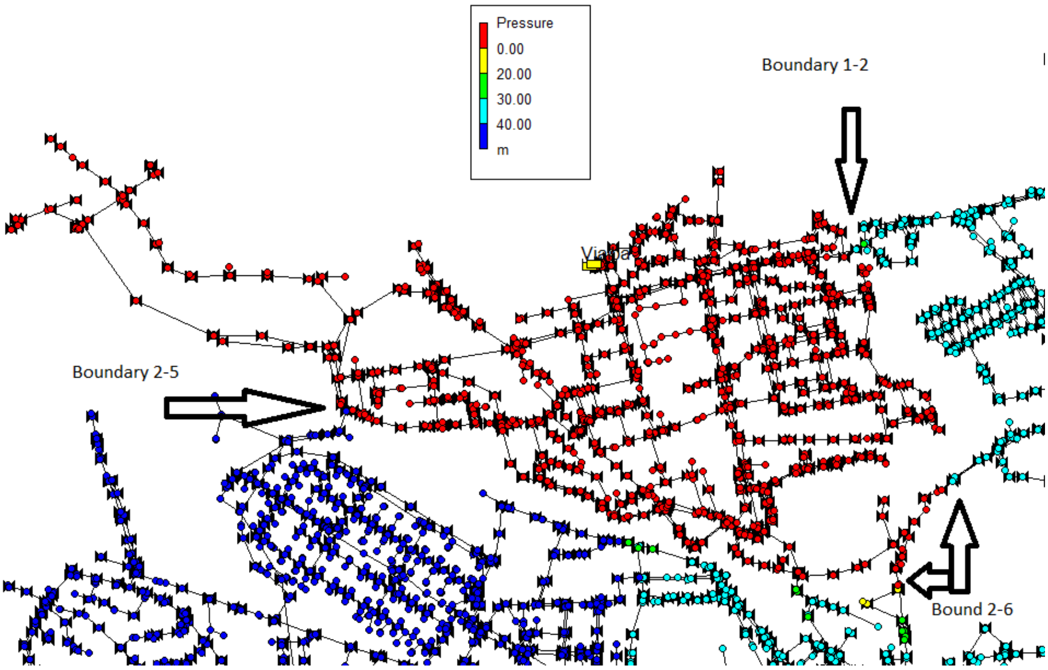


Figure 7-34. Example of non-idle boundaries solution where the sector contains the pumping station of Vialba. The decision variables are closed pumps creating a pressure deficient solution.

An evolutionary algorithm can be used for generation of new sectorizations for a fixed number of sectors and the configurations may evolve accordingly. However, this hybridization is not performed here for 3 reasons:

i) the optimizations of sectorization are computationally expensive, and

ii) the utility had some preferred sectorizations, which may be of interest and that limited the number of configurations run. For example, the second formulation is run also for 2, 3 and 9 sectors. Part of the decision was made by request of the utility, and second due to the large number of possible sectorizations which may be obtained for each configuration.

iii) The hydraulic kernel used for the simulation of the WDN is EPANET 2.0 is single-threaded, while EPANET 2.2 (released in July 2020) is multi-threaded. At the moment that the sectorization runs were performed there was no possibility to use the latter.

7.5 Summary

A sectorization problem is solved for the Full WDN of Milan. The problem was formulated with two levels composed of the identification of cut-set valves and a subsequent MOO. The identification of cut –set valves guarantees that the Full WDN of Milan can be split into individual subsectors, and it can be performed using a legacy algorithm such as Dijkstra's Shortest Dissipated Power Path (SDPP). Here, an important innovation with respect to other methodologies for optimization was introduced, which allows the use of multiple pumping

stations as sources. In a second level of analysis the MOO is performed and options for decision support to the utility of Milan (and potentially other utilities interested in developing sectorization on their own) were presented.
Two different formulations for the MOO were presented, a simple one in which both the cut-sets and the status of pumps are used as decision variables in the optimization algorithm. This formulation creates additional computational and configurational issues (i.e. idle sectors with no pumps active, idle boundaries inside sectors) that became harder and harder to overcome. For that, a second formulation of the MOO was performed using pre-set clustering of subsectors into larger subsectors. This second formulation showed that it is possible with a simple algorithm (card collector) to split the system in multiple ways and perform the pump schedule to obtain the best possible solution (schedule) of operation of the system. Regarding the immediate results presented, the system of Milan seems to show that a sectorization is actually not necessary and that the operation into a single Pressure Management Zone (PMZ) is enough for the operation. However, due to additional issues present in the system which were not treated in this research (i.e. leakages, water quality), which could enable such operations in the system. In this case, it would be recommended that the system of Milan is operated and split in 9 sectors (all results for this particular case are presented in the Appendix), and in a later stage, once this work has been carried out by the utility, a limited number of pumping stations can be changed to operation with VSP.

8 CONCLUSIONS AND RECOMMENDATIONS

8.1 Summary

The general objective of this research is to develop and demonstrate methods for optimal operation of large distribution networks. Two different aspects have been considered throughout, energy efficiency and pressure management. This has been achieved by using hydraulic simulators coupled with heuristic search algorithms.

The research proposes and investigates efficient methods for developing model-based pump scheduling for efficient energy management of large WDN's. Two different algorithms have been tested for the matter, NSGA-II and AMGA2, showing that the gains in a small isolated sector in the south of Milan can reach 20% savings for daily energy consumption and after performing field tests it was demonstrated that there is a reduction of pressure of 5.5 m (10 m for most of the day) with the use of an optimised scheduling. In addition, two types of constraints have been tested in this research showing that the use of local constraints of pressure for pump scheduling can provide similar results to the ones of a WDN fully monitored (Global constraints).

The application of Pump Scheduling for Full Milano WDN shows that the approach is valid for all hours within the day as the analysis is performed for different increased consumptions between 0.3 and 1.6 the average historical consumption.

The energy minimization presents a trade-off with respect to lack of resilience for all the cases analysed, however when a decision needs to be made for daily operations, the solutions with minimum energy consumption is more favourable than the ones which improve the resilience of the system. In this regard, the resilience only increases marginally in a system with over dimensioned pumps. Even Abbiategrasso has a topology which is more close to a branched network than to a looped network and in this case the gains in resilience are insignificant.

Different methods for model-based optimal sectorization for efficient energy management of large WDN's have been investigated, proposed and further developed. Two different formulations have been developed taking into account the particular characteristics of the Full WDN of Milan. The first formulation takes into account a MOO which includes a set of cut-valves and pumps simultaneously. The second formulation takes into account the creation of a specific number of sectors for a limited number of configurations, followed by MOO for pumping scheduling optimization. In general, it can be concluded that the second formulation shows more robustness from both scientific perspective and practical implementation perspective. This is because the formulation allows the user to predefine the number of sectors required, and provides the pump schedule for each sector in a single optimization run.

The energy reduction in a fully connected system with the topology and topography of Milan is of significance. Even though the combination of topography and topology are complex, it is possible to perform gains with pressure management in the system.

This research has developed and demonstrated methods for optimised pressure management in large WDN's with complex topography and multiple sources. This has been achieved for the pump scheduling formulation and for both sectorization formulations. In the case of sectorization, pressure reductions of the order of 12-16 m were achieved with the methods formulated and proposed in this research.

The research also demonstrates that it possible to perform sectorization for energy reduction in large WDN with current tools freely available. The only commercial software used in this research is MATLAB®, however the related methods presented here can be easily translated into other programming languages such as Python (of very common use these days), if required.

The sectorization of the system in 9 sectors is better in terms of pressure, but rather more expensive in terms of physical interventions. If any utility decides to operate its WSS as a single PMZ (01 sector), it is better for energy efficiency. However, a single sector does not solve the pressure management in the long run, as pumping stations operate as ON/OFF pumps. In the case of Milano, the exception for this pump operation is the sector of Abbiategrasso where VSP's are currently in operation. If a utility wants to increase their pressure management with the installation of additional VSP's, the additional costs incurred must be compared with the additional gains.

8.2 Conclusions

Two categories of conclusions that are achieved will be presented here. The first category is regarding scientific innovative components which were presented and investigated. Secondly, as this research presents components highly relevant for the industrial sector, many practical aspects need to be dealt prior to implementation.

Scientific innovative components

For pump scheduling many algorithms have been applied in literature, but only a limited number of cases demonstrate the possibility of bringing such outcomes in real applications. One of the most relevant aspects from an innovative perspective is the fact that the pump scheduling has been thoroughly investigated. The application of evolutionary heuristic methods is not novel, however a comparison between a legacy algorithm and a relatively new (at least at the time of the ICeWater project) algorithm are presented. Secondly, two different optimization approaches were introduced, one taking into account a single chromosome with all pump speeds for all pumps in the system, and a second one in which the optimization is performed one time step at a time. Thirdly, two types of constraints, Global in which the WDN is fully monitored, and Local in which selected nodes (pre-selected from the real system) are used to constrain the function evaluations. A comparison is also made among the two main types of decision variables, namely binary, representing typical pump switches and real (for VSPs), which may be useful for future planning of a utility. Subsequently, a link between the pump schedules and the expected pressures in a calibrated system where presented. It needs to be pointed that the use of a calibrated model almost guarantees better performance and understanding of the theoretical results and the practical implementation.

For sectorization, most of the literature focuses entirely on systems with a limited number of sources. For demonstrative purposes that works to a great extent, in small WDNs. However, in the case of Milan new methods needed to be developed and brought together, due to the extent of the network, its topology, and the topography associated with this system. A combination of algorithms available since the 1950's, related with Graph Theory were linked together with a two-level model-based optimization approach for minimization of energy and lack of resilience. Other authors have used graph theoretical approaches, however, mainly for other purposes, such as partitioning or water balance, which was not the main purpose of the methods presented here. In such cases authors identify locations of installation of additional elements in the system. This research contributed and proposed the possibility to operate the system as separate sectors. An additional extension to what is called shortest path algorithm is presented known as Shortest Dissipated Power Path (SDPP,) but with the possibility to make use of the pumping stations as sources and not only gravity sources as in existing literature.

For the two-level model-based optimization for Sectorization proposed, a first formulation has been developed with a great deal of computational inefficiencies, namely, what has been defined as idle boundaries and idle sectors. Needs not to be forgotten that the sectorization proposed is still a combinatorial optimization problem where the number of bounding cut-sets between sectors corresponds to the order of 2^{38}~ $10^{11.4}$ configurations. In this case, the second level became yet another combinatorial optimization problem (another pump scheduling). In general, and for simplicity, only Binary variables were used, as the water supply system was until 2017 operated with pump switches and not with VSP's. The search space is in the order of 2^{103}~10^{31}. To put this into perspective, the total number of possible configurations for operation of Full WDN of Milan for Formulation 1 is on the order of 10^{42}. Given that each simulation run of such a large WDN for a single time step the time of computation can vary between 30-250 s, a total enumeration by means of brute-force search is not feasible within the bound of the life of several generations. It was necessary to make use of large HPC systems available (Microsoft® Azure and SURFSara). The use of such cloud computing services for sectorization of large WDN is in itself novel.

In Formulation 2 of model-based optimization for Sectorization, the inefficiencies of idle boundaries and idle sectors of Formulation 1 have been removed. A simple card collector algorithm was applied to obtain larger sectors and thus reducing the number of cut-sets to be operated (in practice). Results are presented for a vast number of configurations were attempted. In fact options can be offered to the utility for case of 1 (current operation), 2, 3, 9 and 18 sectors. Additional optimization runs (not included) were performed to predefine whether or not the objective functions can be combined with the 3 performance criteria discussed in the document. Such results include MOO formulations for 3 objectives, 4 objectives and 5 objectives, and these resemble to a great extent to the results obtained for sectorization cases already presented.

Practical aspects

This research deals with several practical aspects. First of all, the utility MM had originally in their archive a WDN model which was not calibrated and seldom used. This model has been extended, adjusted, fine-tuned, and, more importantly, calibrated. That model has then been used for both the pump scheduling. Regarding the calibration, the model lies within the reasonable bounds of error (<7.5%).

A proof of concept is made regarding the hydraulic model's validity is its application for pump scheduling in the real system. In this case, a field test using a schedule obtained using the model-based optimization for Abbiategrasso was performed in 2015 as presented in §6.7.2. The results obtained from such practical application demonstrated to the decision makers at MM the value of performing additional interventions and the obtained gains in terms of water, energy and pressure. This represents valuable outcome, as in many cases research is posed form a theoretical perspective only, without demonstration of possible implementation.

Regarding the pressures obtained after application of pump schedules in Abbiategrasso, it is proven that the WDN model also represents to a great extent the operation in the real system. No further analysis was elaborated to define the reduction of leakages in Abbiategrasso, however from the results obtained it is evident that the Night Flow Analysis (NFA) on Abbiategrasso provides an improvement compared to the previous operation without the use of pump schedule.

Insight regarding pressure management of the Full WDN is also practical outcome of this research. Many different practical conclusions can be derived, as there is possibility for comparing the outcomes of two different sectorization methodologies. For example, if the utility at the time decided to continue to operate as a single PMZ, then it was necessary to perform a thorough pump schedule of the system and implementation of VSP's for some of the pumping stations. Indeed, this solution reduces the pressure in the system, but the outcome is not as promising as the one obtained with other cases or configurations. In the view of the author, one practical conclusion which can be made for the case study is to perform the sectorization of the WDN into 9 sectors. As presented in Chapter 7 (and Chapter 9, Appendix). The case of 9 sectors improves the pressure management of the system, and, at the same time, only two or three pumping stations would require installation of VSP's to reduce pressure in the northwest and southeast. This comes with a drawback, which is that a larger number of additional assets to be introduced in the field, with the additional interventions and issues to customers due to construction works.

The research also highlights a practical aspect of decision making. From a MOO perspective the outcome is always a Pareto front (and its associated Pareto set), however even though such alternatives can have a limited number, it is always possible to perform only one implementation. Even if the utility selects a sectorization into 2, 3 or 9 sectors, the practical implementation can be made only once. To overcome this, visual analytics can play a significant role as decision support tool. All analysis presented in Chapter 7, and supplementary material in Appendix, can be easily generated within seconds with the developed visualisation scripts. In particular, the use of specific visualization methods, such as HRV, Level diagram, trade-off index, help to understand the relevance of particular solutions and objectives for each configuration, while the comparison of pump schedules using dendrogram can help illustrate how separated are two pump schedules in terms of energy consumption. All of this is possible because the models used for such analysis (although not perfect) have been thoroughly revised and calibrated.

Social impact

Social impact of this research is translated directly to customers. They pay their water bills and as a customer myself, I would want to have feedback from my utility and transparency from the operators regarding not only the continuity of service but also the sustainability of supply. This research has a direct impact on customers of MM as the reduction of energy costs and pressure in the system guarantees that the utility will operate in a more sustainable way. In general, that is the purpose of the utilities of the future - to make the customer lives better. As a side note, recently (Nov 2020) water started to be traded as commodity in Wall Street, the water which MM pumps for treatment and subsequent supply, may very well become a traded good in the future.

This research was funded in the context of EU international projects and cooperation. Results can be easily extended to other utilities as the products from such projects are mostly freely available. I'd like to make a parenthesis with my home country, Colombia. Research institutes and centers are still today seen as groups of people with theoretical knowledge, but where practical applications are rather scarce. Usually universities and institutes are invited by the government to participate in large infrastructure projects and to solve large water management issues (e.g. mainly after disasters) when basically there is no affordable solution. The ideal case is the one as the one of the European Commission where research such as the one done with ICeWater project can offer direct impact to the lives of millions of people. Industrial partners benefit from the exposition and benchmark of their tools, research institutes continue the development of new methods and water companies gain knowledge about their system and improve their operations. As a contrast, the coordination and results obtained with a project such as ICeWater would not be possible for even the largest water utilities in Colombia. This is not a matter of capacity in terms of funding, but rather a complete misunderstanding of the relations between industrial partners, research institutes and government (which manages most of the water utilities) about their role for the development of knowledge and implementation of concepts on the infrastructure at the regional and national level.

Most of this research has been realized with the use of open software (with the exception of MATLAB®). The Open science principle establishes that data and models are to be shared with others. Fortunately, this research has been communicated and disseminated in multiple instances. The role of a researcher is ingeniousness and dissemination!

8.3 Limitations

Pump scheduling

The main limitation for the proposed approaches and algorithms are the demands. Usually, the setup of a model requires two types of information. The first one is the base demand, and the second one is the demand pattern. Based on historical records and forecast models (not covered in this research) it is possible to obtain both of the accurate representation of base demands and hourly variability. During the field tests, information from the prior day of monitoring was used. While the results proved to be promising for the utility, still an additional layer of integration with demand forecasting models needs to be performed.

Second limitation is the dependence on calibrated model. Interventions and additions of elements continuously occur in the field, and maintaining an updated model for planning future operations remains a challenging task. In this regards, it was not possible to communicate with MM to obtain the current version of their WDN model for comparison purposes. However, most likely these models have been kept continuously updated and new user case requirements are still being implemented by the utility.

Currently, most utilities make emphasis in the use of real-time or near real-time control of a WSS. The use of methodologies for control theory or Model Predictive Control (MPC) fell out of the scope of this research. In particular this is evident for Abbiategrasso model, where the pump speeds are provided every hour. This is basically due to the formulation as a model-based optimization. In reality, the SCADA system of Abbiategrasso contains in itself a set of rules, which update the operation via VSP of the system as changes in pressure occurs in some nodes of the system. If one wanted to perform a multi-objective optimization for pump scheduling of the whole system to mimic this form of operation, it would require 1440 decision variables (with a resolution of each minute of a day) per each booster pump. This makes the problem untraceable and the decision space larger that can be simulated in a lifetime. Running a pump scheduling optimization due to the magnitude of the decision space, would take centuries for the engineers to come with a feasible result. However, the fact that the pressure management to be performed in Milan includes also the need of a sectorization optimization, the approach used for pump scheduling every hour is sound as decisions about which areas to isolate and how to operate the pumps in each individual sector can occur only once in practice. In addition, in order to apply Control Theory or even MPC some valuable prior knowledge of the systems' internal behaviour is needed. Such as threshold of pressures, flows and fluctuations of flow directions. At the time of the development of the WDN models this was already a challenge in itself given the complexities of the system. This indicates that building such complex WDN models adds value for future endeavours which any utility may face.

Sectorizations limitations

For the Formulation 1 of sectorization it was not possible to limit the number of times that idle sectors and idle boundaries appeared as part of the solutions. As a matter of fact, the final solution, basically proposed that the system continues to be operated as a single PMZ. This was supposed to be overcome by Formulation 2. And it did. However, the second formulation contains a very large number of possible configurations of sectorization for each pre-determined number of sectors. Some cases were run and analysed, however the spectrum of possible configurations is so vast that in the end the number of sectors was basically fixed by the utility, following their preferences. In a sense, this portrays that the sectorization proposed is optimal, but only for a specific number of sectors and configuration. The decision space explored is rather limited with respect to the number of possible configurations. Yet again, in a research with impending industrial components decisions need to be made on the spot, and once the investment is done there is no possibility of turning back to an old configuration.

One aspect which was not considered during the research on sectorization was the fact of changing the demand, both base and demand patterns. In fact, the optimization runs were performed taking into account the maximum demand factor as a single snapshot of the network. This is an aspect that can affect the sectorization. How? The first level of sectorization is based on a graph theoretical analysis of the WDN simulated in EPANET. That means that a different distribution of demands and patterns can originate a different set of initial cut-valves, deriving different number of initial subsectors. However, going deeper into this aspect is beyond the scope of this research, and remains for future investigations. This subject in itself could be a PhD research, for example using a stochastic demand simulator and running robust MOO around the sectorization.

From another perspective, but also related to the previous paragraph, the research proposes the implementation of several interventions in the WDN, however the algorithm does not provide the order in which such interventions are to be performed by the utility. There is no ranking or prioritization of interventions proposed. This is a limitation, as a concerted effort will be needed at the utility throughout such implementations. In addition, the fact that the interventions are not performed simultaneously all over the city, because of both city restrictions and the limited availability of number of field operators, once the interventions start to occur the pressures in the system would change. Such intermediate changes in the pressure of the WDN are not considered here. A possible work-around would be to have a third level of sectorization which uses a Greedy algorithm applied to the interventions to determine the optimal order which minimizes for example functionality of supply (Paez, et al., 2020) (Castro-Gama, 2018).

One aspect to consider is the fact that the computational time of each sectorization configuration run was on the order of months. However, with current cloud services and following Moore’s law, the simulation runs performed in 2015 would be 8 times faster in 2021 (6 years later).

It is also highlighted that this research is just a small step on the subject of sectorization, and further work will continuously be carried out by other researchers in future.

8.4 Recommendations and future work / Outlook

Several other MOO algorithms for PS can be applied. Their use is dependent on the needs of the utility or characteristics of the case where these are to be applied. In the literature many applications for pump scheduling exists, however most of them are for benchmark models. Given complexities of large WDNs identified also in this thesis the selection of MOO algorithms in such cases requires further research. One possible area of future work is the application of several other MOO algorithms.

Another aspect to be considered is that for the further implementation of the formulations and algorithms used, the number of case studies similar to the ones in this thesis, large WDNs, needs to be increased. This thesis was addressing only the cases in Milan, mainly for two reasons. First, there is some reluctance among utilities to share the information of their WDNs, and, secondly, because it was hard to come up with such problems as the ones present in Milan during the available time of the ICeWater project, when the main research was carried out. In this regard, the methods presented here should be applied in other systems. For example, through KWR Water Research Institute, a contact was established with Water Supply Department (WSD) Hong Kong, where an additional subsystem parallel to freshwater needs to be optimised. In Hong Kong’s case saltwater is pumped with boosters to be used for the flushing of toilets in the four subareas of the supply system. This shows that additional considerations may be taking place such as the additional energy due to increased water density and a completely different customer demand.

Future considerations regarding the algorithms presented are related to the lack of possibility for parallelization. At the time of running the simulations there was a limited number of proprietary EPANET libraries which were able to use multi-threading. Currently, with the development of EPANET 2.2 the possibility of using multiple thread instances of the hydraulic simulator is real. In addition, due to the funding of the US EPA, this software application continues to be freely available for any user willing to apply it. Once the multi-thread is linked with an MOO which allows parallelization, the times of computation can be dramatically reduced, as much more efficient use of the available resources will be possible. In fact, this is the future of Internet as a Service (IaaS) for the water industry, as more and more cloud computing services allow running large optimization jobs. One aspect to further develop in the case of application of the pump scheduling and sectorization approaches is the possibility to integrate them in larger dashboard systems as web services. Such content is not covered in this document, however, much of the work in this area needs to be constantly updated as the landscape of programming languages and frameworks changes every 3-5 years. In fact, current developments among commercial software vendors are nowadays similar, with online versions next to their desktop applications for an additional cost.

One of the aspects which has not been discussed is the fact that there is difference between the pump scheduling presented here and the (near) real-time operation. The SCADA system operates with certain rules based on control theory which trigger the activation or not of pumps in the Full WDN. Such rules of operation force the operation based on trigger thresholds of pressure. This behaviour cannot be simulated with the current configuration of PS and sectorization approaches. However, it was demonstrated in the case of Abbiategrasso that the correct application of the proposed Optimised Case solution in the SCADA can bring gains with respect to the current operation of the system. In addition, for the case of the Full WDN, it needs to be remembered that the solutions provided are indicative of the behaviour of the whole system. The WDN can be used within DSSs for the application of different user cases.

One possible aspect of further development is the planning of operations, which should be communicated to customers. Such web services already exists and to mention just one www.waterstoringen.nl in the Netherlands can be visited to identify disruptions at any time in the water supply of the country. Such initiatives should be fostered in other parts of the world as this increases the good-standing of the utility and its visibility and transparency with customers.

The number scenarios explored with this research are leveraged by demand changes due to customer behaviour and topology changes in the system all the time. However, these change from season to season and from year to year. One possible way to circumvent the demand changes is the application of Machine Learning (ML) or Artificial Intelligence (AI) algorithms for the selection of the most relevant scenarios at a particular time of the day in a particular season of the year. Another possible use of ML/AI is the possibility of creating robust forecasting algorithms for WDN model demands. Topology changes in large WDNs occur continuously, as new pipes are installed, old pipes are broken, or branches are decommissioned. In this thesis a methodology was presented to include new elements in the WDN model and avoid inconsistencies between different departments of the same water utility. However, there is an intensive volume of field work still to be done to verify simple information such as the status of valves (whether open or closed). It is necessary then then to create a larger number of topology scenarios of the WDN which can be used also in other use cases than pump scheduling, pressure management and sectorization.

The sectorization algorithm in its Formulation 1 considers cut-set valves & pumps simultaneously as decision variables in MOO. This algorithm is very inefficient due to the presence of idle sectors and idle boundaries inside sectors. However, it is the hope of the author that further research on this formulation will continue, that will overcome the identified difficulties and open possibility for more automated identification of viable optimal sectors.

9 APPENDIX

9.1 Results of sectorization Formulation 2 for two sectors

There is a large number of possible configurations of sectorization available for the system of Milan in the scenario with two sectors. In an early analysis more than 1,000 configurations were obtained from the possible subsets. However, due to computational limitations not all of the configurations can be used for MOO under a PS. In that case, an engineering selection of configurations was performed. A selection of 11 configurations were used for MOO. From these configurations their best solution of pump schedules based on minimum energy, level diagram and hyper-radial is selected for visualization. The lowest possible energy consumption found was 5,834 kWh for solution $\boldsymbol{S_{10688}}$ in Configuration 2-10. A complete analysis of Configuration 2-10 results from MOO is presented in the following section.

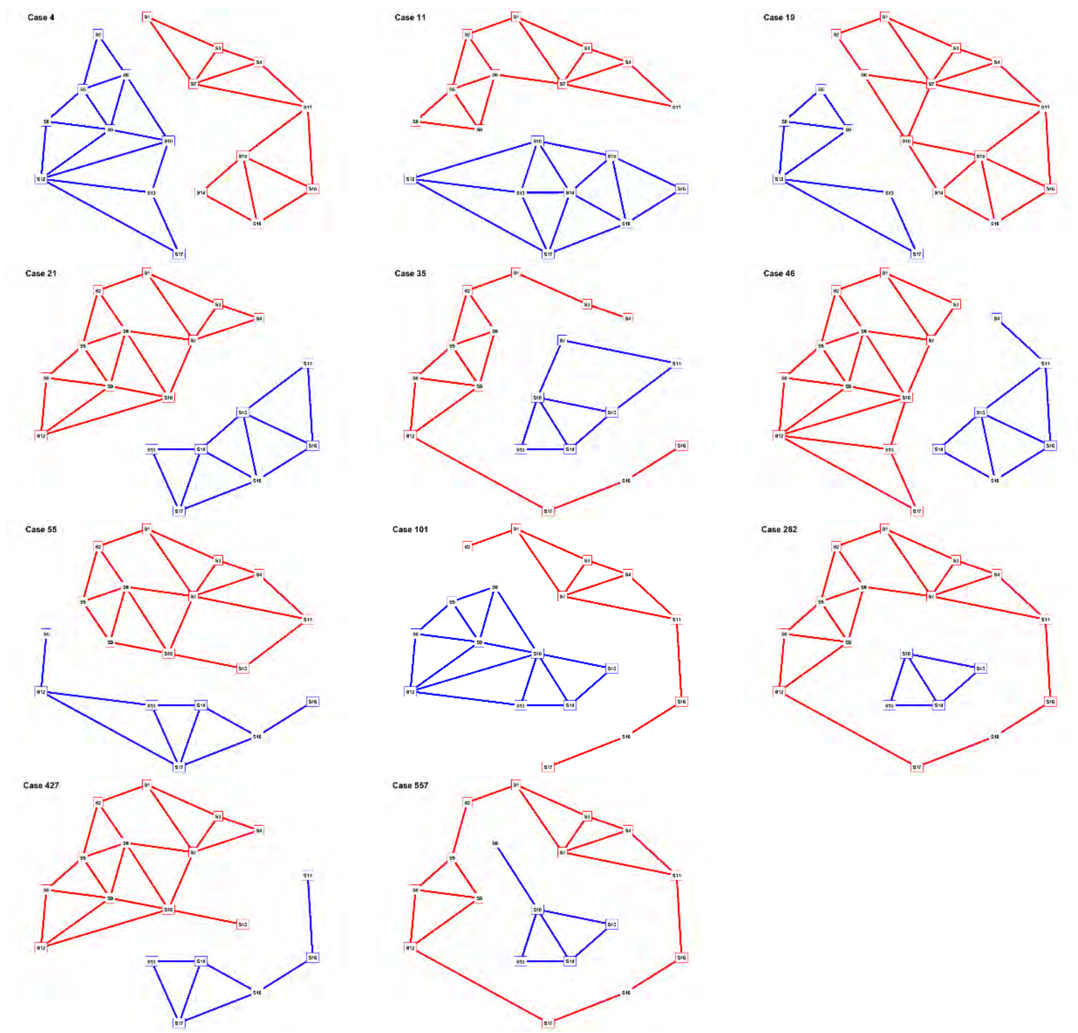


Figure 9-1. Sectorization configurations for scenario with two sectors for Milan.

Table 9-1. Scenario with 02 sectors. All configurations analysed.

Configuration	Idx sol	Lack of Resilience $1\text{-}I_R$ [%]	Total Energy E_T [kWh]	Additional Performance Indicators P_{max} [m]	P_{min} [m]	P_{ave} [m]
2-1	9 506	3.44	5 904	72.92	30.36	42.71
2-2	8 970	3.75	5 978	66.20	30.35	44.02
2-3	7 872	3.54	6 057	73.21	30.11	43.59
2-4	9 694	3.79	5 895	72.21	30.18	43.82
2-5	6 206	3.42	6 156	66.71	30.01	43.24
2-6	8 831	3.37	5 905	66.77	30.40	42.42
2-7	9 000	3.54	5 989	71.42	30.13	43.20
2-8	7 295	3.82	6 273	72.31	30.25	45.16
2-9	11 704	3.59	5 919	67.70	30.20	43.19
2-10	10 688	3.85	5 834	67.89	30.18	43.88
2-11	10 599	3.84	6 016	67.88	30.18	44.61

9.1.1 Analysis of solutions for Configuration 2-10

First of all, the configuration is presented in Figure 9-2.

$S_1 = \{s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8, s_9, s_{10}, s_{12}, s_{15}\}$

$S_2 = \{s_{11}, s_{13}, s_{14}, s_{16}, s_{17}, s_{18}\}$.

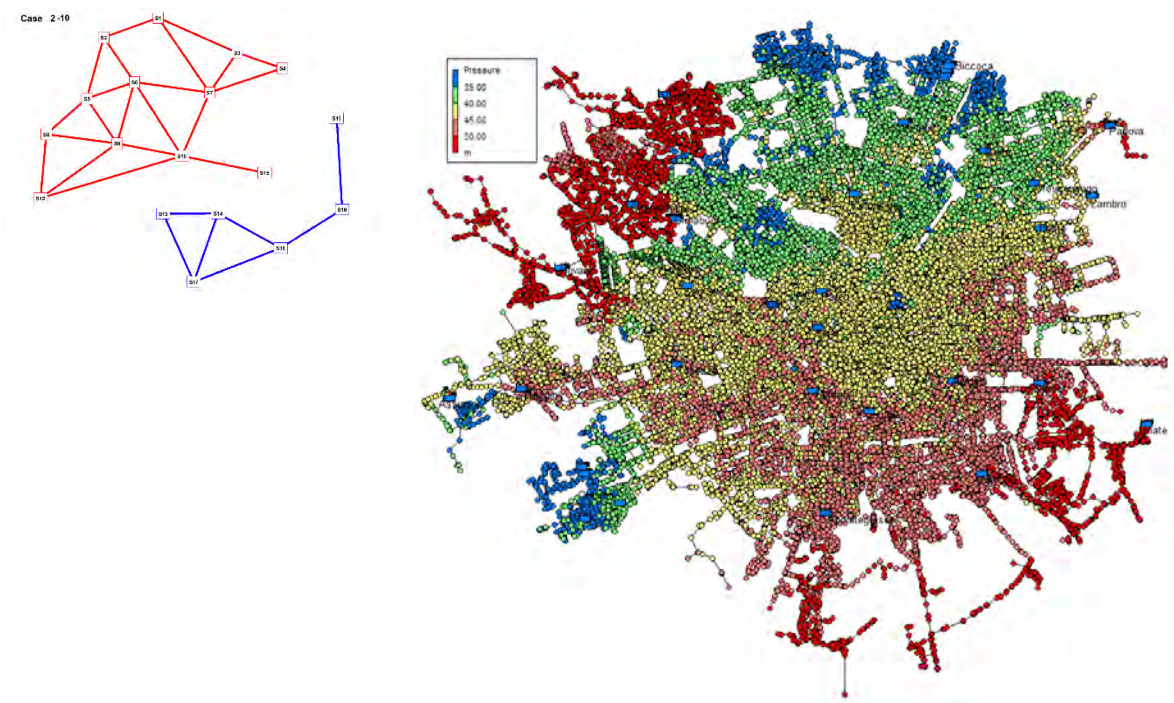


Figure 9-2. Graph configuration 2-10. Right presents the pressure variation for the minimum energy solution obtained through pump scheduling.

Figure 9-3, shows the different 2D scatter plots possible with the 2 objectives (energy and lack of Resilience) and three additional performance criteria (P_{max}, P_{min}, P_{ave}) for all function evaluations. The figure shows a classification by colour for the average pressure (P_{ave}), and a classification by marker size for minimum pressure (P_{min}).

Figure 9-3, upper left corresponds to the real optimization which was run (trade-off of objectives), while the other two plots correspond to the simultaneous responses of the other performance criteria (not used as objectives in the optimization). Both the sizes of the markers and red colours approach the ideal point in all plots. This shows that there is a progressive evolution towards an optimal solution.

The minimum energy obtained is 5,834 kWh for a lack of resilience of 3.86%, a minimum pressure of 30.2 m, a maximum pressure of 67.89 m and average pressure of 43.88 m. It is interesting that the evolution of solutions as the MOO progressed tends to create two different clusters of solutions as displayed in the second scatter (upper right). However, the number of coloured solutions corresponds to only 6% of all function evaluations ran during MOO.

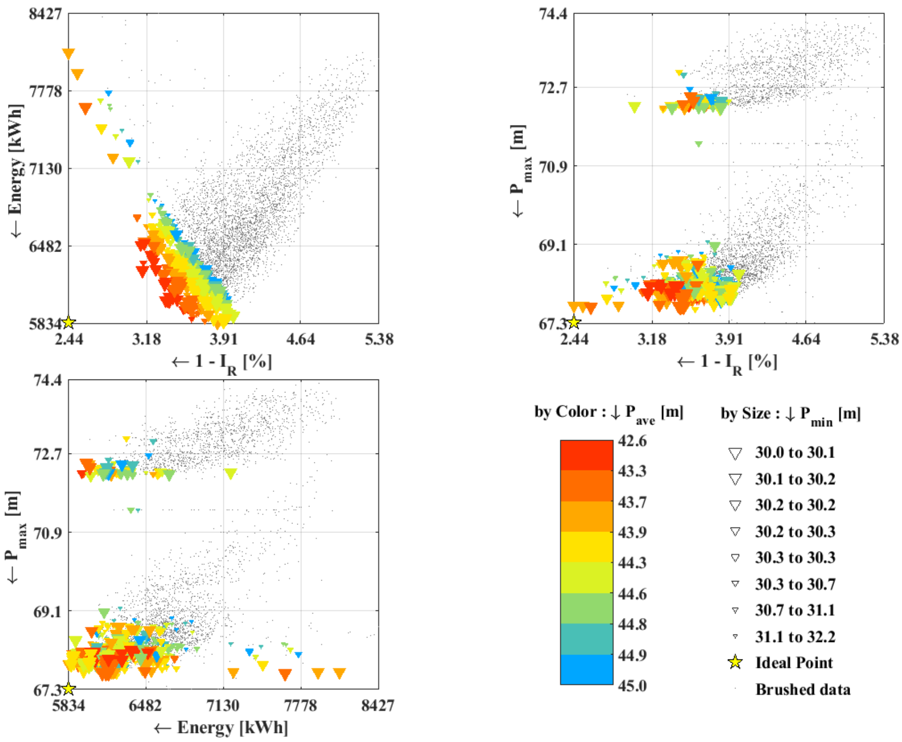


Figure 9-3. Scatter of all possible solutions as 2D plots (Configuration 2-10: 02 sectors).

The same solutions are presented in Figure 9-4. In this case a 3D scatter plot is presented where the same criteria are applied for both colouring and sizes of triangles. The z-axis corresponds to the maximum pressure criteria. It is easy for example to visualize how some solutions which belong to the Pareto front in Figure 9-3 also display a higher maximum pressure above 70 m. On the other hand, most of the solutions are located near the Pareto front (E_T vs $1\text{-}I_R$).

Parallel Coordinates plot is presented in Figure 9-5. Solutions shown present average pressure below 45 m. The bulk of solutions present a low average pressure and low minimum pressure simultaneously. Only a few solutions have a high maximum pressure magnitude (above 70 m). In terms of energy consumption and lack of resilience the configuration allows for several different solutions close to the Pareto front.

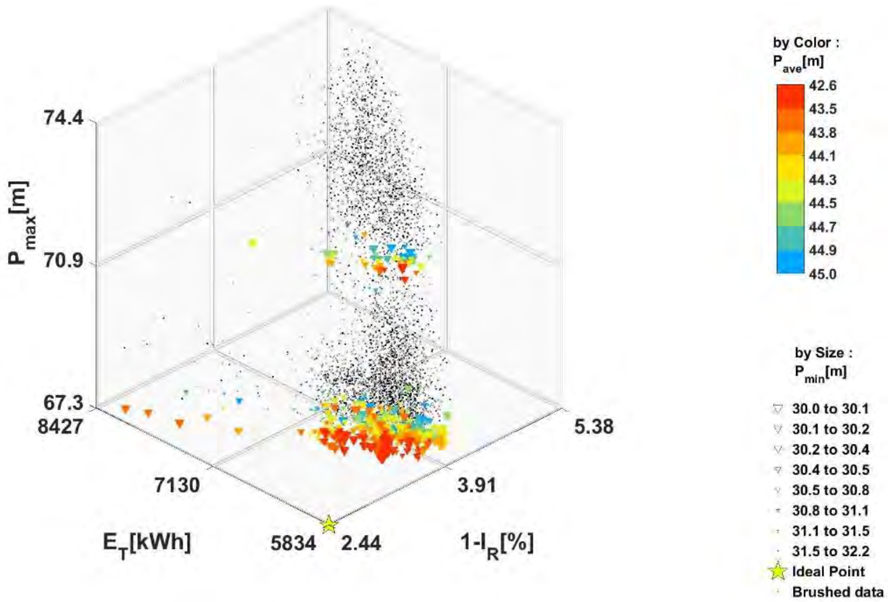


Figure 9-4. Scatter of possible solutions as 3D plots (Configuration 2-10: 02 sectors).

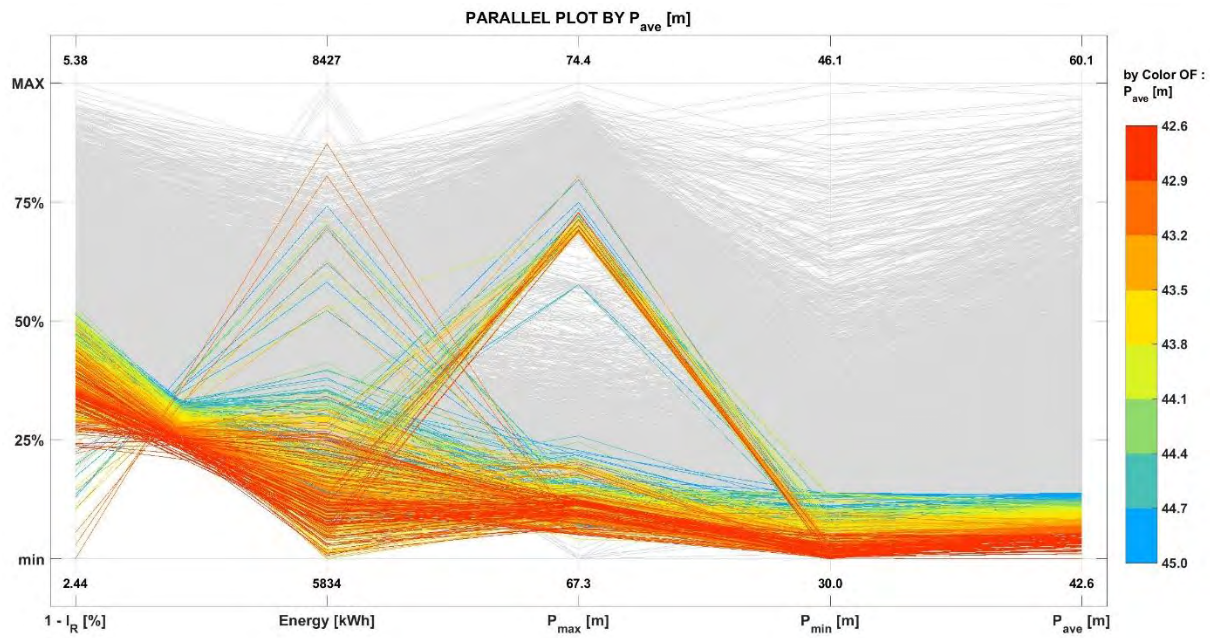


Figure 9-5. Parallel plot of the objective for Configuration 2-10.

In order to be able to identify trade-offs among solutions, the last 2,000 function evaluations are selected and the Trade-off Index (λ) is estimated as presented in Figure 9-6, where OF_1: 1 - I_R, OF_2: Energy, PC_1: P_{max}, PC_2: P_{min}, PC_3: P_{ave}. Inside each square the small squares represent the average trade-off index of a particular solution vs all other solutions between those two objectives. In this particular configuration both the correlation (***r***) and the trade-off index show that lack of resilience and energy consumption (OF_1-OF_2) that there is no significant correlation between the two objectives, however, there is a 40.9% of trade-offs among the solutions. Besides maximum pressure and energy consumption (OF_2-PC_1), which present a trade-off index of 32.2% there are no other significant criteria which expose trade-offs.

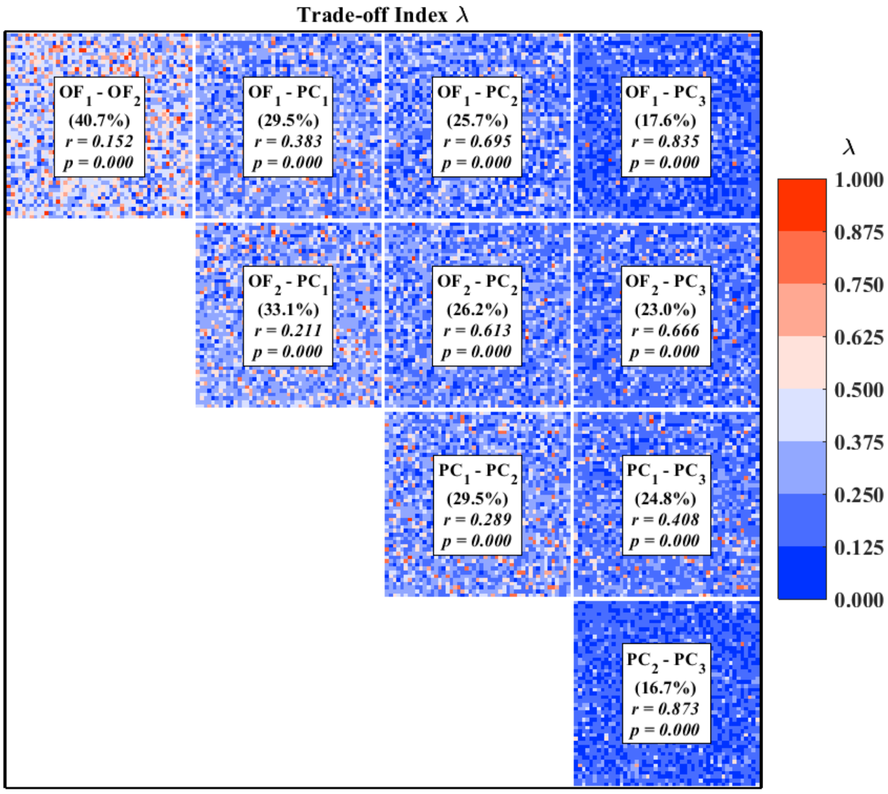


Figure 9-6. Trade-off index for last 2,000 solutions of Configuration 2-10. OF_1: 1 - I_R, OF_2: Energy, PC_1: P_{max}, PC_2: P_{min}, PC_3: P_{ave}.

In order to perform an unbiased selection for the best possible solutions among all solutions, level method and HRV are performed as well to the set of solutions of Configuration 2-10. Figure 9-7, shows the level diagram for Configuration 2-10, showing the best solution (yellow square) obtained being S_{9219} (read as solution 9,219 of all solutions). This solution presents a Lack of Resilience of 3.14%, E_T consumption of 6277 kWh, maximum pressure of 67.99 m, minimum pressure of 30.03 m and average pressure of 42.58 m. It is evident than by selecting this solution there will be an increase in energy consumption and maximum pressure with respect to Configuration 1-3.

The second method for unbiased selection of solutions is Hyper-Radial Visualization (HRV). Figure 9-8, shows the HRV after applied to the solutions obtained for Configuration 2-10. In this case four different solutions are identified as the more relevant by this method (S_{10238}, S_{9727}, S_{9219} and S_{6929})

Solution S_{9219}, has been identified also by the level diagram of the solutions. S_{10688}, corresponds to the solution with the lowest energy consumption of the system as presented in Table 7-5. Solution, S_{6929}, is identified as a third possible solution although this solution is only of importance by looking at the lack of resilience (2.46%) while the energy consumption is high (8097 kWh). Solution, S_{9727} is relevant only for HRV which contain energy and pressure criteria vs the rest.

As a final form of visualization of results a classification of the objective space solutions was performed using Self Organizing Maps (SOM) for a total number of nine clusters arranged in a 3x3 topology. Again, results are shown after 1,000 iterations, when convergence is met. Figure 9-9, shows the SOM for solutions of Configuration 2-10.

In this case all objectives and criteria trade-offs are presented, while the colouring scheme represents the cluster to which each solution belongs to. This visualization is able to present different areas of the solutions which display similar characteristics.

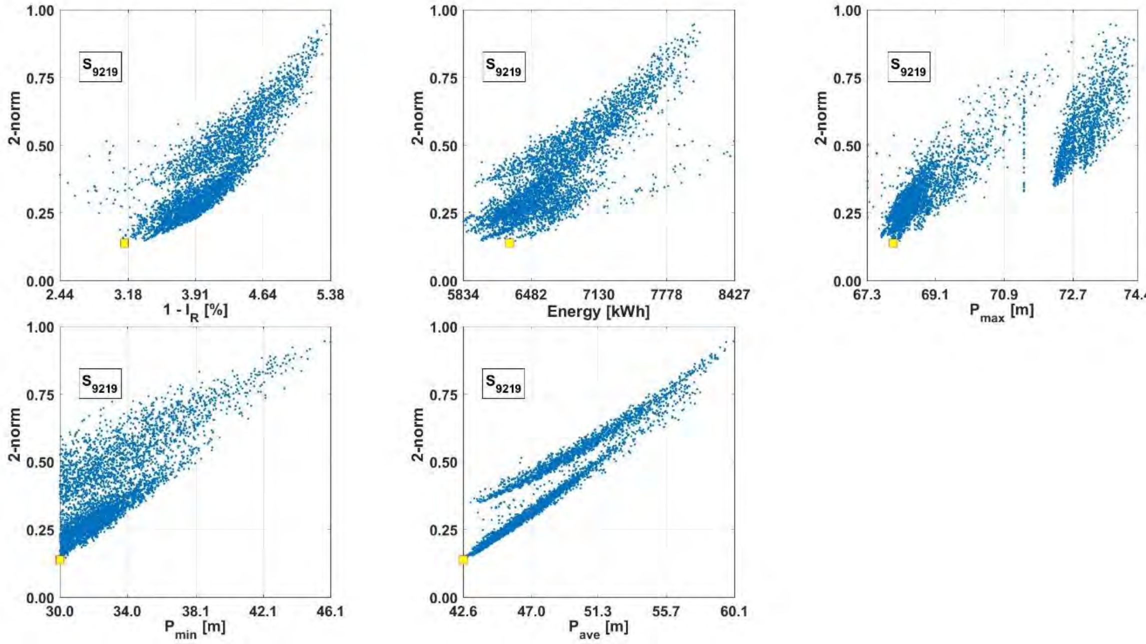


Figure 9-7. Level diagram Configuration 2-10. Best solution identified id = 9,219.

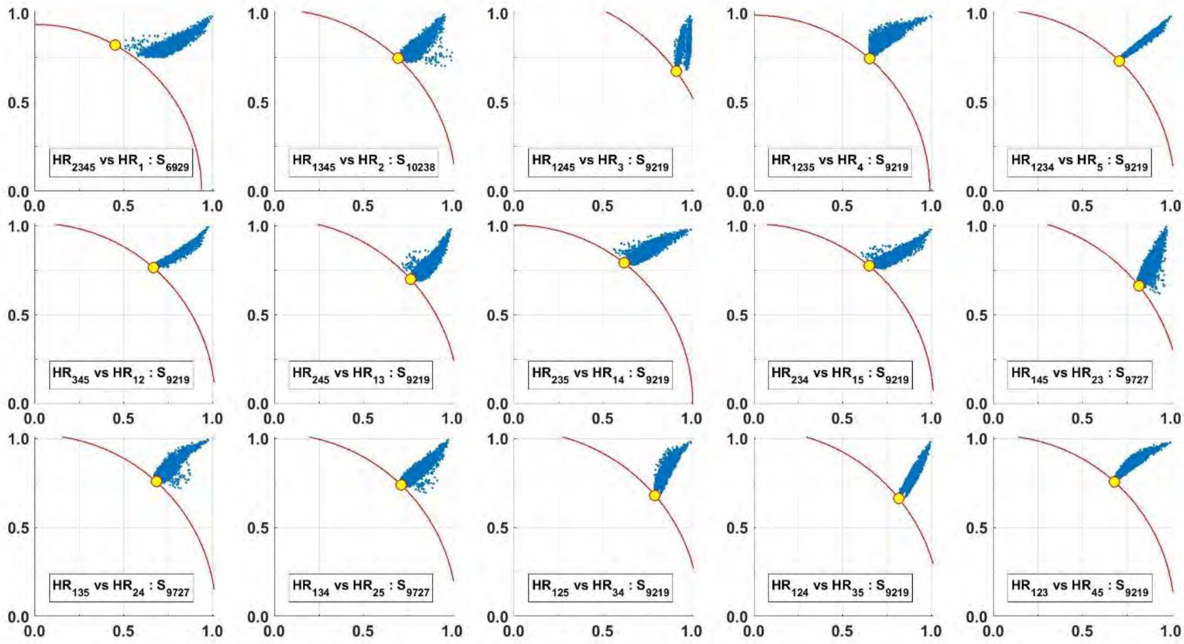


Figure 9-8. Hyper-Radial Visualization of objectives for Configuration 2-10.

Cluster 9 contains the set of best feasible solutions available in terms of low magnitude of maximum pressure, average pressure, energy consumption and resilience. Solutions corresponding to Cluster 1, 2, 3, 4 and 5 appear to be far away from the Pareto front (dominated) and tend to present high magnitude of maximum pressure. This cluster corresponds to early solutions of the MOO.

The resulting Pareto front of Configuration 2-10 is presented in Figure 9-10A, where the solutions have been ranked in order of minimum energy consumption. Solutions have been ranked being 1 the solution in the Pareto front with the lowest energy. The solution with minimum energy is S_{10688}. A total of 19 function evaluations belong to the Pareto front. This is due to the complex operation of the system and the selection of Binary decision variables. Although the Pareto front is composed of a size equal to the population (100), most of the solutions start overlapping as it was for Configuration 1-3 and Configuration 18-3 as well.

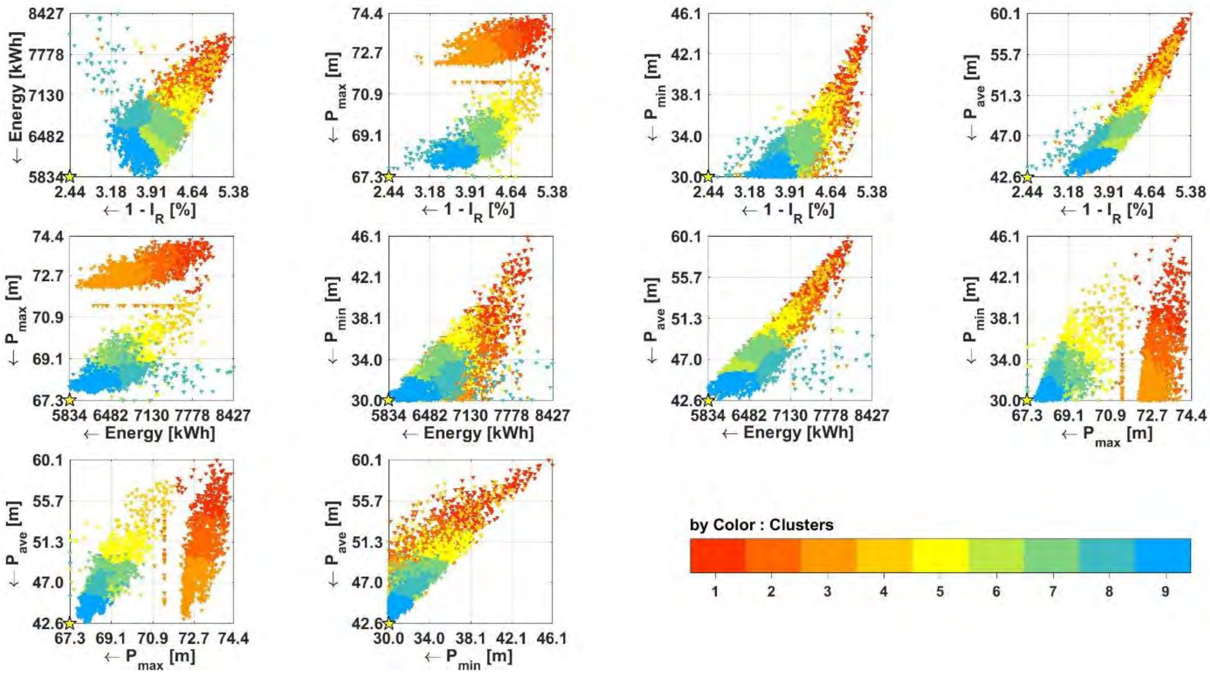


Figure 9-9. Self organizing Map into 9 clusters for objective space of Configuration 2-10.

A dendrogram of hamming distance among pump schedules is presented in Figure 9-10B. In that way, it is possible to see for example that the number of different pumps in operation between ranked solutions 5-6, 18-19 and 10-13, 8-12 and 7-11 of the Pareto front is just 1 pump (ON/OFF). Also the best solution 1 differs from solution 14 in only 6 pumps.

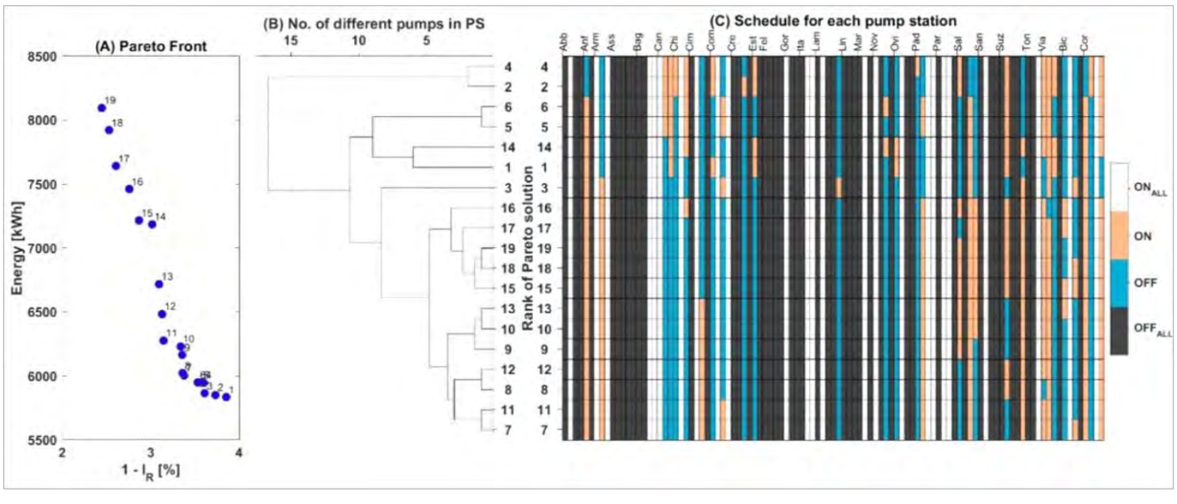


Figure 9-10. Pareto front and set of Configuration 2-10. (left) Pareto front, (center) dendrogram of Hamming distance of pump schedules among solutions and (right) resulting pump schedule or Pareto Set.

Finally, a comparison between the pump schedules (Pareto set) is presented in Figure 9-10C, rearranged accordingly with the rank and position in the dendrogram. In Figure 9-10C it is shown that some pumps remain active in all solutions (ON_{ALL}). On the other hand, some pumps remain inactive (OFF_{ALL}) for all Pareto solutions (see Table 9-2).

Table 9-2. Pump schedule of Configuration 2-10. Pumps which remain ON for all solutions and OFF for all solutions.

ON_{ALL}	Abbiategrasso (2), Armi (1 and 3), Baggio (3 and 4), Cantore (1), Chiusabella (2), Cimabue (2), Comasina (2 and 4), Gorla (1), Italia (2 and 3), Lambro (2), Martini (2), Novara (1), Ovidio (2), Padova (3 and 4), Parco (2 and 3), San Siro (2), Tonezza (3), Bicocca (2) and Corsico (3)
OFF_{ALL}	Abbiategrasso (1, 3 and 4), Anfossi (4), Assiano (all), Baggio (1 and 2), Cimabue (1 and 4), Crescenzago (1, 2 and 4), Este (2), Feltre (1 to 4), Gorla (2 and 3), Italia (1), Lambro (1, 3 and 4), Linate (1, 2 and 3), Martini (1 and 3), Novara (2 and 4), Ovidio (3 and 4), Parco (1 and 4), Salemi (2), San Siro (1, 3 and 4), Suzzani (1, 3 and 4), Tonezza (1 and 2), Vialba (4) and Bicocca (4).

9.2 Results of sectorization for Formulation 2 with three sectors

There is a large number of possible configurations of sectorization available for the system of Milan as 3 sectors. In an early analysis 2,000 configurations were obtained. Due to computational limitations not all of the configurations can be used for MOO under a PS. In that case an engineering selection of cases was performed. A selection of 9 configurations were used for MOO. Such configurations and their 2 best solutions (pump schedules) based on minimum energy, level diagram and hyper-radial visualization are presented in Table 9-3. The lowest possible energy consumption found was 5,660 kWh for the solution S_{11378} in Configuration 3-9. A complete analysis of Configuration 3-9 results from MOO will be presented in the following section.

Table 9-3. Scenario with 03 sectors. All configurations analysed.

Configuration	Idx sol	Lack of Resilience 1-I_R [%]	Energy E_T [kWh]	Additional Performance P_{max} [m]	P_{min} [m]	P_{ave} [m]
3-1	9 307	3.99	5 866	58.28	30.53	44.71
3-2	9 833	3.75	5 892	72.29	30.95	43.91
3-3	8 201	3.82	5 829	67.01	30.27	43.93
3-4	7 994	3.60	5 826	70.89	30.07	42.96
3-5	9 518	3.38	5 813	68.16	30.07	42.06
3-6	11 001	4.01	5 868	64.83	30.00	44.55
3-7	9 206	3.57	5 666	55.75	30.12	42.44
3-8	16 930	3.21	5 746	64.41	30.05	41.43
3-9	11 378	3.11	5 660	71.05	30.06	40.92

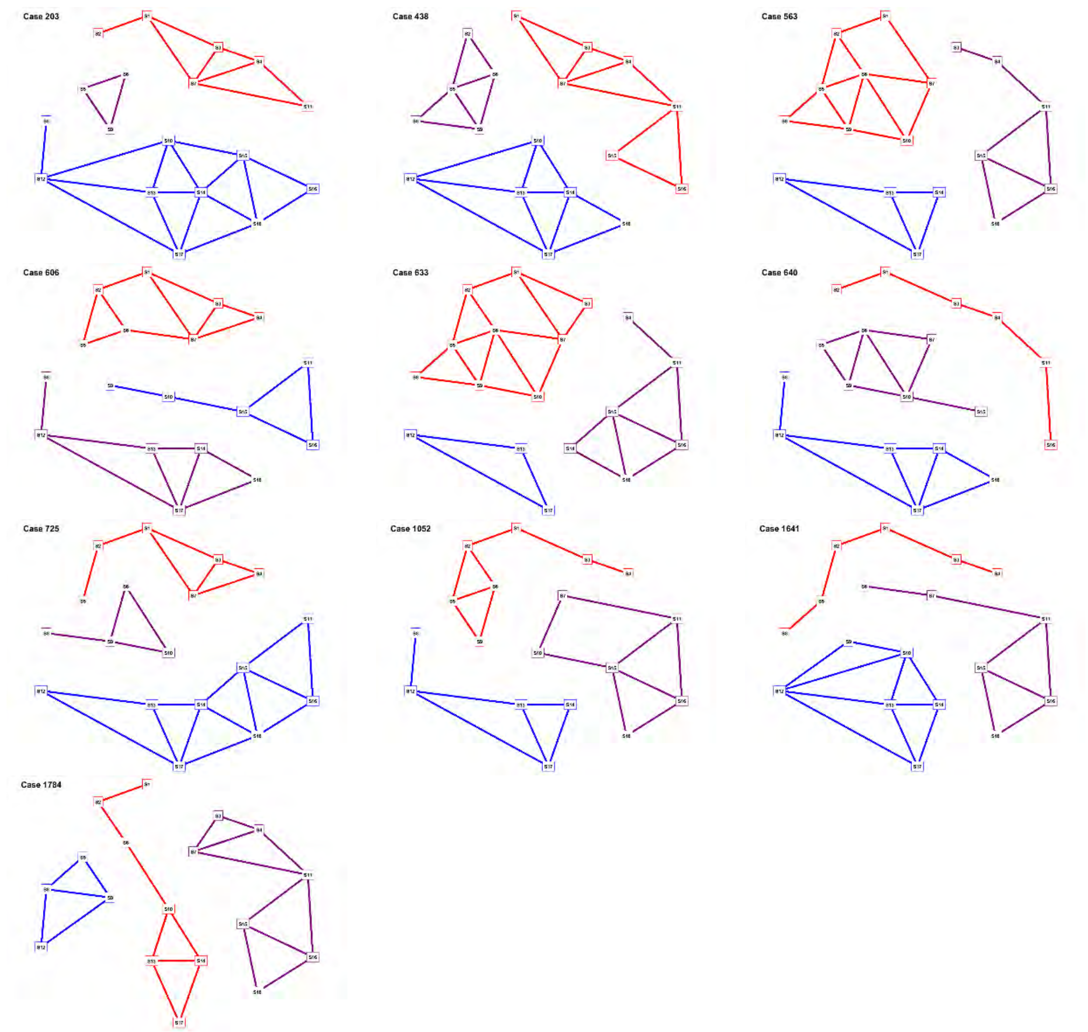


Figure 9-11. Configurations of sectorization as 3 sectors.

9.2.1 Analysis of solutions for Configuration 3-9

First of all, the configuration of this case is presented in Figure 9-12.

$\boldsymbol{S_1} = \{s_1, s_2, s_3, s_4, s_5, s_8\}$,

$\boldsymbol{S_2} = \{s_6, s_7, s_{11}, s_{15}, s_{16}, s_{18}\}$ and

$\boldsymbol{S_3} = \{s_9, s_{10}, s_{12}, s_{13}, s_{14}, s_{17}\}$

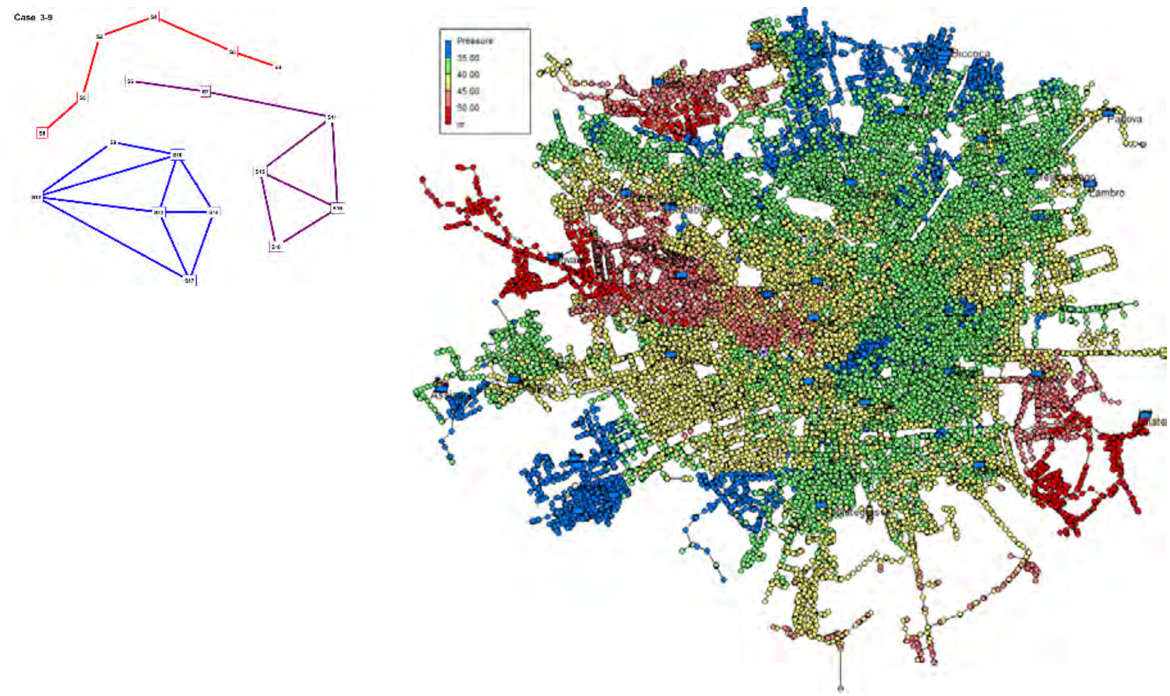


Figure 9-12. Left graph configuration of Configuration 3-9. Right presents the pressure obtained with the minimum energy solution of pump scheduling.

Figure 9-13 shows the different 2D scatter plots possible with the 2 objectives (Energy and Lack of Resilience) and 3 additional performance criteria (Pmax, Pmin, Pave) for all function evaluations. The figure shows a classification by colour using the average pressure (Pave), and a classification by marker size by minimum pressure. Figure 9-13 upper left corresponds to the set of objectives used during optimization, while the other two plots correspond to the simultaneous responses of the other performance criteria (not used for optimization). Both the sizes of the markers and red colours approach the ideal point in all plots. This shows that there is a progressive evolution towards an optimal solution. The minimum energy obtained is 5,660 kWh for a lack of resilience of 3.11%, a minimum pressure of 30.06 m, a maximum pressure of 71.05 m and average pressure of 40.92 m.

It is interesting that the evolution of solutions as the MOO progressed tends to create two different areas of solutions as displayed in the second scatter (upper right). However, the number of coloured solutions corresponds to only 9.7% of all function evaluations ran during MOO. Also by looking at the evolution of the Pareto front it is important to see that although the energy consumption is similar to other cases presented for other number of sectors, most of the solutions are located with a maximum pressure above 70m. This is a drawback for the presented configuration given that there is currently no possibility for the utility to operate pumping stations using VSP rather than in Abbiategrasso.

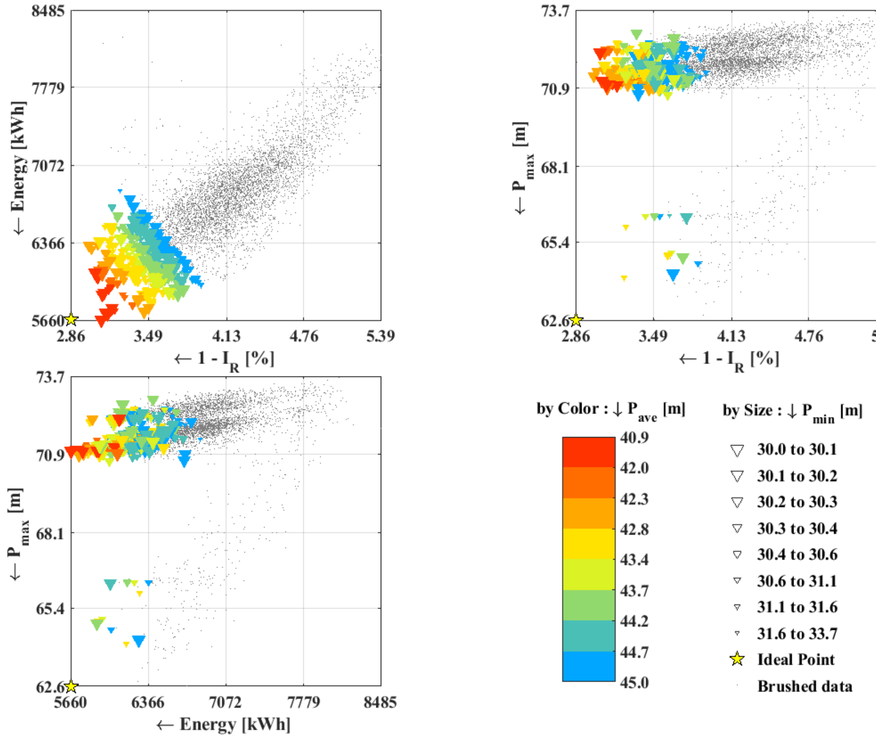


Figure 9-13. Scatter of all possible solutions as 2D plots (Configuration 3-9: 3 sectors).

In Figure 9-14, the 3D scatter plot is presented where the same criteria are applied for both colouring of triangles and sizes as for the 2D scatter plots. The z-axis corresponds to the maximum pressure criteria. It is easy for example to ratify (visually) how most some solutions which belong to the Pareto front are located in an area of high magnitude of maximum pressure above 70 m. On the other hand, the solutions located under that threshold of maximum pressure are not located near the Pareto front (E_T vs 1-I_R).

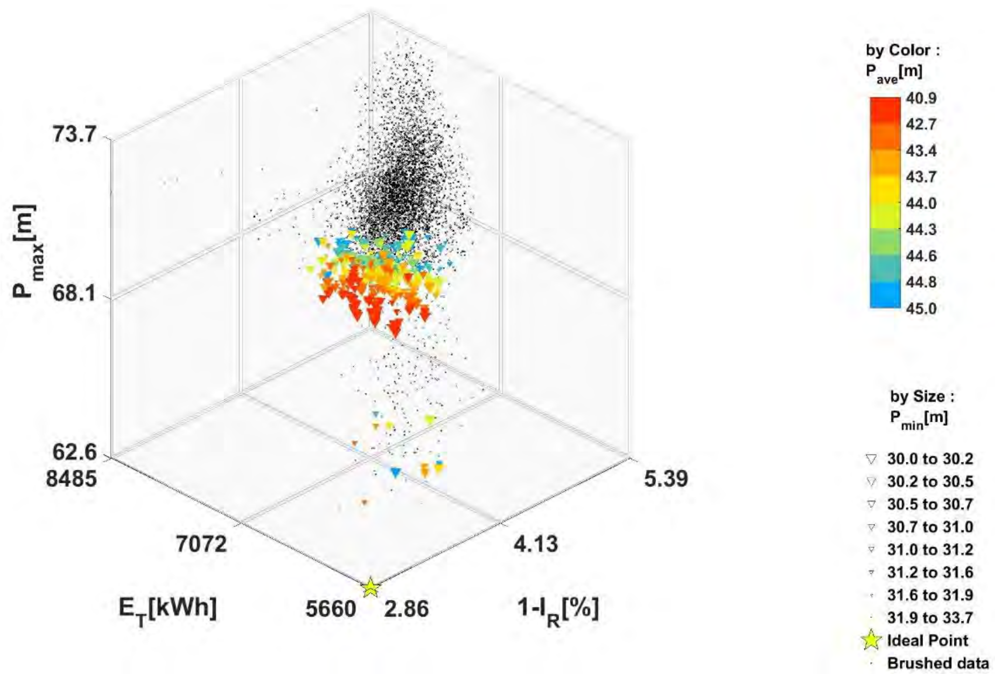


Figure 9-14. Scatter of possible solutions as 3D plots (Configuration 3-9: 03 sectors).

Using a Parallel Coordinates plot (Figure 9-15), solutions shown present average pressure below 45 m. Most solutions are contained with a low average pressure but a high value of maximum pressure simultaneously.

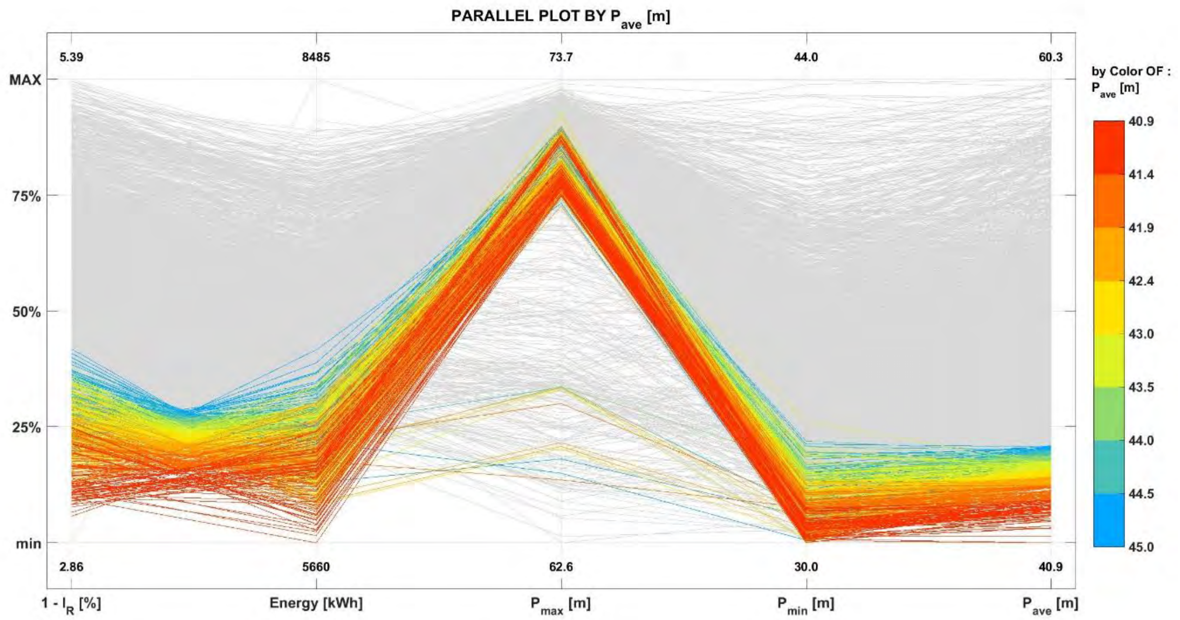


Figure 9-15. Parallel plot of the objective for Configuration 3-9.

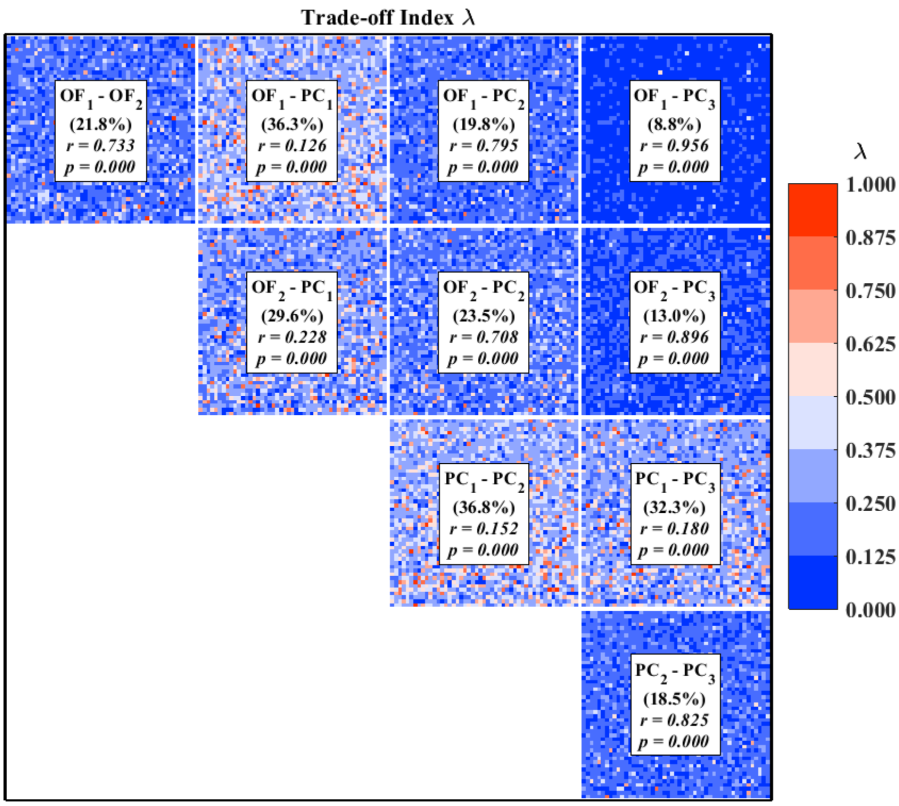


Figure 9-16. Trade-off index for last 2,000 solutions of Configuration 3-9. OF_1: 1 - I_R, OF_2: Energy, PC1: P_{max}, PC2: P_{min}, PC3: P_{ave}.

Trade-off Index (λ) is estimated as before and presented in Figure 9-16, where OF_1: 1 - I_R, OF_2: Energy, PC_1: P_{max}, PC_2: P_{min}, PC_3: P_{ave}. In this particular configuration no particular trade-off displays an index higher than 40%. The most significant trade-off (PC_1-PC_2: 35.7%) occurs between maximum pressure and minimum pressure. This confirms the result obtained in the parallel plot of objectives and criteria.

In order to perform an unbiased selection for the best possible solutions among all solutions level method and HRV are performed as well to the set of solutions of Configuration 3-9.
Figure 9-17, shows the level diagram for Configuration 3-9, showing the best solution (yellow squares) obtained is $\boldsymbol{S_{13696}}$. This solution presents a Lack of Resilience of 3.25%, E_T consumption of 6,160 kWh, maximum pressure of 64.11 m, minimum pressure of 31.06 m and average pressure of 42.80 m. It is evident than by selecting this solution there will be an increase in energy consumption and minimum pressure with respect to the minimum energy solution.
The second method for unbiased selection of solutions is Hyper-Radial Visualization (HRV). Figure 9-18 shows the HRV after applied to the solutions obtained for Configuration 3-9. In this case, 2 different solutions are identified as the more relevant by this method ($\boldsymbol{S_{11378}}$, and $\boldsymbol{S_{13696}}$) Solution $\boldsymbol{S_{13696}}$ has been identified also by the level diagram of the solutions. $\boldsymbol{S_{11378}}$ corresponds to the solution with the lowest energy consumption of the system as presented in Table 9-3.

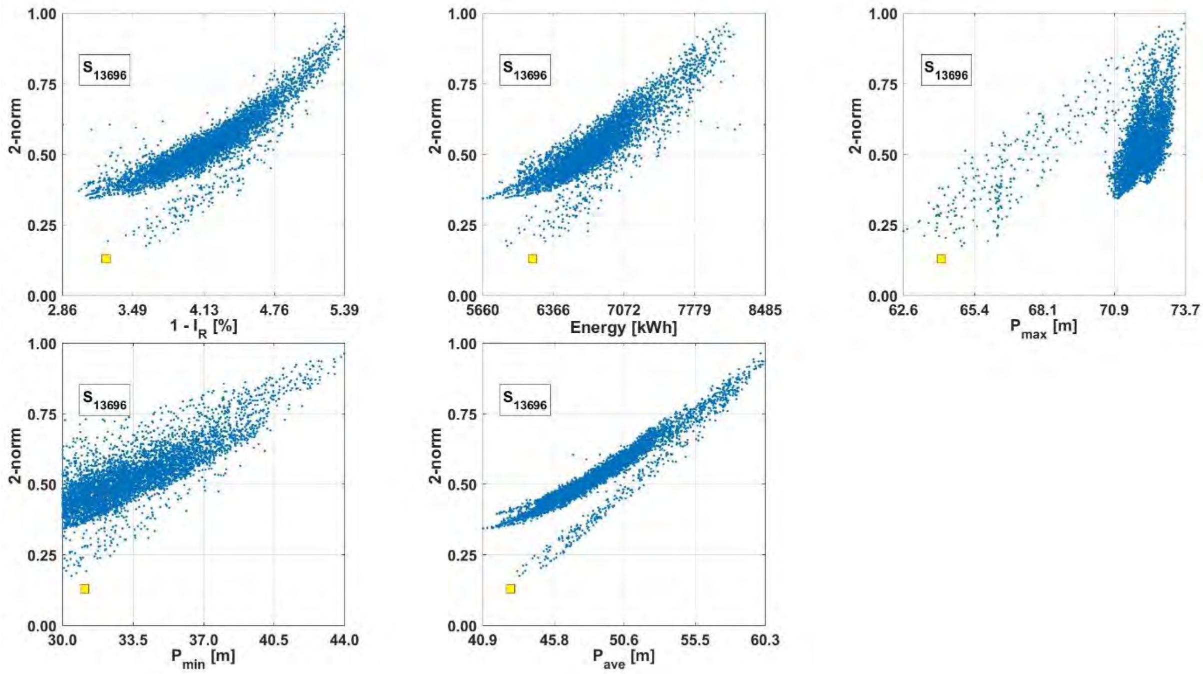


Figure 9-17. Level diagram Configuration 3-9. Best solution identified id = 13,696.

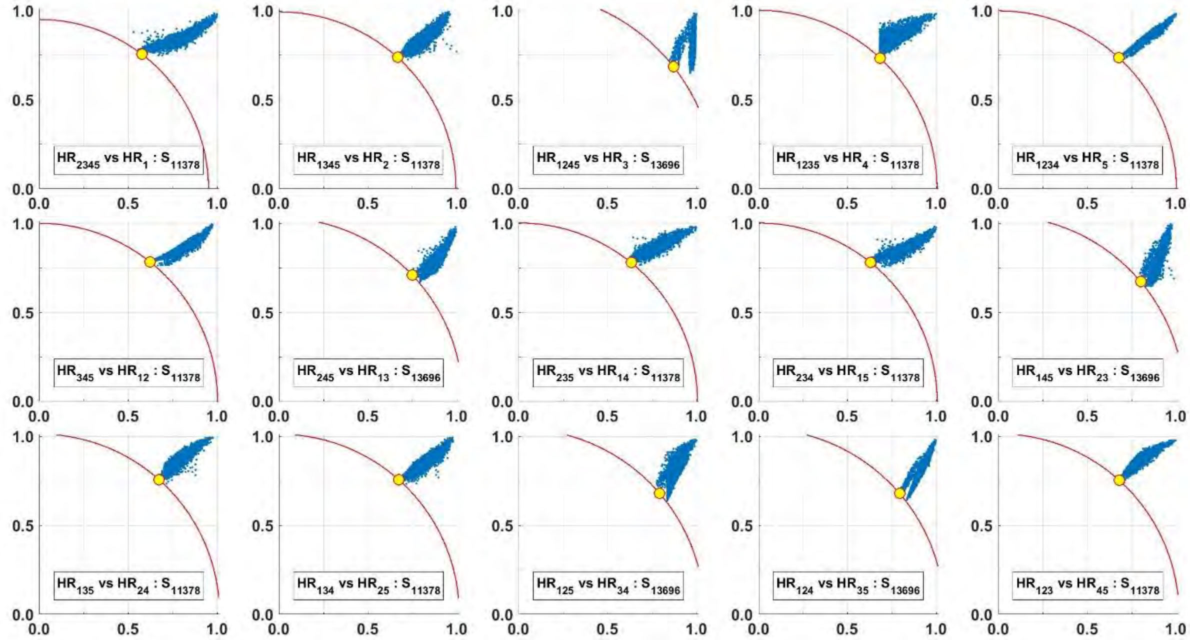


Figure 9-18. Hyper-Radial Visualization of objectives for Configuration 3-9.

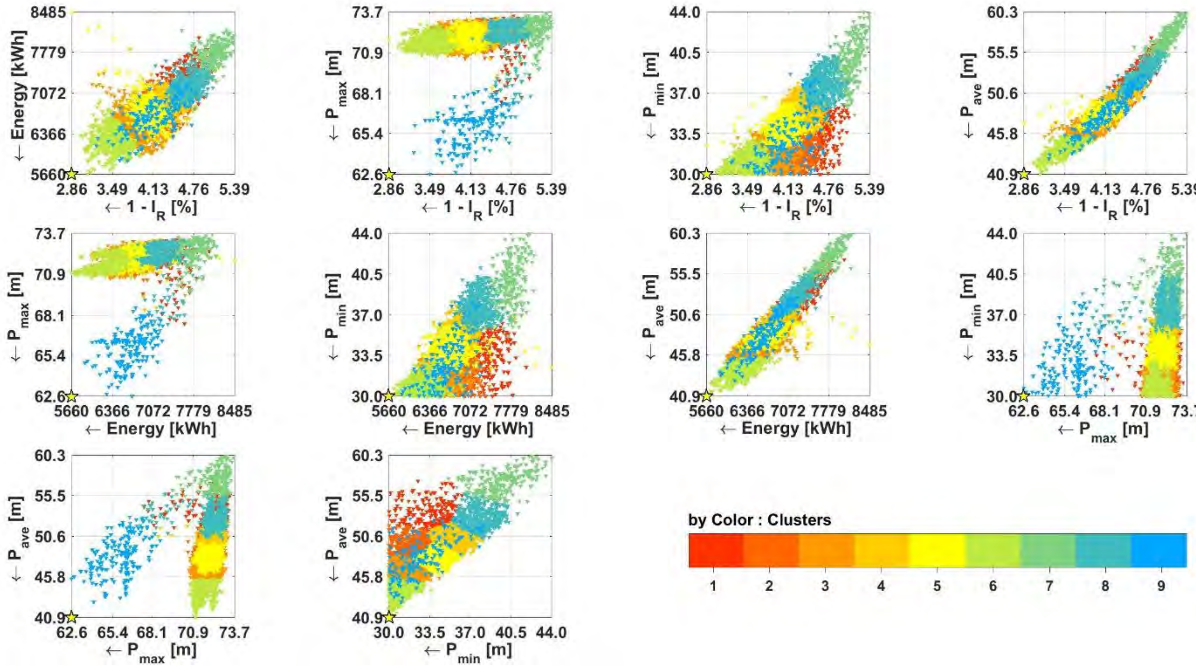


Figure 9-19. Self organizing Map into 9 clusters for objective space of Configuration 3-9.

As a final form of visualization of results a classification of the objective space solutions was performed using Self Organizing Maps (SOM) for a total number of 9 clusters arranged in a 3x3 topology. Again results are shown after 1,000 iterations, when convergence is met. Figure 9-19, shows the SOM for solutions of Configuration 3-9. Cluster 9 contains the set of best feasible solutions available in terms of low magnitude of maximum pressure. Cluster 6 contains solutions closer to the Pareto front. Cluster 7, contains solutions which can be regarded as dominated.

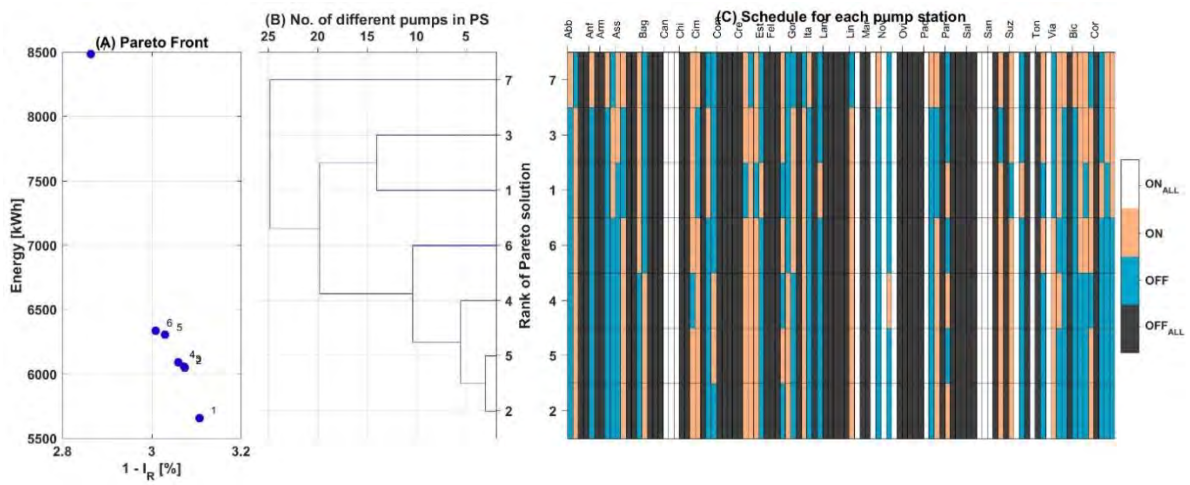


Figure 9-20. Pareto front and set of Configuration 3-9. (left) Pareto front, (center) dendrogram of Hamming distance of pump schedules among solutions and (right) resulting pump schedule or Pareto Set.

The resulting Pareto front of the Configuration is presented in Figure 9-20A, where the solutions have been ranked in order of minimum energy consumption. Solutions have been ranked being 1 the solution in the Pareto front with the lowest energy. The solution with minimum energy is $\boldsymbol{S_{11378}}$. A total of 7 function evaluations belong to the Pareto front. This is due to the complex operation of the system and the selection of Binary decision variables. Although the Pareto front is composed of a size equal to the population (100), most of the solutions start appearing to have multiplicity as it was for Configuration 1-3 and Configuration 18-3 as well.

A dendrogram of hamming distance among pump schedules is presented in Figure 9-20B. In that way, it is possible to see for example that the number of different pumps in operation between ranked solutions 1-3 of the Pareto front is just 14 pumps (ON/OFF). Among solutions 2-5 the difference becomes only 3 pumps.

Finally, a comparison between the pump schedules (Pareto set) is presented in Figure 9-20C rearranged accordingly with the rank and position in the dendrogram. In Figure 9-20C, it is shown that some pumps remain active in all solutions (ON_{ALL}). On the other hand, some pumps remain inactive (OFF_{ALL}) for all Pareto solutions (see Table 9-4).

Table 9-4. Pump schedule of Configuration 3-9. Pumps which remain ON for all solutions and OFF for all solutions.

ON_{ALL}	Cantore (1, 2 and 3), Linate (2), Martini (2), Novara (1 and 3), Padova (1), Salemi (3 and 4), San Siro (1), Suzzani (2 and 5), Tonezza (3)
OFF_{ALL}	Abbiategrasso (3 and 4), Anfossi (4), Armi (1), Assiano (3 and 4), Baggio (2, 3 and 4), Chiusabella (1 and 2), Cimabue (2), Crescenzago (1), Este (2), Feltre (1 and 2), Gorla (2), Italia (2), Lambro (all), Linate (3), Martini (1), Novara (4), Ovidio (1 to 4), Padova (4), Parco (2, 3 and 4), Salemi (1 and 2), San Siro (2 and 4), Suzzani (4), Tonezza (1), Vialba (4) and Corsico (1)

9.3 Results of sectorization for Formulation 2 with nine sectors

There is a large number of possible configurations of sectorization available for the system of Milan as 9 sectors. In an early analysis 2,000 configurations were obtained. Due to computational limitations not all of the configurations can be used for MOO under a PS. In that case an engineering selection of cases was performed. A selection of 10 configurations were used for MOO. Such configurations and their 2 best solutions (pump schedules) based on minimum energy, level diagram and hyper-radial visualization are presented in Table 9-5. The lowest possible energy consumption found was 5,488 kWh for the solution S_{11524} in Configuration 9-7. A complete analysis of Configuration 9-7 results from MOO will be presented in the following section.

Table 9-5. Scenario with 09 sectors. All configurations analysed.

Configuration	Solution	Lack of Resilience 1-I_R [%]	Energy E_T [kWh]	Additional Performance Indicators P_{max} [m]	P_{min} [m]	P_{ave} [m]
9-1	9 123	3.60	5 756	62.82	30.11	42.85
9-2	8 292	3.65	5 755	58.26	30.41	43.09
9-3	7 933	3.54	5 529	72.27	30.67	42.11
9-4	9 652	3.56	5 493	57.01	30.26	41.91
9-5	10 777	3.52	5 637	59.23	30.28	42.23
9-6	9 759	3.42	5 741	71.06	30.24	42.21
9-7	11 524	3.39	5 488	57.67	30.04	41.43
9-8	9 613	3.22	5 829	61.28	30.05	41.94
9-9	7 711	3.47	5 635	70.88	30.19	42.02
9-10	8 432	3.54	5 625	63.72	30.15	42.41

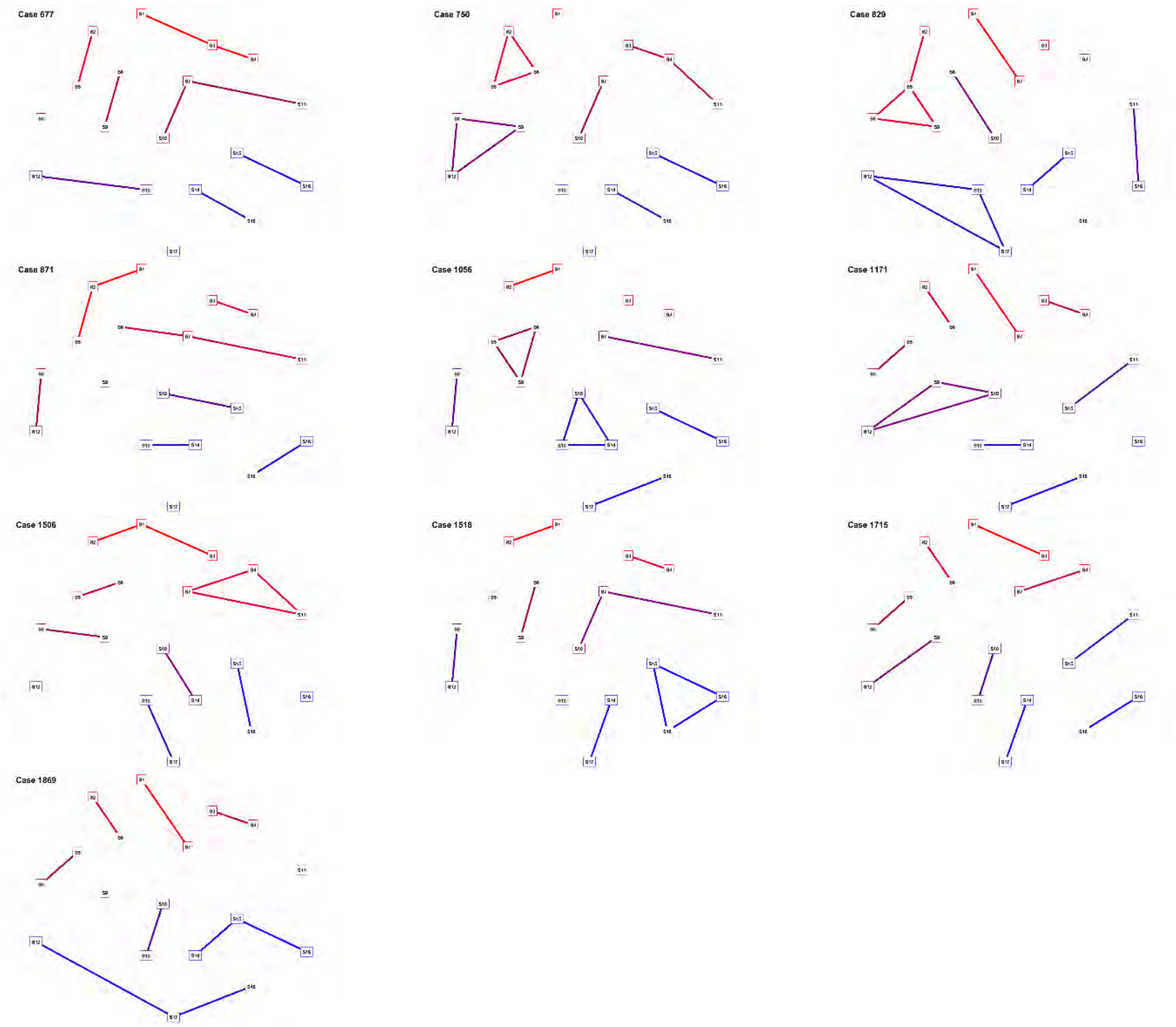


Figure 9-21. Configurations for sectorization with 09 sectors.

9.3.1 Analysis of solutions for Configuration 9-7

First of all the configuration is presented in Figure 9-22. The sectors are:

$\boldsymbol{S_1} = \{\boldsymbol{s_1}, \boldsymbol{s_2}, \boldsymbol{s_3}\}$, $\boldsymbol{S_2} = \{\boldsymbol{s_4}, \boldsymbol{s_7}, \boldsymbol{s_{11}}\}$, $\boldsymbol{S_3} = \{\boldsymbol{s_5}, \boldsymbol{s_6}\}$,

$\boldsymbol{S_4} = \{\boldsymbol{s_8}, \boldsymbol{s_9}\}$, $\boldsymbol{S_5} = \{\boldsymbol{s_{10}}, \boldsymbol{s_{14}}\}$, $\boldsymbol{S_6} = \{\boldsymbol{s_{12}}\}$,

$\boldsymbol{S_7} = \{\boldsymbol{s_{13}}, \boldsymbol{s_{17}}\}$, $\boldsymbol{S_8} = \{\boldsymbol{s_{15}}, \boldsymbol{s_{18}}\}$, $\boldsymbol{S_9} = \{\boldsymbol{s_{16}}\}$.

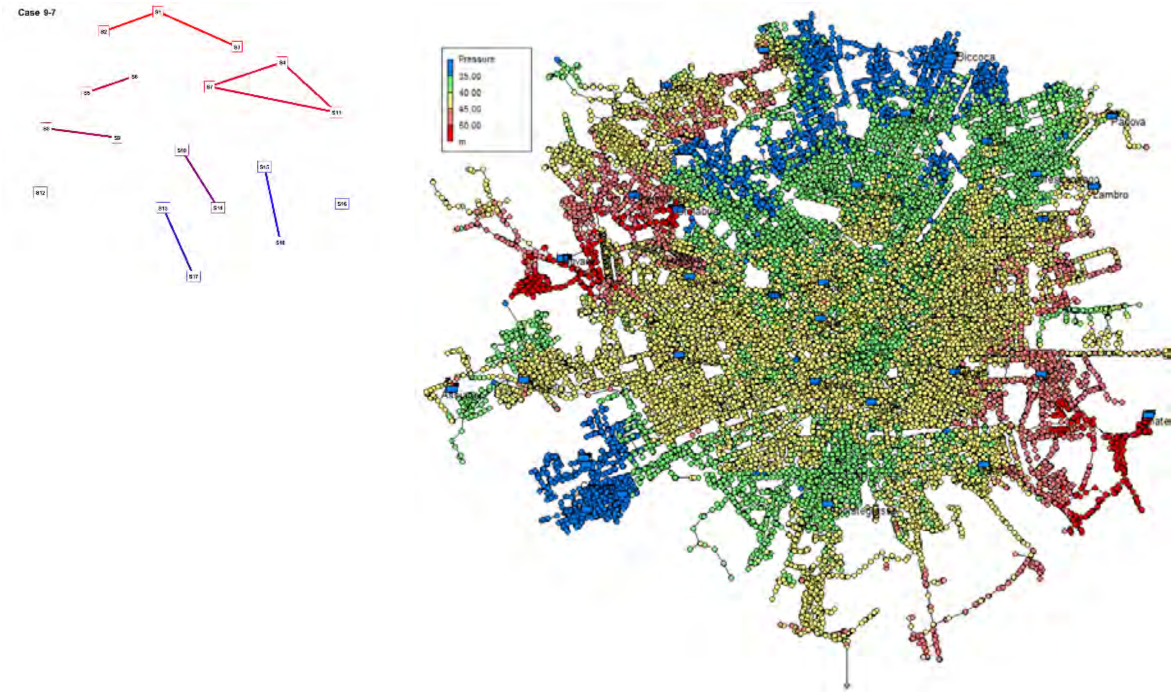


Figure 9-22. Graph configuration of Configuration 9-7. Right presents the pressure obtained with the best solution of pump scheduling.

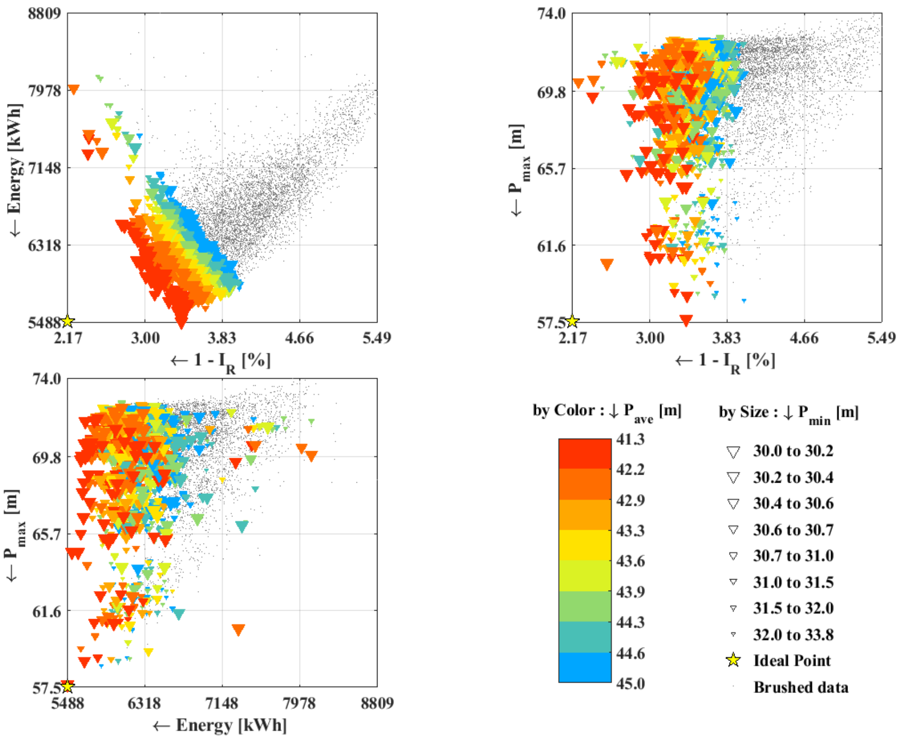


Figure 9-23. Scatter of all possible solutions as 2D plots (Configuration 9-7).

Figure 9 23 shows the different 2D scatter plots possible with the 2 objectives (Energy and Lack of Resilience) and 3 additional performance criteria (Pmax, Pmin, Pave) for all function evaluations. The figure shows a classification by color using the average pressure (Pave), and a classification by marker size by minimum pressure. Figure 9 23 upper left corresponds to the set of objectives used during optimization, while the other two plots correspond to the

simultaneous responses of the other performance criteria (not used for optimization). Both the markers with larger size and red colour solutions approach the ideal point in all plots. This shows that there is a progressive evolution towards an optimal solution. The minimum energy obtained is 5,660 kWh for a lack of resilience of 3.39%, a minimum pressure of 30.04 m, a maximum pressure of 57.67 m and average pressure of 41.43 m.
It is interesting that the evolution of solutions as the MOO progressed tends to create to different areas of solutions as displayed in the second scatter (upper right). In this case, the number of coloured solutions corresponds to only 22.5% of all function evaluations ran during MOO. Also by looking at the evolution of the Pareto front the average pressure follows its progression. There is no distinction of solutions as in previous cases where there was a threshold on maximum pressure among the solutions.

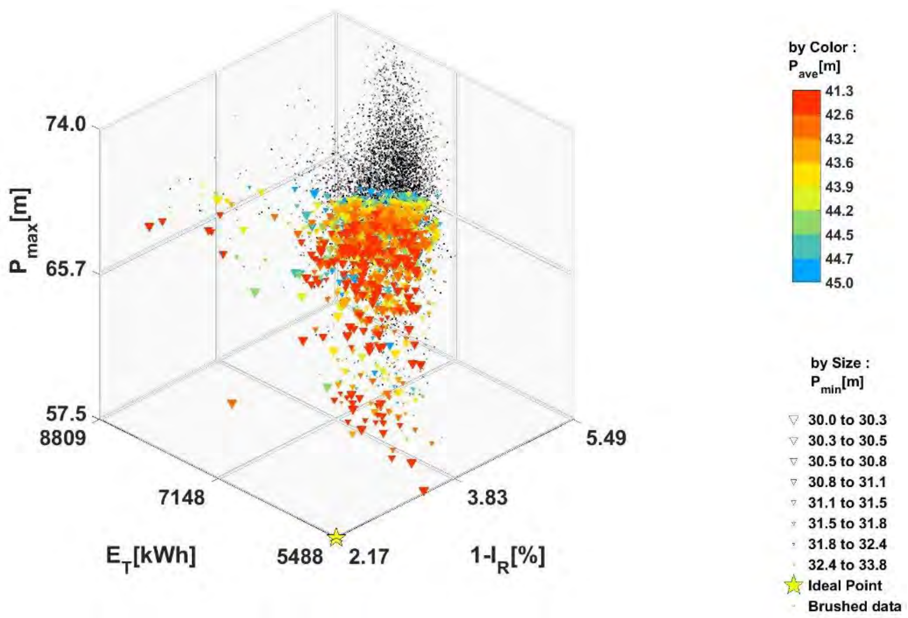


Figure 9-24. Scatter of possible solutions as 3D plots (Configuration 9-7).

In Figure 9-24, the 3D scatter plot is presented where the same criteria are applied for both colouring of triangles and sizes as for the 2D scatter plots. The z-axis corresponds to the maximum pressure criteria. It is of notice that among solutions which are coloured there is a wide spread among maximum pressure.

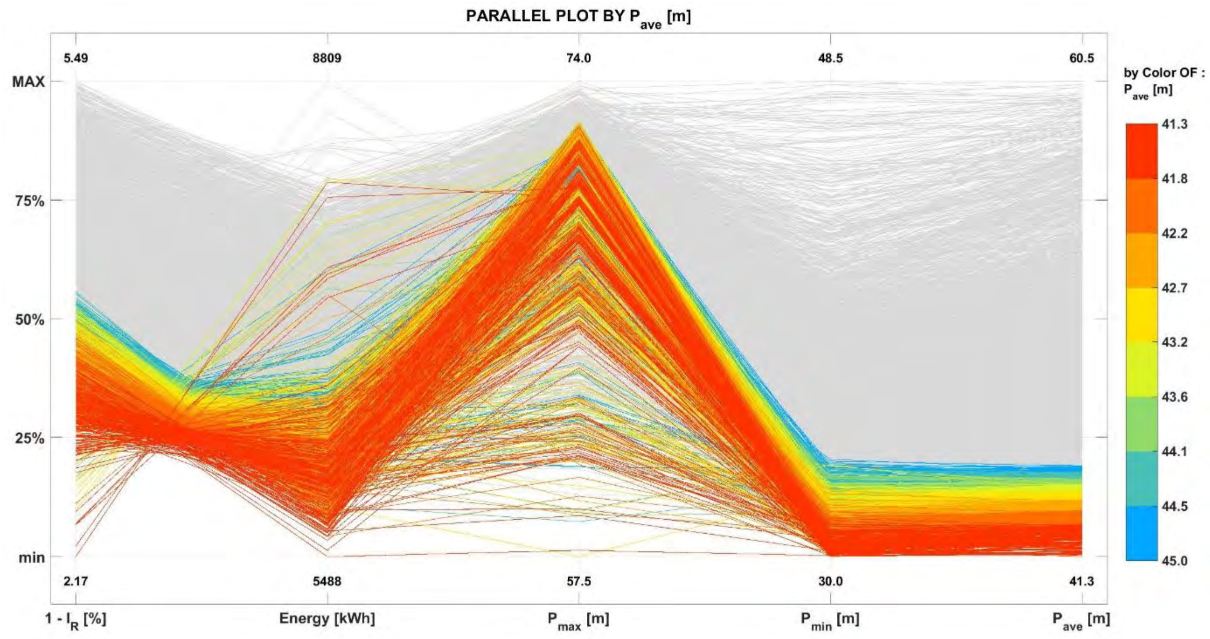


Figure 9-25. Parallel plot of the objective for Configuration 9-7.

Using a Parallel Coordinates plot (Figure 9-25), solutions shown present average pressure below 45 m. Most solutions are contained with a low average pressure. Most solutions seem to indicate that there is high correlation between average and minimum pressure. Indeed by using this visualization it is confirmed that the solutions are widely spread in terms of maximum pressure.

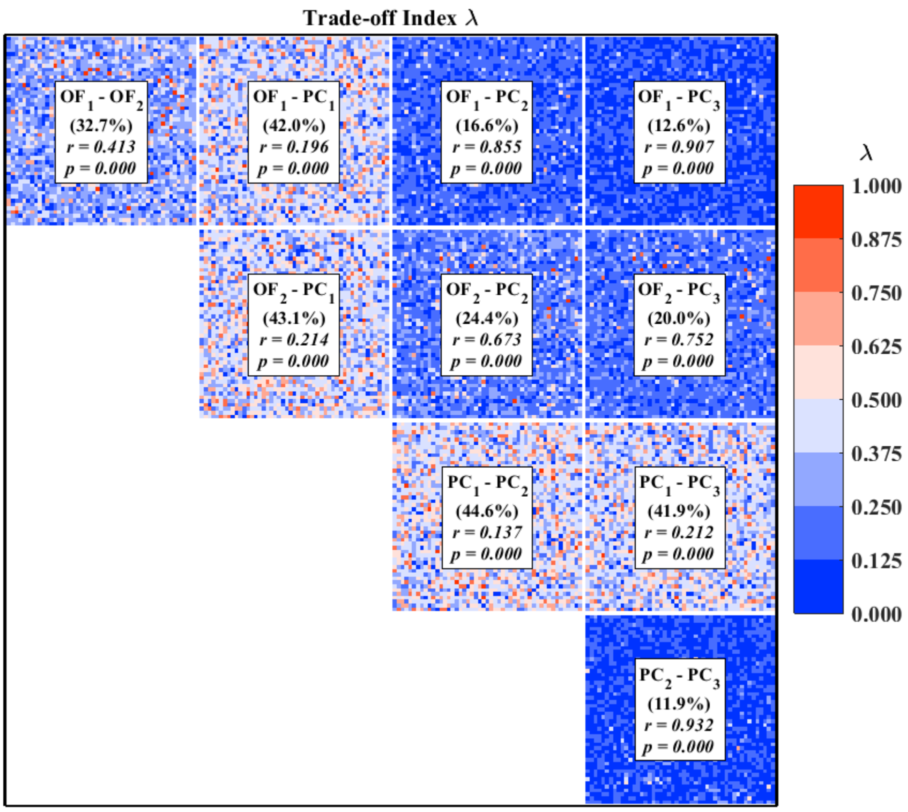


Figure 9-26. Trade-off index for last 2,000 solutions of Configuration 9-7. OF_1: 1 - I_R, OF_2: Energy, PC1: P_{max}, PC2: P_{min}, PC3: P_{ave}.

Trade-off Index ($\boldsymbol{\lambda}$) is estimated as before and presented in Figure 9-26, where OF_1: 1 - I_R, OF_2: Energy, PC1: P_{max}, PC2: P_{min}, PC3: P_{ave}. In this particular configuration several trade-offs display an index higher than 40%. That is the case for maximum pressure and minimum pressure (PC1-PC2: 44.4%), energy consumption and maximum pressure (OF_2-PC1: 42.5%), lack of resilience and maximum pressure (OF_1-PC1: 42.2%) and maximum pressure and average pressure (PC1-PC3: 41.7%). It is also confirmed that there is no trade-off between minimum pressure and average pressure, as it was presented in the parallel plot of objectives.

Level method and HRV are performed as well to the set of solutions of Configuration 3-9. Figure 9-27, shows the level method diagram for Configuration 3-9, showing the best solution (yellow squares) obtained is $\boldsymbol{S_{13391}}$. This solution presents a Lack of Resilience of 3.01%, E_T consumption of 5981 kWh, maximum pressure of 60.92 m, minimum pressure of 30.02 m and average pressure of 41.53 m. It is evident than by selecting this solution there will be an increase in energy consumption and minimum pressure with respect to the minimum energy solution.

Hyper-Radial Visualization (HRV) results are presented in Figure 9-28 for Configuration 3-9. In this case 2 different solutions are identified as the more relevant by this method $\boldsymbol{S_{11524}}$ and $\boldsymbol{S_{13391}}$) Solution $\boldsymbol{S_{1339}}$ has been identified also by the level diagram of the solutions. $\boldsymbol{S_{11524}}$ corresponds to the solution with the lowest energy consumption of the system as presented in Table 9-5.

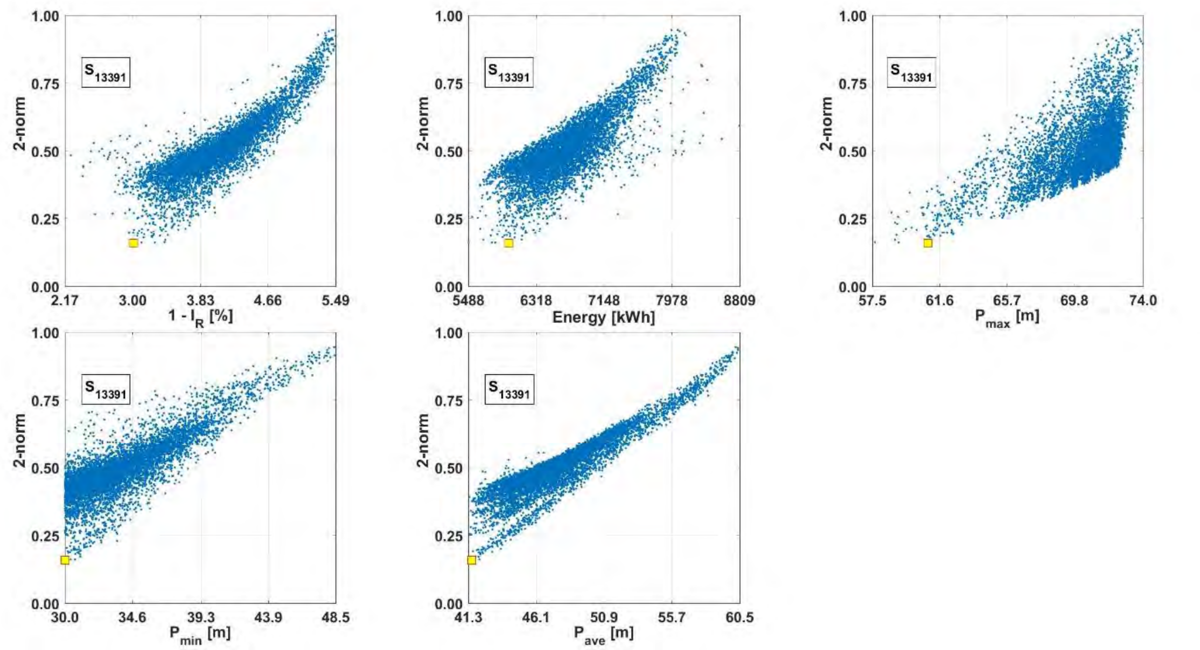


Figure 9-27. Level diagram Configuration 9-7. Best solution identified id = 13,391.

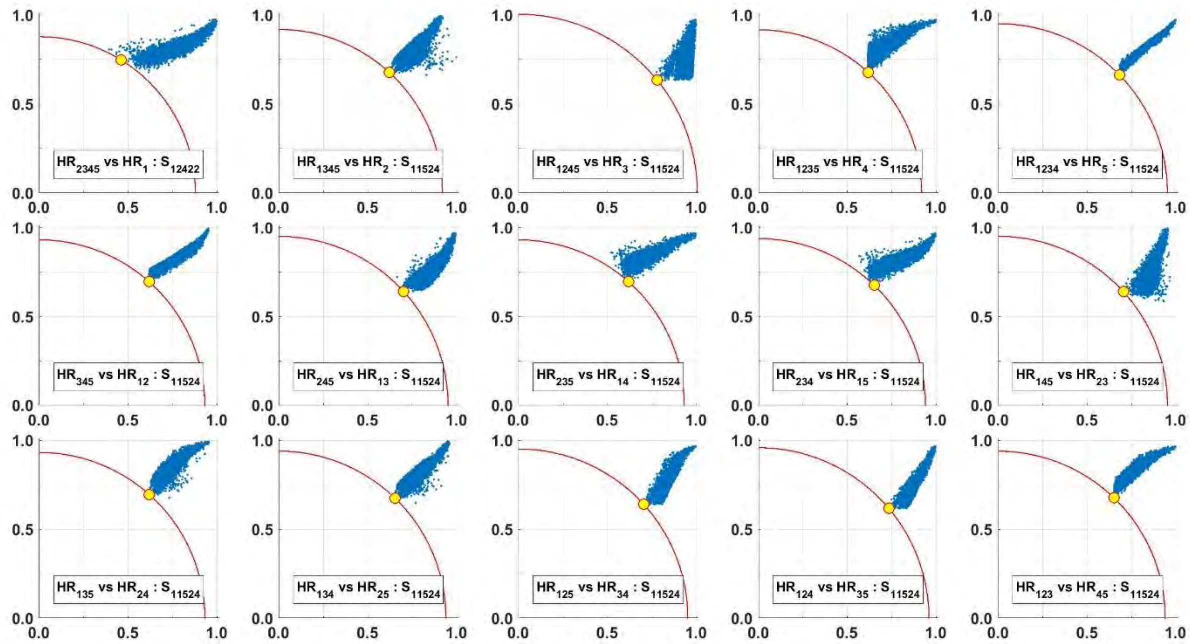


Figure 9-28. Hyper-Radial Visualization of objectives for Configuration 9-7.

A classification of the objective space solutions was performed using Self Organizing Maps (SOM) with 9 clusters arranged in a 3x3 topology. Again results are shown after 1,000 iterations, when convergence is met. Figure 9-29, shows the SOM for solutions of Configuration 3-9. Cluster 4 and 7 correspond to dominated solutions. Cluster 9 contains solutions with the lowest maximum pressure. Cluster 5 presents solutions with low lack of resilience and high energy consumption.

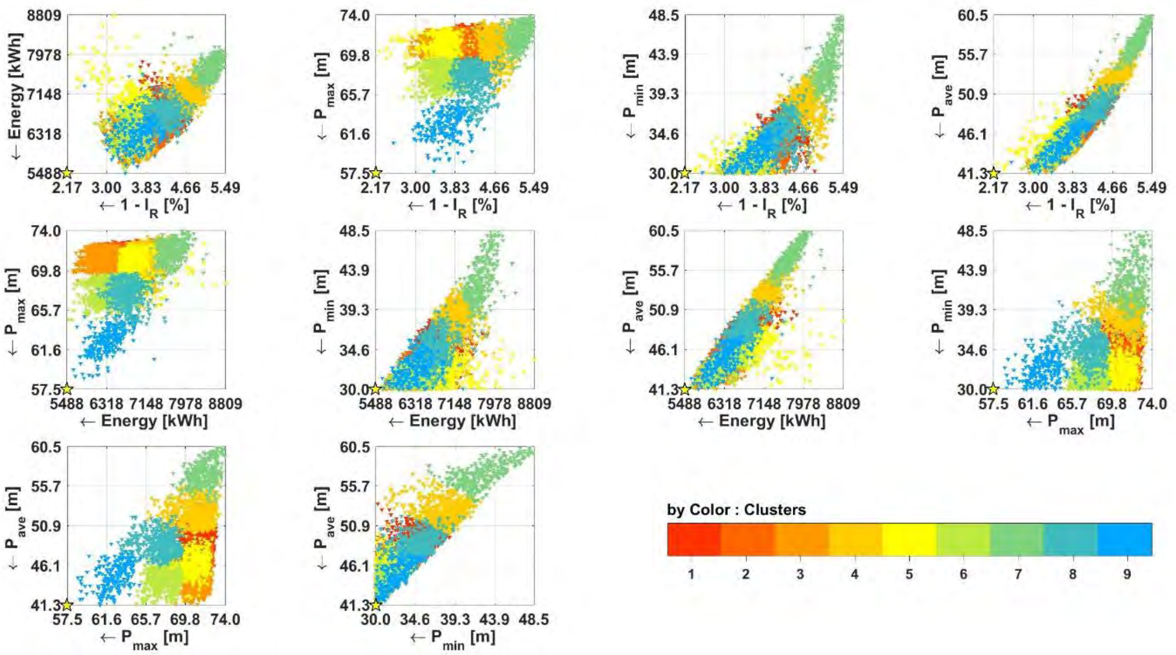


Figure 9-29. Self organizing Map into 9 clusters for objective space of Configuration 9-7.

The resulting Pareto front of the Case is presented in Figure 9-30A, where the solutions have been ranked in order of minimum energy consumption. Solutions have been ranked being 1 the solution in the Pareto front with the lowest energy. The solution with minimum energy is $\boldsymbol{S_{11524}}$. A total of 20 function evaluations belong to the Pareto front. This is due to the complex operation of the system and the selection of Binary decision variables. Although the Pareto front is composed of a size equal to the population (100), most of the solutions start appearing to have multiplicity as it was for Configuration 1-3, Configuration 18-3 and Configuration 2-7 as well.

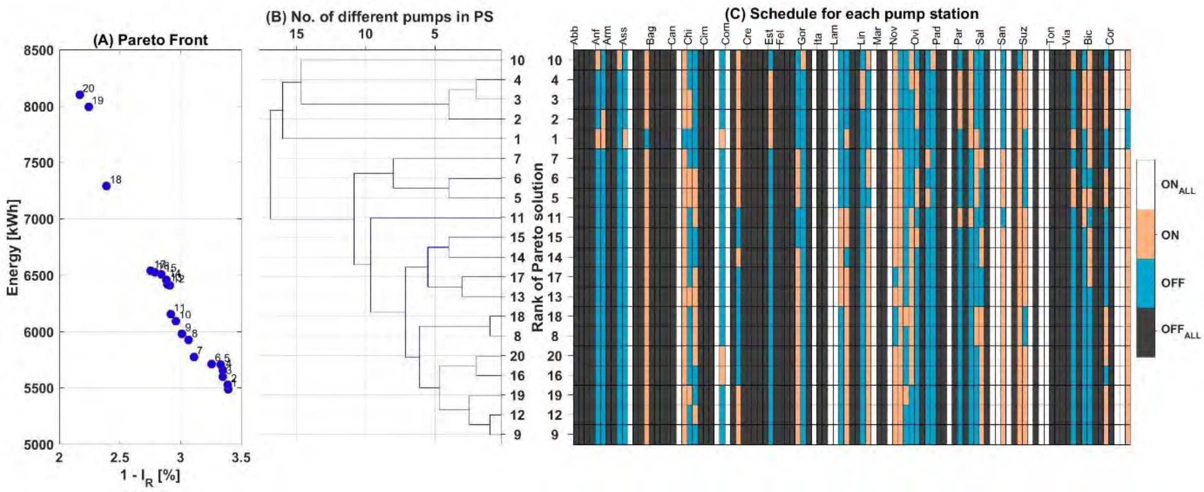


Figure 9-30. Pareto front and set of Configuration 9-7. (left) Pareto front, (center) dendrogram of Hamming distance of pump schedules among solutions and (right) resulting pump schedule or Pareto Set.

A dendrogram of pump schedules is presented in Figure 9-30B. In that way, it is possible to see for example that the number of different pumps in operation between ranked solutions 9-12 and 8-18 of the Pareto front is just 1 pump (ON/OFF). Among solutions 3-4 and 16-20 the difference becomes only 2 pumps.

Finally, a comparison between the pump schedules (Pareto set) is presented in Figure 9-30C, rearranged accordingly with the rank and position in the dendrogram. In Figure 9-30C, it is shown that some pumps remain active in all solutions (ON_{ALL}). On the other hand, some pumps remain inactive (OFF_{ALL}) for all Pareto solutions. See Table 9-6.

Table 9-6. Pump schedule of Configuration 9-7. Pumps which remain ON for all solutions and OFF for all solutions.

ON_{ALL}	Assiano (2), Cantore (2) Cimabue (3), Comasina (1), Gorla (3), Italia (3), Lambro (1), Linate (3), Martini (3), Padova (3), Salemi (3 and 4), San Siro (2), Suzzani (2, 4 and 5), Corsico (2 and 3)
OFF_{ALL}	Abbiategrasso (all), Armi (1 and 2), Assiano (3 and 4), Baggio (all), Cantore (1), Chiusabella (3), Cimabue (1 and 2), Crescenzago (1), Comasina (2 and 4), Crescenzago (1 to 4), Este (2), Feltre (1 to 3), Gorla (2), Italia (1 and 2), Lambro (4 and 5), Martini (1 and 2), Novara (4), Ovidio (2), Padova (1, 2 and 4), Parco (2), Salemi (2), San Siro (3), Suzzani (3), Tonezza (1, 2 and 3), Vialba (1 and 3) and Bicocca (2 and 3) and Corsico (1)

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Mario Erik Castro Gama was born in Bogotá, Colombia. He obtained his undergraduate education as a Civil Engineer at National University of Colombia, Campus Bogota, following also the advanced track in Hydraulics and Environment. He worked in consultancy projects during eight years in his country for diverse renewable energy technologies (mainly hydropower). Performing inventory, feasibility, refurbishment and decommission studies. Worked as consultant for the generation and commercialization departments of diverse energy companies.

In 2012, he completed his Master studies at IHE Delft Institute for Water Education (Delft, Netherlands). During his MSc he specialized in Water Science Engineering - Hydroinformatics, obtaining his MSc degree with distinction for his thesis in Statistical inference for flooding events in the Yellow River.

He was then offered the opportunity to participate as a PhD fellow in the ICeWater project, funded by the European Commission. This project allowed him to develop his research in collaboration with partners from companies related to ICT for water resources and in collaboration with two utilities.

Between 2014 and 2018 was a lecturer for Civil Engineering at De Haagse Hogeschool on diverse subjects of hydraulics and water engineering. He also led the internationalization of the Civil Engineering program during that tenure.

Subsequently, he joined KWR Water Research Institute where he has worked as a scientific researcher for Water Infrastructure (WIS) team of the Water Science and Technology (WST) Department. He was involved in projects of the theme Hydroinformatics. Also, he has worked as liaison for Future-Proof Water Infrastructure (FPWI) of the international Watershare platform.

Since March 2021 joined Vitens N.V., the largest drinking water company on the Netherlands, as Senior Specialist of Water Infrastructure at the Water Expertise Center. His job focuses on research in the intersection among Asset Management, Smart Water, Hydroinformatics and model-based simulation of infrastructure. Since 2024, Also member of the SWAN Utility Advisory Group.

Peer Reviewed publications

1. **Mario Castro-Gama**; L.E. Machado-Hernandez; C.A. Castro-Gama Robust STS for HP cascades. MDPI Hydrology (Special Issue) in Preparation.
2. Ayala-Cabrera, D.; **Castro-Gama, M.**; Quintiliani, C.; Hoseini-Ghafari, S. (202x) A Multi-step Optimization Approach to Rehabilitate a Deteriorated and Intermittent Water

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3. Melina Denardi; Jezabel Bianchotti; **Mario Castro-Gama**; Gabriel Darío Puccini. (2024) Managing Nighttime Pressures for Background Leakages Control in Water Distribution Networks using Simulated Annealing. J. Water Resources Planning and Management. Accepted for publication 20-Jun-2024.
4. BMFM Fayaz, **M Castro-Gama**, L. Alfonso-Segura (2024) A Multi-step Data Assimilation framework to investigate the effect of measurement uncertainty in the reduction of water distribution network model errors. Water Resources Management. https://link.springer.com/article/10.1007/s11269-024-03809-9.
5. **M Castro-Gama**, Y Hassink-Mulder. (2024) Optimal charging station placement for autonomous robots in drinking water networks. Journal of Hydroinformatics 26 (1), 350
6. BMFM Fayaz, **M Castro-Gama**, L. Alfonso-Segura (2023) Improving Water Distribution Network Models with Data Assimilation: Unleashing the Power of Real-Time Improvements. The Maldives National Journal of Research 11 (Special Issue), 107-116
7. Bianchotti, J.; Denardi, M.; **Castro-Gama, M.**; Puccini, G. (2021) Sectorization for Water Distribution Systems with Multiple Sources: A Performance Indices Comparison. MDPI Water Journal. https://doi.org/10.3390/w13020131 .
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Netherlands Research School for the
Socio-Economic and Natural Sciences of the Environment

D I P L O M A

for specialised PhD training

The Netherlands research school for the
Socio-Economic and Natural Sciences of the Environment
(SENSE) declares that

Mario Erik Castro Gama

born on the 13th of April 1980 in Bogota, Colombia

has successfully fulfilled all requirements of the
educational PhD programme of SENSE.

Delft, the 19th of November 2024

SENSE coordinator PhD education

Dr Ir Peter Vermeulen

The SENSE Director

Dr Jampel Dell'Angelo

The SENSE Research School declares that Mario Erik Castro Gama has successfully fulfilled all requirements of the educational PhD programme of SENSE with a work load of 38.8 EC, including the following activities:

SENSE PhD Courses

- Environmental research in context (2013)
- Research in context activity: PhD incubator (2013)

Other PhD and Advanced MSc Courses and trainings

- Introduction to Computer Science and Programming Using Python. EdX online (2017)
- Advanced workshops on ICT for ICeWater project – MINLP using Constrained Programming. SIEMENS(2014)
- Advanced workshops on ICT for ICeWater project - , ICT test beds for water infrastructure. TOSHIBA (2015)

Management and Didactic Skills Training

- Supervising of 3 MSc students with thesis (2014-2015, 2016-2017)
- Lecturer of Summer Course, Hydroinformatics modeling in MATLAB, IHE Delft, Delft, the Netherlands (2012, 2013)
- Lecturer of River Modelling with HEC-RAS, Module 8, IHE Delft, Delft, the Netherlands (2013)
- Lecturer of Modeling System Development in MATLAB, Module 3, IHE Delft, Delft, the Netherlands (2014)
- Organization General Assembly for EU-FP7 ICeWater funding project, Delft (2014)

Selection of Oral Presentations

- *Decision Support System for daily and long term operations of the system of Milano, Italy.* 13th International Conference on Computing and Control in the Water Industry, 2-4 September 2015, Leicester, United Kingdom
- *Pump scheduling for large water distribution networks.* Water Distribution System Analysis conference 24-28 July 2016, Cartagena, Colombia
- *Decision Support System for daily and long term operations of the system of Milano, Italy.* 12th International Conference on Hydroinformatics, 21-26 August 2016, Incheon, South Korea
- *The ICeWater approach to managing urban water distribution systems: Experiences from pilot trials and cost-benefit analysis.* 14th International Conference on Computing and Control in the Water Industry, 7-9 November 2016, Amsterdam, The Netherlands

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Utilities worldwide are continuously improving operations to meet changing demands, incorporate new technologies, and manage aging infrastructure. To better handle these changes, digitalization and decision support systems are increasingly adopted.
This research explores optimizing energy use and pressure management in WDNs through pump scheduling and network sectorization using open software (hydraulics and heuristic algorithms), supported by High-Performance Computing (HPC) resources.
The research, part of the EU's HP7 ICeWater project (2012-2015), was applied to the water supply system of Milan, Italy, operated by Metropolitana Milanese S.p.A. The Abbiategrasso Pressure Management Zone (PMZ) was with Pump Scheduling research focus and the entire Milan WDN was used for research on sectorization. Pump scheduling was optimized using two algorithms (NSGA-II and AMGA2), considering different objectives like total energy and resilience. Sectorization involved a two-level optimization algorithm to manage pressure and energy by dividing the network into sectors.
The findings underscore the importance of advanced modelling tools and optimization algorithms for utilities to improve WDN operations and decisionw-making. Field testing demonstrated that significant energy savings can be achieved, particularly with the adoption of Variable Speed Pumps (VSPs). The results demonstrated up to 16% energy savings and enhanced operational cost efficiency.

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