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Entity-based System Dynamics for Bridge Asset Management

Exploring the Effects of Spatial Maintenance Cluster Strategies on Infrastructure System Performance

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By

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Preface

I want to express my gratitude to my supervisors at the TU Delft, Willem Auping, and Jan-Anne Annema, for their guidance and support in the last months. Special appreciation to Arjen Ros and Michel Kuijer from Copernicos Groep, whose trust, expertise, and resources made this thesis possible. I want to thank Stefan Salome for his valuable help with the code for the EMA Workbench connection. Finally, I owe a big thanks to my family, my roommate, and especially my girlfriend for their support and enthusiasm during the last months of my time here in Delft.

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Management summary

The Netherlands is on the verge of initiating its most extensive maintenance project in history. The Dutch government will have to invest an estimated minimum of 260 billion Euros for the renewal of its aging civil structures like bridges, viaducts, and tunnels. This large maintenance operation is labeled as the replacement and renovation task. Within the replacement and renovation task, so-called 'Baby Boomer bridges' require the most attention. These bridges, accounting for a substantial portion of the 85,000 bridges in the Dutch inventory, face challenges stemming from prolonged stress and corrosion issues. The Merwedebrug's narrowly averted catastrophe in 2016 served as a wake-up call, highlighting the critical need for proactive and strategic maintenance practices. A key challenge in the replacement task is the limited construction capacity, especially with an expected surge in maintenance between 2040 and 2080. Efficient and systemic asset management is pivotal in minimizing the required capacity increase and to help 'flatten the curve'.

One of the core strategies identified by the Dutch government to facilitate the transition towards more systemic and efficient infrastructure asset management is to cluster bridge maintenance projects. Project clustering involves consolidating multiple maintenance projects with similar characteristics or geographical proximity into one portfolio. Existing research has highlighted the positive impacts of project clustering on project-specific performance indicators. However, there is a lack of studies examining the broader implications of different clustering strategies on the entire transport system. The current literature predominantly comprises retrospective studies analyzing historical project data, providing valuable insights into project clustering effectiveness but falling short of assessing its influence on future infrastructure system behavior. This research aims to bridge this gap by conducting an exploratory modeling analysis to explore the effects of different maintenance cluster strategies on the performance of the transport infrastructure network.

This thesis employs Entity-based System Dynamics (SD). Entity-based SD is a relatively new modeling methodology and can be seen as a combination of agent-level (ABM) modeling and macro-level (SD) modeling. This combination allows for the modeling of the (spatial) behavior and attributes of individual bridges, roads and regions, while retaining the capability of doing macro-level analyses. Furthermore, as the bridge maintenance problem is subject to deep uncertainty, Entity-based SD was paired with the Exploratory Modeling and Analysis methodology. This allows for the exploration of the repercussions of various combinations of assumptions about uncertain factors in the system. To allow for the combination of the two methodologies, a novel EMA Workbench-Ventity connector was constructed for this thesis.

Because Entity-based SD is still a relatively novel methodology, there is a lack of spatially explicit applications within the existing scientific literature. As such, this thesis pursues two objectives, (1) developing, and reflecting on the added value of a novel spatially explicit Entity-based SD modeling method when modeling the effect of bridge maintenance cluster policies on the wider infrastructure system, and (2) identifying maintenance cluster policies that are effective at facilitating a steady and predictable maintenance capacity demand. To pursue these two objectives, an abstract network was constructed using the Entity-based System Dynamics methodology.

The analysis of the model outcomes shows that the model was able to generate spatially explicit relationships between traffic flows and bridge degradation. The model was also able to capture the performance of maintenance cluster strategies and showed expected behavior. Six policies were tested with the model, three variations of geographical clustering (small, medium, and large), construction type clustering, construction year clustering, and a no clustering policy. The model results indicate that larger maintenance clusters bring about more fluctuating changes in capacity utilization, while smaller clusters lead to a higher total number of expected projects over a 100 year simulation period. Larger clusters also result in a higher average load capacity for the bridge set, mainly due to increased preventive maintenance. Despite larger clusters generally outperforming no cluster policies, their overall effectiveness is diminished, especially concerning the critical outcome of change in capacity utilization. A geographical cluster policy with small clusters, an average of 1.9 bridges per cluster, stands out for its more stable maintenance capacity utilization compared to a no cluster policy option and slightly better performance in other key outcomes.

As such, policymakers should implement policies that encourage the formation of small maintenance clusters. However, as the network specification plays a crucial part in the performance of cluster policies, policymakers should adopt a flexible approach, considering the specific characteristics of the infrastructure network when formulating maintenance clustering policies. Future applications for the model could add additional external effects to the model, introduce finite maintenance capacity and a finite maintenance project size, or include dynamics in the model that allow for the modeling of traffic jams.

At a methodological level, it can be concluded that Entity-based SD is a suitable approach to infrastructure modeling. The added value of the novel spatially explicit Entity-Based SD approach can be described in five points. First, the method holds a high degree of replicability. Because entity types can be independently defined, infrastructure components can be individually modeled and reused in other models. Additionally, the method makes use of externalized network initialization data, which separates the dynamics of infrastructure components and the network specification data, allowing for components to be altered individually without the need to alter the other. Second, the computational requirements of the approach are limited compared to other infrastructure modeling approaches. Third, similar to SD modeling, the model is made up of a clear model structure with stocks, flows, and causal links which enhances communicability and supports group model building with stakeholders. Fourth, as an extension of SD modeling, the method provides a holistic approach to infrastructure modeling, which means that it enables the modeling of not only individual infrastructure components but also the broader system in which these components operate. Lastly, the approach is capable of coping with high degrees of uncertainty due to the EMA Workbench connector that was constructed for this thesis.

Based on the arguments presented in this thesis, the novel spatially explicit Entity-based SD approach is considered to be a suitable new avenue for infrastructure modeling. However, this study should be considered as a first investigation into this approach and is therefore incomplete. Although the abovementioned added values have been identified during the course of the thesis, some limitations and future improvements still exist. Firstly, the Entity-based SD methodology offers limited documentation, as the maturity of the approach is low. Secondly, the approach is not meant to generate precise forecasts. As such, if this is the objective of the modeler or stakeholder, Entity-based SD should not be considered as a candidate approach. Future applications of this modeling approach could look at the performance of the approach when modeling larger networks. Therefore, spatial Entity-Based SD should not be seen as a replacement for current infrastructure modeling approaches. Rather, it should be viewed as a new addition to the scientific field of infrastructure modeling.

Contents

1 Introduction

The Netherlands is on the eve of the biggest maintenance operation in its history (Ministerie van Infrastructuur en Waterstaat, 2018). In the coming decades, the country has to invest an estimated minimum of 260 billion Euros to renew its aging inventory of civil constructions such as bridges, viaducts, and tunnels (Rasker et al., 2023), which is around sixty percent of the total expenditures of the Dutch government in 2024 (Ministerie van Algemene Zaken, 2023). Recognizing the urgency of this concern, the Dutch government redirected resources from new construction projects to prioritize essential maintenance of existing transport infrastructure in 2023, this project is labeled the replacement & renovation task (Ministerie van Infrastructuur en Waterstaat, 2023).

Within the replacement & renovation task, so-called 'Baby Boomer bridges' require the most attention (FIEC, n.d.). The Netherlands has a sizeable bridge inventory, 85.000 bridges, ranging from smaller pedestrian bridges to larger viaducts embedded in the Dutch highway network (Kompeer & Schellevis, 2021). Baby Boomer bridges refer to bridges built in the post-war era (1950 to 1980), when The Netherlands experienced mass construction of infrastructure during a period of high economic growth. Most of the 85.000 bridges in the Dutch bridge inventory were constructed in the years after the Second World War (Smits, 2016). The challenge faced by post-war bridges is primarily attributed to two key factors. Firstly, these post-war bridges have been subjected to far more stress and fatigue than they were initially designed for (Snijder & Hesselink, 2018). Secondly, it is estimated that 60% of the post-war bridges in Europe suffer from steel corrosion-related issues (European Commission, 2019).

The Netherlands narrowly escaped a catastrophe in 2016, when the Merwedebrug was preventively closed due to visible damage of the construction. The investigation into the closure later concluded that the bridge had a safe residual lifetime of only six days (NOS, 2019). The problem posed by aging Baby Boomer bridges is a problem recognized by all countries in the European Union (FIEC, n.d.). This has become apparent due to some recent tragedies in the EU. Between 2013 and 2018, 9 bridges collapsed in Italy (European Commission, 2019). More recently, in 2019, the Morandi bridge in Genoa collapsed, resulting in the loss of 43 lives (Calvi et al., 2019; Mattioli, 2019). Additionally, in 2018, the French government expressed its concern as it noted that 7% of the 12.000 bridges in the French highway system was at risk of collapsing (Calvi et al., 2019).

The biggest challenge in the replacement & renovation task, is the limited construction capacity, in terms of workers and material resources (Kompeer & Schellevis, 2021). Due to the age of the Baby Boomer bridges, sizeable maintenance waves are expected between 2040 and 2080. This will require the Dutch government to increase their yearly maintenance capacity from an average of 5 bridges per year, to as much as 50 bridges per year (Copernicos Groep, n.d.). Due to the growing housing shortage in the Netherlands, with an expected 900.000 new houses to be built before 2030, further shortages in the supply of construction workers and materials are expected (Rasker, 2023). Furthermore, due to a lack of political priority for infrastructure maintenance in recent years (G20, 2021), experts have warned that the managers of civil constructions are not in control of the situation. Although regaining control will take many changes on technical, economical, organizational and political levels, the basis for a successful execution of the Dutch replacement & renovation task is fundamentally improved asset management (Bleijenberg, 2022). In order to meet the replacement and renovation demand in the coming decades, efficient asset management is paramount to minimalize the required capacity increase and to help 'flatten the curve'.

Infrastructure asset management is a field characterized by deep uncertainty and complexity (G20, 2021; Lempert, 2003). The complexity stems from the physical and digital interdependencies of infrastructures, their interactions with the surrounding environment, and the non-linear interactions between the physical components and agents in the system (Oughton et al., 2018). Over time, the complexity in infrastructure asset management has risen to a level where institutions responsible for infrastructure asset management can no longer cope (G20, 2021; Godau, 1999; Grafius et al., 2020). This is problematic, as economies become increasingly reliant on the quality of transportation infrastructure, due to the efficiency and complexity of supply chains. This heightened dependence expands the importance of proper infrastructure asset management, extending beyond solely safety-related considerations (Organisation for Economic Co-operation and Development, 2021; The World Bank, 2021). For example, the closing of the Leverkusen bridge in Germany for 4 months incurred additional user costs of €80 million due to loss of time and additional fuel consumption (European Commission, 2019). On the other hand, neglecting maintenance also has significant implications as negligence over a period of 3 years multiplies the costs of maintenance by 3 to 6 times (European Commission, 2019). Considering the size and complexity of the replacement and renovation task, a systemic and efficient approach to transport infrastructure asset management is needed (Copernicos Groep, n.d.; Daulat et al., 2022; Godau, 1999; Parlikad & Jafari, 2016).

One of the core strategies identified by the Dutch government to facilitate the transition towards more systemic and efficient infrastructure asset management is to cluster bridge maintenance projects (Rijkswaterstaat, n,d.). Project clustering refers to the bundling of multiple maintenance projects with similar characteristics or geographical proximity into one portfolio, and is seen as a way to simplify large and complex problems (Gómez et al., 2013). Qiao et al. (2019) found that small clusters of bridge maintenance projects outperformed stand-alone projects in terms of project duration, work-zone duration, costs of demobilization and efficiency in equipment and material mobility between projects. Xiong et al. (2017) found evidence of economies of scale when clustering infrastructure projects, by analyzing a set of 4776 infrastructure projects executed in the US between 1995 and 2010. The United States Federal Highway Administration (FHWA) has since also confirmed that the clustering of infrastructure projects is a proven and efficient way to reduce costs, improve efficiency, and prevent delays (Federal Highway Administration, 2022). There are various asset and project characteristics that can be used as a determining factor for the selection of clusters. Assaf and Assaad (2023) performed a comparative analysis of 23 different decision-making factors for project clustering, they found that the most critical decision-making factors are the geographic proximity, the similarity in project types, the homogeneity of work types, and the condition rating of projects.

However, there is a lack of existing research on the impact of various clustering strategies (i.e., different decision-making factors) on the broader transport system. Studies such as Qiao et al. (2018), Qiao et al. (2019) and Xiong et al. (2017) limit their scope to project-bound performance indicators, such as the project duration and the project costs. While this has confirmed the importance of project clustering in effective infrastructure asset management, there is little information to be found on the impact of project clustering on factors such as travel time or system-wide capacity utilization. Furthermore, the literature currently consists of retrospective studies (Assaf & Assaad, 2023; Qiao et al., 2019; Xiong et al., 2017) that analyze the performance of project clustering using historical data from projects. These studies provide valuable insights into the effectiveness of project clustering, but do not offer insights into the effect of project clustering on the future behavior of the infrastructure system. This thesis therefore sets out to address this gap in the literature by performing an exploratory modeling analysis on the effects of various cluster strategies on the functioning of the transport infrastructure network.

This thesis will employ a modeling approach as the development of new computational models is key to supporting governments in shifting to the desired bridge infrastructure management approach (Organisation for Economic Co-operation and Development, 2021). Computational modeling can help policymakers explore and understand different policies and dynamics without the need to experiment with the real-world infrastructure system (Süsser et al., 2021). Furthermore, computational models allow for the exploration of the consequences of assumptions about uncertain factors. In systems that are subject to deep uncertainty, such as infrastructure asset management systems, computational models are necessary to support the reasoning of decisionmakers (Auping, 2018).

Multiple methodological approaches to infrastructural modeling are currently used in the scientific literature (Hasan & Foliente, 2015). Agent-based modeling (ABM) can be used as a bottom-up approach to infrastructure modeling. ABM starts with defining the individual actors (agents) in the system and their potential interactions, the simulation of interactions between actors generate the system-level behavior. In transportation modeling, ABM is specifically appropriate for systems in which human actions and decision-making are critical (Bernhardt, 2007). Bonabeau (2002) suggests that ABM is most applicable when the appropriate level of description and/or complexity is not known beforehand, and when describing a system from the perspective of the activities of its agents is more natural than describing the system through its processes. Another strong aspect of ABM, in the context of this research, is its ability to capture complex interactions between agents in space. However, due to the primary focus on the behavior of individual agents, rather than the macroscopic behavior of the system, ABM is deemed not appropriate for the scope of this research.

A second methodology is network-based modeling. Two categories of network-based approaches can be distinguished, (i) flow-based approaches and (ii) topology-based approaches. Topology-based approaches are well suited to analyze vulnerabilities in large infrastructure systems. However, these approaches cannot capture information on individual asset performance, which will not allow for the modeling of individual bridge degradation in the context of this research. Ouyang (2014) argues that the topology-based modeling approach cannot be used to inform decision-makers when applied without supporting methodologies. The flow-based approach can capture flow characteristics of interdependent infrastructure assets. The flow characteristics are combined with detailed information on the operations of individual assets. Nurre et al. (2012) employed a flow-based approach to model the restoration of services in infrastructure systems after disruption by an extreme event. The method developed in the study was found to be suitable for long-term scenario planning activities and real-time restoration activities. Ibanez and McCalley (2011) used a flow-based approach to develop a model for robust long-term infrastructure investment planning, which has the ability to identify what, when, and where infrastructure investments should be made. Downsides to the flow-based approach is that the computational cost is very high in larger models due to the high degree of detail, and the accessibility of input data is low relative to other modeling approaches (Ouyang, 2014).

A third option is System Dynamics (SD), which offers a top-down approach to infrastructure modeling. This approach is able to capture the dynamic and evolutionary behavior of complex and interdependent infrastructure systems, and is considered to be well-suited for the modeling of transportation infrastructure systems (Abbas & Bell, 1994; Fontoura & Ribeiro, 2021; Shepherd, 2014). One of the key strengths of SD is its ability to explicitly account for feedback interactions between supply and demand in transportation. This feature is essential for understanding the complex dynamics of transportation, where changes in supply and demand influence one another. Additionally, SD allows for the integration of the transport sector with other related sectors, facilitating a comprehensive view of the interconnectedness of various components in a system. SD can account for nonlinearity, time delays and feedback loops, such as the feedback loop between supply and demand in transportation. This is particularly important because linear approaches are inadequate for capturing the complexities of transportation systems (Jifeng et al., 2008). SD models can help identify the parameters and variables that policymakers can influence to improve system performance, providing valuable insights for decision-makers. Additionally, SD can capture both the short- and long-term behavior of transport systems, which offers support for long-term infrastructure planning. SD, however, is not able to capture component-level dynamics like changes in the topological locations of assets (Ouyang, 2014). This is a crucial limitation of SD modeling in the context of this research.

Attempts have been made to extend the SD methodology to include a spatial component. For instance, Maxwell and Costanza (1997) introduced the Spatial Modeling Environment (SME). The SME can be used to link together non-spatial SD models to create a spatial model. BenDor and Metcalf (2006) find that the use of the SME provides an accessible way for modelers to expand their SD models spatially, without the need for significant technical expertise. Schwarz and Pruyt (2016) introduce a hybrid modeling and simulation approach, which integrates SD with ABM and GIS (Geographic Information System) software. The approach allowed for the dynamic switching between ABM and SD during runtime. Although the approach was found to be effective at modeling the spatial spread of the Zika virus at different levels of aggregation, a critical downside to this approach is the necessity to create multiple models in different simulation software. Another approach is the use of subscripts in SD modeling software to model smaller-scale dynamics in a stock (Fallah-Fini et al., 2013). Benaich and Pruyt (2015) employed this approach to explore the effectiveness of various traffic and congestion policies. By using subscripts, road sections could be created inside stocks in the model. They found this approach to be a potential method for building and analyzing road networks. However, they noted that building complex networks can become a time-consuming task because the subscripts have to be modified manually. One suggestion made by Benaich and Pruyt (2015) to avoid this issue is to employ an Entity-based SD approach.

Although flow-based network modeling is more efficient and accurate in modeling traffic flows through a network (Benaich & Pruyt, 2015), SD provides a more holistic approach (Sterman, 2002), which enables the modeling of not only individual infrastructure components but also the broader system in which these components operate. The maintenance planning problem covers more than just traffic flows, such as the demand for maintenance works that make the more holistic approach of SD the best fit for this research. Due to the spatial limitation of SD, this thesis will extend upon the SD methodology and employ an Entity-based SD modeling approach. Entity-based SD is a relatively new modeling methodology and is a combination of agent-level (ABM) modeling and macro-level (SD) modeling. This combination is considered to offer many benefits for this thesis. Firstly, this combination will allow for the modeling of the behavior and attributes of individual bridges, roads and regions, while retaining the capability of doing macro-level analyses. The entity-based approach also allows for the easy reuse of components, which makes the network building significantly less time-consuming and complex compared to traditional SD (Benaich, 2015). Secondly, because Entity-based SD is a form of SD modeling, it retains all the benefits of SD in the context of infrastructure modeling mentioned in the previous section. Section 2.1 will cover Entity-based SD in more detail.

The bridge maintenance problem is subject to deep uncertainty (Lempert, 2003; Liu & Frangopol, 2006; Rittel & Webber, 1973). Deep uncertainty is defined as conditions where analysist or parties involved cannot agree on (1) the probability distributions used to represent uncertainty in key model variables, (2) the design of conceptual models that describe the relationship between variables in the system, and (3), the valuation of the desirability of alternative outcomes (Lempert, 2003). When faced with deep uncertainty, computational models can be used to explore the repercussions of various combinations of assumptions about uncertain factors in the system (Auping, 2018). The type of computational models fit for analyzing systems that are subject to deep uncertainty were first introduced in Bankes (1993), and is labeled as Exploratory Modeling and Analysis (EMA). Therefore, the Entity-based SD methodology will be paired with EMA to support the exploratory analysis of the bridge maintenance problem.

As Entity-based SD is a relatively new methodology, however, no spatially explicit applications of the methodology can be currently found in the scientific literature. As such, this thesis will pursue two objectives, (1) developing, and reflecting on the added value of a novel spatially explicit Entity-based SD modeling method when modeling the effect of bridge maintenance cluster policies on the wider infrastructure system, and (2) identifying maintenance cluster policies that are effective at facilitating a steady and predictable maintenance capacity demand. These objectives are translated into the following set of research (sub-) questions:

1. How can spatial relationships between variables be captured in Entity-based SD models and what is the added value of this approach when analyzing spatially explicit bridge maintenance cluster policies?
    a. How can we develop a replicable spatially explicit Entity-based SD model that is capable of analyzing bridge maintenance cluster policies?
    b. Which bridge maintenance cluster policies are effective at facilitating a steady and predictable maintenance capacity demand?
    c. What is the added value of a spatially explicit Entity-based SD model in analyzing spatially explicit bridge maintenance cluster policies?

The rest of this thesis is structured as follows. Chapter 2 will introduce the methodological background that is used in this thesis. Chapter 2.3.2 contains the documentation of the step-by-step construction of the Python connector between the EMA Workbench and the Entity-based SD modeling software Ventity, which has been constructed for the purpose of this thesis. In chapter 3, the design of the spatially explicit Entity-based SD model is presented. Chapter 4 presents the analysis of the model results. Chapter 5 provides a reflection on the added value of the spatially explicit Entity-based SD modeling approach and a reflection on the model results. Lastly, chapter 6 presents the conclusion of this thesis.

2 Methodology

This section will elaborate upon the methodology applied in this thesis. Section 2.1 introduces Entity-based SD and discusses its relevance to answer the research question. Section 2.2 provides an overview of the modeling conventions within SD and the additions introduced in the Entity-based SD methodology. Section 2.3 presents the Exploratory Modelling and Analysis (EMA) methodology and its role in dealing with uncertainty. Furthermore, section 2.3.2 contains the step-by-step documentation on the construction of the Python connector between the EMA Workbench and the modeling software Ventity, which has been constructed for the purpose of this thesis. Section 2.4 introduces Robust Decision Making as the foundation of the experimental setup of this thesis. Section 2.5 describes scenario discovery as one of the analyses that will be done in this thesis. Lastly, section 2.6 presents feature scoring.

2.1 Entity-based System Dynamics

Entity-based SD (Entity-based SD) is a modeling methodology developed by Yeager et al. (2014) in response to the limitations of traditional SD modeling. These limitations can be categorized in two main categories, (1) modularity and (2) agent detail. Firstly, the lack of modularity in traditional SD can negatively impact the speed at which large models can be constructed, as model components cannot be duplicated or reused. In the context of infrastructure network modeling, Benaich and Pruyt (2015) found that this drastically increases the complexity and time investment needed to model large networks. Secondly, traditional SD modeling is not able to capture agent-level behavior. While many systems can be represented through aggregate behavior, the modeling of many other complex systems requires the ability to capture and define agent-level behavior (Yeager et al., 2014). For instance, if you want to model the effect of different maintenance bundling strategies on the road infrastructure system that these bridges are part of, only capturing the aggregate behavior of all bridges does not suffice. Rather, the behavior of individual bridges is crucial, as temporarily closing one bridge will have effects on the traffic flow, and thereby the rate of degradation, of nearby bridges.

Entity-based SD addresses the two categories of problems by introducing entities (known as objects or agents in other modeling methodologies), which are smaller models of each type of component that is part of the system that is to be modeled. Entities can represent a wide variety of components, such as products, organizations, countries and physical entities (Yeager et al., 2014). Through the addition of entities, Entity-based SD integrates SD with Agent-based Modelling, which creates the possibility to avoid their individual limitations and to benefit from the full potential of their complementary characteristics. This allows the Entity-based SD methodology to provide a more complete representation of complex dynamic systems (Nava Guerrero et al., 2016). In this thesis, Ventity version 5.0 beta 6 by Ventana Systems was used to construct the model. The documentation of the construction of the spatially explicit Entity-based SD model is presented in chapter 3.

2.2 Modeling in Ventity

This section will provide information on the modeling process in Ventity by describing the modeling conventions within SD, and highlighting the additions introduced in Entity-based SD. The information on SD modeling conventions is largely based on chapter 1.1.1 of Auping (2018).

Equation 1 is a fundamental equation in SD modeling for capturing the dynamics of accumulative processes. The equation expresses how the stock variable $s(t)$ evolves over time t by considering its initial value $s(t_0)$ and the cumulative effect of the net flow $f(t) - g(t)$ into or out of the stock over the specified time interval. SD models are in effect big sets of integral equations (like equation 1) that are numerically solved by SD modeling software and represented by diagrams such as the one depicted in figure 1.

$$s(t) = s(t_0) + \int_{t_0}^{t} f(t) - g(t)dt, \qquad (1)$$

In addition to stocks and flows, SD also contains constants and auxiliaries. Constants do not change value during the time period over which a system is modeled. Auxiliaries refer to variables that are not stocks or flows.

Figure 1 displays a simple SD model where *a(t)* represents an auxiliary and $c1, c2$ and $c3$ represent constants. The initial value of the stock, $s(t_0)$ is equal to s_0. Inflow $f(t)$ is a function of $s(t)$ and *c1, w*hile outflow $g(t)$ is a function of $a(t)$, $s(t)$ and constant $c3$. Lastly, auxiliary $a(t)$ is a function of $s(t)$ and $c2$.

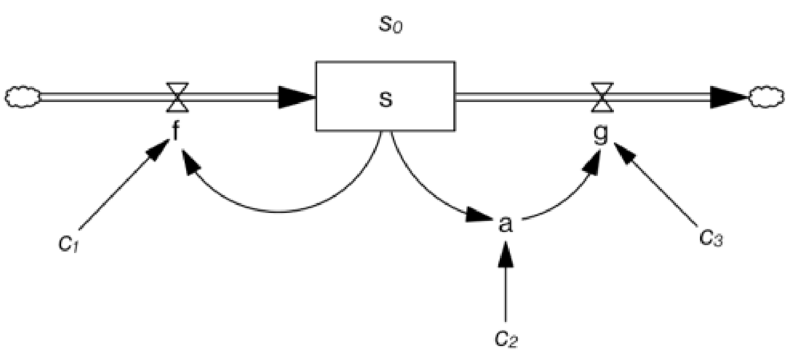

Figure 1: A simple stock-flow structure (Auping, 2018)

The elements of SD (SD) modeling, including stocks, flows, and auxiliary variables, make SD an appropriate choice for bridge and road infrastructure modeling. Stocks represent accumulations and memory within the system. For instance, stocks could symbolize the vehicles present in a given region or city or they could represent the fatigue damage of individual bridges. Flows can be used to change these stock levels by representing traffic movement and changes in fatigue damage. Moreover, feedback loops, fundamental in SD, can be integrated into the model. Two key types of feedback loops can be distinguished, balancing and reinforcing. In a balancing loop, an increase in a variable may lead to a decrease over time as the system adjusts. For instance, in response to bridge closures, commuters adjust their routes which affects the traffic distribution in the system. The increase in traffic on alternative routes can lead to congestion and slower travel times, which stimulates commuters to reconsider their routes and creating a balancing loop as traffic redistributes to alleviate congestion.

In reinforcing loops, an increase in a variable leads to further increases over time, creating exponential growth. Maintenance on one bridge increases the likelihood of subsequent maintenance needs across the network, as this leads to increased wear and tear on other bridges, accelerating the need for additional repairs. The effect of bridge maintenance results in a reinforcing loop, where the deteriorating condition of bridges induce more frequent maintenance requirements. Together, the incorporation of accumulations, flows, and feedbacks in road infrastructure modeling captures the complexity and non-linear nature of these systems, providing a comprehensive approach for analyzing and understanding the dynamics the system.

Ventity contains a few important extensions to SD. These extensions can be summarized in 6 categories (Yeager et al., 2014): (1) Entity types, (2) attributes, (3) collections, (4) aggregation, (5) references, and (6) actions. Firstly, entity types allow for the creation (or reuse) of model definition for every unique type of component in the system. Each entity type can be defined using traditional stock and flow diagrams. Secondly, each entity has one or more attributes, through which individual entities within entity types can be accessed. To illustrate this with an example: There could be an entity type named ‘Country’ with the attributes ‘Country name’, ‘Language’ and ‘Continent’, within this entity type you could then have the entities ‘United States’ and ‘The Netherlands’. Through the attributes, it is possible to access sets of countries based on their language and continent or to access individual countries through the ‘Country name’ attribute. The third category refers to collections of entities, which contain all the entities of a specific type. Collections make it possible to access aggregate values such as the sum, average, min or max. In Ventity it also possible to make sub collections based on a specific attribute value. For the country example, sub collections could be made for Language and Continent so the modeler can easily access aggregate values for all countries from the same continent (or with the same language). Fourth, references enable disaggregate systems to be linked to each other. A reference is an information or causal link between entity types, which allows entity types to access values of variables from another entity type. Lastly, actions are model components that assist the modeler in, for instance, creating new entities during a model run or conditionally changing values of attributes. Actions provide access to certain agent-based and discrete event capabilities in Ventity.

2.3 Exploratory Modelling & Analysis

The infrastructure planning problem described in the introduction can be characterized as a wicked problem (Chester et al., 2019; Rittel & Webber, 1973). Rittel and Webber (1973) introduced the term wicked problem to describe complex issues that lack simple solutions due to their loose formulation, their lack of stopping rule and the involvement of diverse stakeholders that each have their own conflicting perspective. Wicked problems are subject to deep uncertainty (Helmrich & Chester, 2020; Lempert, 2003). In model-based decision support, deep uncertainty refers to uncertainty in which no single probability distribution can be used to represent key parameters in the model (Walker et al., 2013). Some exogenous parameters will cause differences in model results in different future scenarios. In infrastructure planning, an example of this could be the adoption of electric vehicles. Electric vehicles are much heavier than gas-powered vehicles (Bomey, 2023), and a fast adoption of electric vehicles will lead to a higher average weight per vehicle, which in turn will lead to faster degradation of bridges. The faster degradation of bridges will increase the amount of maintenance projects that have to be executed in order to keep the bridges in acceptable conditions.

Many planning problems in public policy are wicked problems, and are therefore subject to deep uncertainty (Lempert, 2003; Rittel & Webber, 1973). Strategic planners and policy analysts are aware that they are dealing with deep uncertainty. However, static plans that depend on a single 'most likely' future scenario, or a small set of hypothesized future scenarios, are still being widely developed and used (Walker et al., 2013).

Exploratory Modelling and Analysis (EMA) is a research methodology that describes the use of computational experiments to aid decision-makers in increasing their system understanding when faced with deep uncertainty (Bankes, 1993). EMA uses model-based scenario techniques to systematically explore a very large collection of possible future scenarios. Different policies (or strategies) are evaluated across the collection of possible future scenarios to determine how various uncertainties impact the effectiveness or failure of these policies (Kwakkel, 2017). Two basic scenario discovery strategies can be identified within the EMA framework: Open exploration and directed search.

1. Open exploration implies performing a series of computational experiments to systematically explore the consequences of the uncertainties in the model (Bankes, 1993).
2. Directed search utilizes optimization techniques to identify the most likely conditions surround particular scenarios that are of interest (Kwakkel & Pruyt, 2015)

Open exploration can be used to answer questions like 'under which circumstances would this policy be effective' or 'which kinds of dynamics can this system express'. Directed search is used to answer question such as 'what is the best (or worst) that can happen' or 'how do rival policies perform relative to each other' (Kwakkel & Pruyt, 2015).

2.3.1 The EMA Workbench

The Exploratory Modelling Workbench (Kwakkel, 2017), or EMA Workbench, is an open source Python library that is used for exploratory modeling. Its purpose is to facilitate the creation and implementation of sequences of computational experiments and aid in the visualization and analysis of the outcomes derived from these computational experiments (Kwakkel, 2017). One of the key features of the EMA Workbench is its access to connectors that allow it to directly interact with simulation or modeling software such as Vensim and NetLogo. A direct connection implies that the user will only need to specify the uncertain factors and their sets of values and the outcomes to perform experiments with the EMA Workbench.

Currently, no such connector exists for the Entity-based SD modeling software Ventity. This implies that no EMA Workbench experiments can currently be run using a model created in Ventity. Therefore, an EMA Workbench-Ventity connector has been developed for the purpose of this study. The next section presents a step by step overview of the development process.

2.3.2 Developing the EMA workbench connection

The EMA Workbench connector developed for this study is not a conventional connector and is therefore not alike to any of the connectors that are currently in use. Rather, it is a data processing tool that utilizes the built-in sensitivity analysis capabilities of Ventity and processes the data into a format that is readable and useable for the EMA Workbench. Figure 2 presents a simplified overview of the components of the EMA workbench connection. The GitHub repository containing the EMA Workbench connector can be found here.

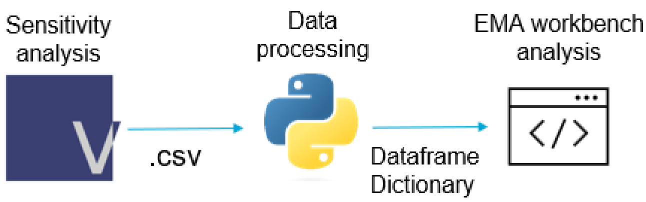

Figure 2: Conceptual overview connector

Firstly, a simple population model with two country entities, one collection entity and two policy scenarios was created in Ventity. This model was then used to perform a sensitivity analysis for each of the two policy scenarios. Ventity allows the user to choose a sampling type, a sample size and the uncertain factors and their range of values for the sensitivity analysis. After completing the sensitivity analysis, Ventity saves a .csv file for all of the entities and collections of entities in the model per policy scenario that the analysis is performed on. For large models, with numerous entities and collections, this leads to a great amount of .csv files that have to be combined to be used as input for the EMA Workbench experiments. The data import section of the connector is therefore automatized, and the .csv files are imported based on the directory that is specified by the user.

There was an initial data format mismatch when attempting to use the sensitivity analysis results from Ventity in the EMA Workbench. Ventity exports the sensitivity analysis results in a long data format (also known as tidy format), while the EMA Workbench requires the data to be in a wide format. A long data format implies that there will be multiple entries for every combination of a run and time value in the rows of the data table, one for each of the entities in the model. Wide format data has a unique combination of variables in each of the rows of the data table. The transformation from long to wide format data required the duplication of each of the columns containing data from variables in the model for the amount of unique entities that have a value for that variable. The figure below displays the required transformation using a simple example with 2 unique entities and 1 population variable.

Long format

Run	Time	Entity	Population
1	1	NL	17
1	2	NL	18
1	1	VS	332
1	2	VS	340

Wide format

Run	Time	Population [NL]	Population [VS]
1	1	17	332
1	2	18	340

Figure 3: Data format transformation

A complication in this data transforming step was the fact that collections of entities contained NaN (Not a Number) values in the column that specified their Entity ID. The solution here was to fill this column with the name of the file that the data table originates from. This is possible because Ventity saves each of the sensitivity analysis files in the following format [policy scenario name]_[entity name].csv. Therefore, in the example above, the collection “Country” containing the entities NL and US would obtain the value “collection_of_country” as the Entity ID. This ensures that the data format transformation works for both entities and collections of entities.

Additionally, the EMA Workbench requires two additional columns of data that are not provided in the exported Ventity files. Firstly, a column that specifies the active policy. In order to analyze the relative performance of policies on the model, the EMA Workbench needs to be able to identify which policy was active in a sensitivity run. The policy column is filled with the name of the policy scenario name part of the file name. Secondly, a column that specifies the scenario that a row in the data table belongs to. For each policy scenario that a sensitivity analysis is performed on, Ventity saves a .csv file for all of the entities and collections of entities in the model. This leads to overlapping scenario values when combining these .csv files into one pandas DataFrame. The addition of a scenario column that assigns a unique scenario number to each sensitivity analysis run of one policy scenario ensures that the EMA Workbench can distinguish between policy scenarios.

After performing these data manipulation steps, the resulting DataFrame containing all the runs per policy scenario could be used to create the input for the EMA Workbench. The EMA Workbench is designed using the XLRM framework, a framework that is regularly used in model based decision support to structure information (Kwakkel, 2017; Lempert, 2003). The figure below shows the XLRM framework, where X stands for the external factors, these are factors that cannot be controlled by decision-makers. R stands for the relationships inside the system, L stands for policy levers and M stands for the performance metrics. In the EMA Workbench the notation of the components is slightly altered, but the underlying framework remains the same. External factors are called uncertainties, policy levers are called levers and performance metrics are called outcomes.

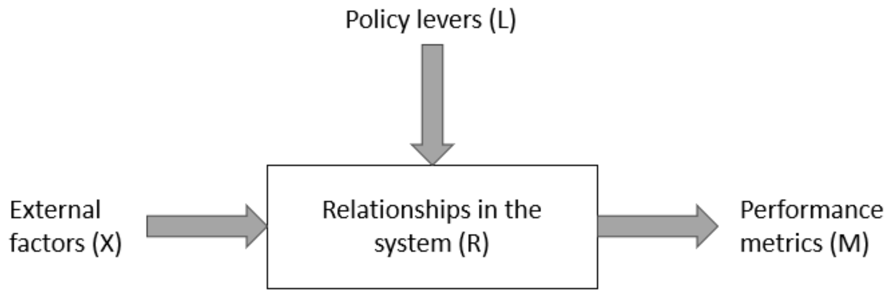

Figure 4: The XLRM framework

The XLRM framework was used to derive the required data components to be filtered from the DataFrame containing all the runs per policy scenario. Firstly, the uncertainties and levers were copied into a new DataFrame. The uncertainties and levers are unique to every Ventity model and are therefore required as a manual input into the connector. Based on the column names that were identified as uncertainties, a new DataFrame was created that included only the columns with the uncertainties and the column that specified the active policy. Secondly, the columns containing the outcomes of interest were converted to a dictionary data type. The dictionary is required to have the names of the outcomes as keys and the time series data as values. Each outcome variable has to have an array of values per unique scenario.

After creating the DataFrame with uncertainties and levers and the dictionary containing the outcomes of interest, all the data requirements for the EMA Workbench have been fulfilled. Analyses could now be run as if the EMA Workbench had an active direct connection to Ventity.

2.4 Robust Decision Making

Robust Decision Making (RDM) (Lempert et al., 2006) is an approach to model-based policy analysis that builds on the Exploratory Modelling and Analysis research framework (Bankes, 1993), and tailors it to facilitate the formulation of policies that can perform satisfactorily under a wide range of possible assumptions. The RDM approach employs various perspectives on the future to facilitate a comprehensive examination of modeling outcomes. This helps in developing a plan that is resilient, minimizes instances of not achieving its objectives, and provides clarity on the conditions under which the plan may not meet its goals (Auping et al., 2015; Lempert, 2003). The RDM approach consists of three steps (Auping et al., 2015):

1. The first step in the RDM methodology is scoping. This involves defining the scope of the analysis by identifying external uncertainties, policies, crucial interconnections, and performance measures. To establish the linkage between actions and their corresponding outcomes, simulation models are created. This step is addressed in sub-question b.
2. The second step is simulation and scenario discovery. A specific policy is selected for assessment, and it is applied across a range of scenarios to identify weaknesses within the policy. Specifically, we look for combinations of uncertainties that lead to the policy failing to achieve its objectives. See chapter 2.5 for an overview of scenario discovery.
3. The third step is policy design. Precautionary measures are identified to counteract these vulnerabilities. This could include adjusting existing policies or formulating new ones. Steps 2 and 3 are repeated for additional policy options as necessary.

The scoping of the analysis is determined using the XLRM framework (Lempert, 2003). The XLRM framework is regularly used in model-based decision support to structure information (See also chapter 2.3.2) (Kwakkel, 2017; Lempert, 2003). The XLRM framework consist of 4 components, uncertainties, policy levers, the model and the outcomes of interest (X, L, R and M, respectively). The model uncertainties are presented in chapter 3.7.1. The outcome metrics, or outcomes of interest are discussed in chapter 3.7.2. The Entity-based SD model is presented in chapter 3 and, lastly, the policy levers are presented in 3.7.3.

2.5 Scenario discovery

In this thesis, the Patient Rule Induction Method algorithm (PRIM) (Friedman & Fisher, 1999) will be used as a tool for scenario discovery. PRIM can be used to find combinations of values for input variables that result in similar values for the outcome values (Kwakkel & Pruyt, 2015).

Scenario discovery consists of three steps. First, the ranges of uncertain parameters in the computational model are defined. This will be done within the sensitivity analysis function of Ventity. Second, the set of computational experiments are run in Ventity using combinations of parameter values. Third, the PRIM algorithm is used on the set of experiments. PRIM generates a set of boxes that represent combinations of input parameters that result in similar (desired) characteristic values for the outcome variables (Kwakkel & Pruyt, 2015). The boxes found by the PRIM algorithm are commonly visualized using a trade-off plot, which presents the trade-off between density, coverage and interpretability of the boxes. The density of a box refers to the amount of experiments in a box that are of interest, the coverage of a box indicates the amount of experiments of interest, compared to the total amount of cases of interest, and the interpretability refers to the amount of dimensions that need to be restricted (i.e., how many parameters are described in the box). Lastly, individual boxes found by PRIM can be investigated. A density of at least 80% is customary for the identification of boxes of interest.

2.6 Feature scoring

Feature scoring is a type of technique often used in identifying the most relevant features for a certain outcome, or set of outcomes (Kwakkel, 2017). A feature scoring algorithm will be applied to the set of experiments generated with the Entity-based SD model to identify the key drivers in the system. The algorithm uses the last available datapoint of each outcome. It then scores each of the input variables based on how much of the variance in each of the outcomes that input variable causes. The feature scoring analysis then presents a heatmap in which the results of the analysis can be seen. Brighter colors indicate that a variable causes a larger amount of variance for an outcome of interest.

As the feature scoring analysis described above only uses the values in the last timestep of each of the experiments, a second temporal feature scoring analysis will be performed as the behavior over time of the outcomes of interest is also relevant. This second analysis analyses the amount of variance that input variables cause in the outcome variables at multiple timestamps of the runtime.

3 Model specification

This section presents the step-by-step construction of the bridge model. First, the road infrastructure network designed for this thesis will be elaborated upon in section 3.1. Section 3.2 presents the design of the spatial component of the model. Section 3.3 presents the model map, which gives an overview of all the entities (or submodels) in the model, and their relationships to other entities. Then, section 3.4 explores each of the entities and sub models. Section 3.5 contains the model validation, and lastly, in section 3.6, the experimental setup of this research will be discussed. To construct the model, Ventity version 5.0 beta 6 was used. The spatially explicit bridge model uses a bridge replacement and renovation model developed by Copernicos Groep B.V. as a base (Copernicos Groep, 2018). An overview of the variables used in the documentation of the model including their definitions can be found in Appendix A.

3.1 Road infrastructure network

In order to effectively model the effects of various spatial maintenance policies on the performance of the road infrastructure system and maintenance capacity utilization, a spatially explicit network is needed as a base for the model. The network is regarded as an assembly of links and nodes, which are basic elements in network theory (Quimpo & Wu, 1997). A node represents a region, while links represent roads that act as connections between the nodes in the network. Each link is capable of containing a bridge. Links containing bridges are the only components of the network that have the possibility of failure (i.e., closure), which results in the traffic flow of that specific link being set to 0 for the duration of the failure. Thus, the bridge network is characterized as a road network with a probability of failure of zero percent for the links without bridges and nodes, similar to the network described in Liu and Frangopol (2005). The figure below presents a simple network consisting of 3 nodes (A, B and C) and 3 links. Links are bidirectional, but in order to correctly implement the network in Ventity, each direction is given a unique name by compounding the origin and destination of the link. In the figure below, that results in the following six links: AB, BA, AC, CA, CB and BC. For the remainder of this thesis, road and region names will be referred to as ID's.

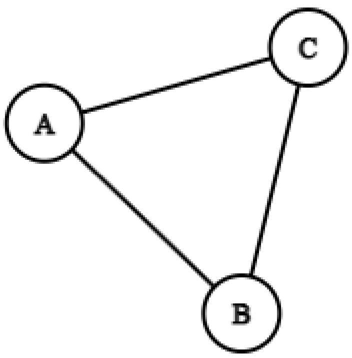

Figure 5: Small network composed of 3 nodes and 3 links.

For the purpose of this thesis, a hypothetical network has been designed to support the development of a proof-of-concept spatial Entity-based SD modeling approach. The network is in essence a larger, more complex, version of the network displayed in figure 5. It has a total of 14 nodes and 27 (bidirectional) links, which results in 58 unique link ID's. The network can be seen in figure 6. Regions B, G, E and F have the highest centrality, indicating that they are the most well-connected nodes in the model. On the contrary, the nodes along the edge of the network, specifically nodes A, M, L, I, K and N have the lowest centrality. This makes those nodes more vulnerable in terms of accessibility when bridges get closed for maintenance. The network contains 2 rivers which indicate the locations of bridges. When a river and a link cross, this indicates that that link contains a bridge, this holds true for both directions of that link.

The model contains 15 bridges that have been selected from a database constructed by Copernicos Groep containing all the bridges in the Netherlands (Copernicos Groep, 2024). Within the database, a smaller subset was made containing only fixed concrete bridges built between 1950 and 1990 (post-war era) that are still in use. From this subset, a random selection was placed into the model. The bridge names have been substituted for more general names (b_1 though b_{15}).

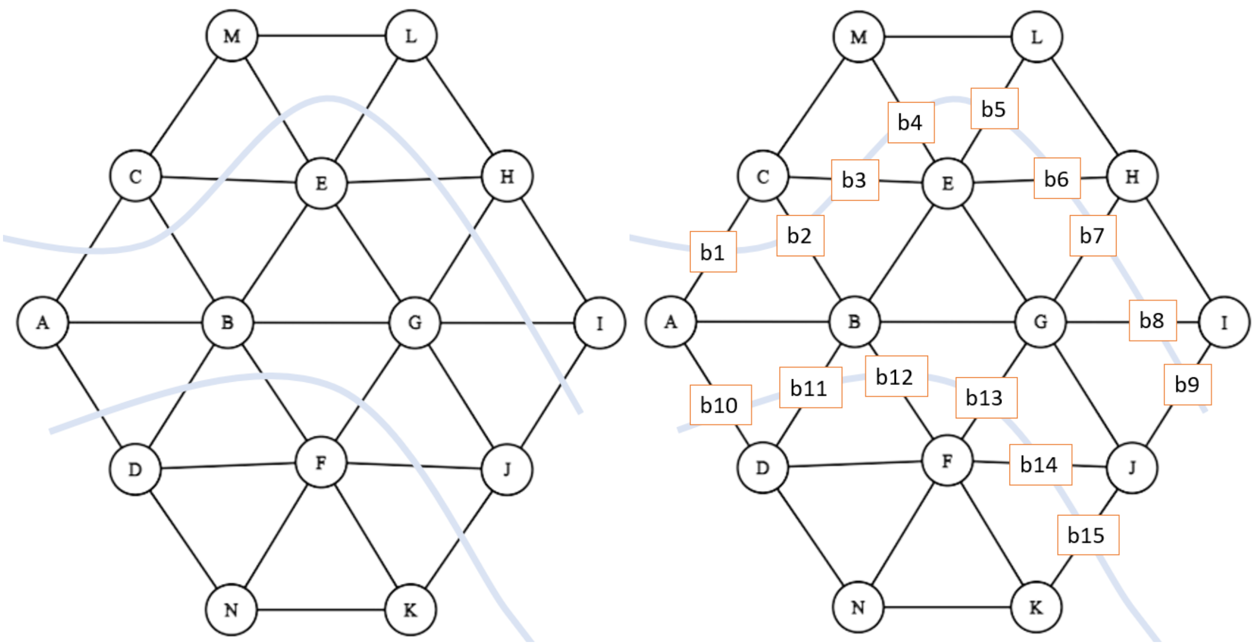

Figure 6: Network including rivers (left) and network with bridge placement (right)

3.2 Spatial component

This chapter will describe how the spatial component of the model was designed in Ventity. The goal of the spatial component was to translate the network presented in chapter 3.1 into an Entity-based SD model, so the model could be used to do spatial analyses. The design of the spatial component was inspired by the GIM GOS 2 model (Ventana Systems, 2022), which is supplied as a sample model with Ventity. This chapter will only provide information related to the design of the spatial component, more information on the dynamics of entities will be provided in chapter 3.5.

An important consideration when designing the spatial component was replicability, as the approach would lose value and relevance if it would be rigidly designed for only one (type of) network, in line with the findings of Benaich and Pruyt (2015). In order to achieve a high degree of replicability, the spatial component was designed using (1) entity types, (2) attributes, (3) references and (4) external network initialization data. Firstly, three entity types were created and initialized to lay the foundation for the spatial component, Region, Road and Region to Region. The Region entity type defines the nodes from the network presented in the previous section. This entity only contains one attribute, RegionID, which allows Ventity to distinguish between Regions. Secondly, the links in the network are defined by the Road entity type. This entity type holds 4 attributes: FromRegion, ToRegion, RoadID and PairID. The FromRegion and ToRegion attributes define the origin and destination of each road entity. The RoadID attribute contains a unique ID for each road that is determined by compounding the origin and destination of the road, the road from Region A to Region B will therefore be assigned the RoadID ‘AB’. Lastly, the PairID was introduced to the model to be able to pair roads that reside on the same link of the network. In essence, this means that roads AB and BA, both residing on the link between Region A and B, get assigned the same PairID. The PairID allows for the closing of roads in both directions in case of bridge maintenance. The third entity type, Region to Region, defines the flow of traffic over a given road from Region x to Region y. This entity types holds the same attributes as the Road entity type.

The Region to Region entity type connects variables defined in the Region and Road entity types through references. The attributes assigned to this entity type are attributes that are referenced from the Region entity type (FromRegion and ToRegion), and the Road entity type (RoadID and PairID). Figure 7 displays a simplified version of the stock-and-flow structure that facilitates traveling between regions, and table 1 presents an overview of the entity types, attributes and references mentioned.

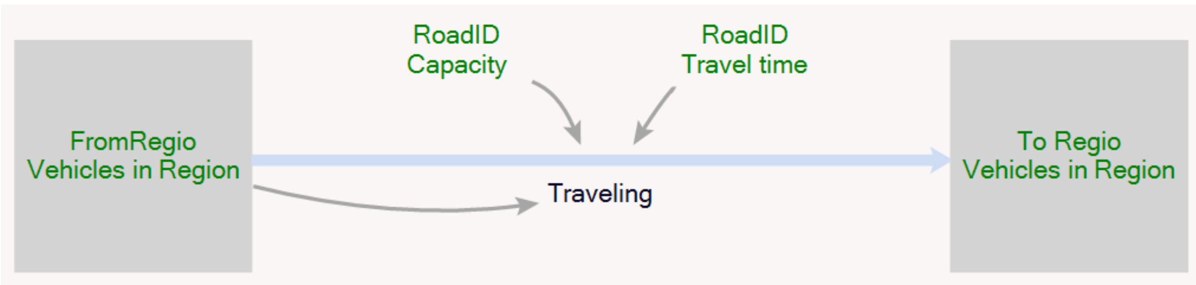

Figure 7: Region to Region traveling

Table 1: Entities used for the spatial component

Entity type	Attributes	References
Region	RegionID	
Road	FromRegion ToRegion RoadID PairID	Region to Region
Region to Region	FromRegion ToRegion RoadID PairID	FromRegion ToRegion Road

The ToRegion and FromRegion stocks in the figure above are references to one 'vehicles in region' stock that is defined in the Region entity type. These attributes have to be categorized as a 'key' to the Region to Region entity type to allow for the creation of two stocks referencing different collections of regions. Each Region entity has an initial amount of vehicles which is defined in the entity initialization dataset. In this dataset, the combination of origins and destinations is also defined for the Region to Region entity type. Using these combinations, the Region to Region entity type is able to link the regions with the road that holds the same origin and destination combination. A Region to Regio entity then assigns the value for road capacity and travel time, using the RoadID of the road, to the flow between two regions.

In a network with only 2 Regions, A and B, and one bidirectional road between the regions labeled AB and BA, the amount of vehicles in Region A $V_A(t)$ is determined as follows:

$$V_A(t) = V_A(t_0) + \int_{t_0}^{t} \left[\min\left(C_{B,A}, \frac{V_B(t)}{Tt_{B,A}} \right) - \min\left(C_{A,B}, \frac{V_A(t)}{Tt_{A,B}} \right) \right] dt, \tag{2}$$

Where $V_n(t_0)$ is defined in the Region entity type and capacity $C_{n,m}$ and Travel time $Tt_{n,m}$ are defined in the Road entity type. The outflow of vehicles is determined as the minimum between the capacity of the road AB per timestep (which is considered to be a constant) and the amount of vehicles in region A $V_a(t)$ divided by the travel time between region A and region B. Similarly, the inflow is determined as the minimum between the capacity of the road BA and the amount of vehicles in region B $V_b(t)$ divided by the travel time between region B and region A. For larger networks, With N regions connected to Region A, the equation looks as follows:

$$V_A(t) = V_A(t_0) + \sum_{i=1}^{N} \int_{t_0}^{t} \left[\min\left(C_{i,A}, \frac{V_i(t) * D_{i,A}}{Tt_{i,A}} \right) - \min\left(C_{A,i}, \frac{V_A(t) * D_{A,i}}{Tt_{A,i}} \right) \right] dt, \tag{3}$$

Equation 3 includes a distribution variable $D_{i,j}$ which determines the share of vehicles in region i traveling to region j, since there are now multiple destinations to choose from for vehicles in any given region.

Lastly, the entities have to be initialized with data that define the spatial relations in the model. Ventity supports external datasets for the initialization of entities in the model, which is beneficial for the replicability of the spatial component presented in this section. The external dataset used for the network in this thesis is an Excel (.xslx) file in tidy format (see section 2.3.2). By using the 'Generate External File Template' function in the Data Sources section in Ventity, the correct data format can be generated easily. In the Excel file, attributes and variables that have been marked as ‘constants’ in Ventity can be given values for each unique entity within an entity type.

Table 2 presents the attributes and values required in tidy format for the small 3 node model presented in figure 5 in section 3.1. Each entity type has a different sheet in the Excel file, but they have been displayed in the same table for convenience.

Table 2: Network initialization data for a small 3 node network

Region		Road						Road to Road			
Region ID	**Initial vehicles in Region**	**RoadID**	**FromRegion**	**ToRegion**	**PairID**	**Capacity[1]**	**Traveltime[2]**	**RoadID**	**FromRegion**	**ToRegion**	**PairID**
A	100	AB	A	B	AB	500	1	AB	A	B	AB
B	100	BA	B	A	AB	500	1	BA	B	A	AB
C	100	BC	B	C	BC	500	2	BC	B	C	BC
		CB	C	B	BC	500	2	CB	C	B	BC
		CA	C	A	AC	500	1	CA	C	A	AC
		AC	A	C	AC	500	1	AC	A	C	AC

When initializing larger networks by hand, filling the Excel file can quickly become a tedious task. Therefore, to decrease the time spent in the network specification, the Excel file has been further modified to enable the automatic filling of certain columns. This automation also decreases the possibility of human error when specifying the network. Firstly, the Region Entity and the FromRegion, ToRegion and Capacity columns belonging to the Road entity type have to be filled in by hand. Then, the RoadID column in the Road Entity type is filled in using the following Excel formula: =D2&E2, assuming that the FromRegion and ToRegion attributes are assigned to columns D and E respectively. Secondly, the PairID in the Road entity type is completed using the following formula: =IF(D2 < E2; D2 & E2; E2 & D2), where the columns D and E again refer to the columns holding the values for the FromRegion and ToRegion attributes. This formula checks if the FromRegion value comes first in alphabetical order compared to the ToRegion, if true, the cell returns the FromRegion+ToRegion value. If false, the formula returns the opposite combinations, ToRegion+FromRegion. This ensures that combinations of the same two regions obtain the same value in the PairID column. Lastly, the Road to Road entity type can be initialized by copying or referring to the values from the overlapping attributes in the Road entity type.

The spatial component was initially constructed using only the Region and Region to Region entity types, where the specific attributes for each road were initialized in the Region to Region entity type. This proved to be a valid approach to construction a spatial component, however this construction made it impossible to later assign bridges (or other assets) to specific roads. This is due to the fact that no subcollections can be made that refer to entity types with more than 1 key. For bridges to be assigned to roads, every bridge has to be assigned a RoadID or PairID that matches that of the road. A subcollection of the bridge entity type was then made using either the RoadID or PairID to aggregate the data of interest per road, so it can be used in the Region to Region entity type to determine if a road should be closed based on the status of the bridge. This last step is only possible when including the Road Entity type, as it only holds one key (RoadID).

[1] Vehicles/hour
[2] Hours

During the modeling process the decision was made to not include a vehicle entity type. This addition would have allowed for more detail and information on individual vehicles in the model. For instance, it is possible to specify the distribution of vehicles in the vehicle entity type by using an action. In this action, the model can create a weighted list of destinations for every vehicle entity, which allocates the distribution of traffic flows on the level of individual vehicles. However, for the purpose of this thesis the aggregated view of traffic flows via the Road and Region to Region entity types was considered to be sufficient. Additionally, the decision was made to analyze the distribution of traffic flows at the road level, as opposed to continuously assigning destinations for each vehicle entity in the model. This choice was driven by the anticipation that determining vehicle-level distributions would incur higher computational costs.

One final important consideration when designing a spatial component is the timestep that is used in the model. The bridge replacement & renovation model, which was used as a base for the spatially explicit model, was modelled with a timestep of 1 and a time unit of year. This led to the model calculating the status of each of the bridges in the model every year, and making renovation or replacement decisions accordingly. However, when modeling traffic flows, the values calculated each timestep become very big, leading to the model to malfunction. The traffic component only showed the expected behavior when the timestep was decreased to 0.125 years or smaller. Unfortunately, the smaller timestep led to the malfunctioning of the replacement & renovation part of the model, as this part was designed to function with a timestep of 1. As of writing this thesis, Ventity does not support more than one integration method so the influence of other methods on this issue cannot be discussed. In order to solve the issue, the traffic flows were divided by a factor of 10.000 to obtain flows of traffic per 10.000 vehicles. Through this decrease in traffic flow values, both sides of the model now showed their expected behaviors. At points in the model where variables are calculated per vehicle, these variables are multiplied by 10.000.

3.3 Model map

Figure 8 shows a highly aggregated model map, that highlights the entity types and actions in the model and their relations to other entity types. A green color indicates a collection of an entity, these collections either hold the aggregate values for all entities in an entity type (denoted as Entitytype[]) or the aggregate values of a subset of entities in an entity type based on a specific attribute. The model can be roughly divided into two submodels, (1) the bridge model, and (2) the spatially explicit traffic flow model. Both parts of the model are connected through the collections Road by PairID and Bridge by PairID. The Bridge by PairID collection is used to indicate which bridges are currently closed due to maintenance works to the Region to Region entity, which in turn affects the distribution of traffic flows in the network. The Road by PairID collection is used to aggregate the yearly traffic load on roads and assigns these values the corresponding bridge entities in the bridge entity type. Section 3.4 presents a detailed overview of every entity type in the model map.

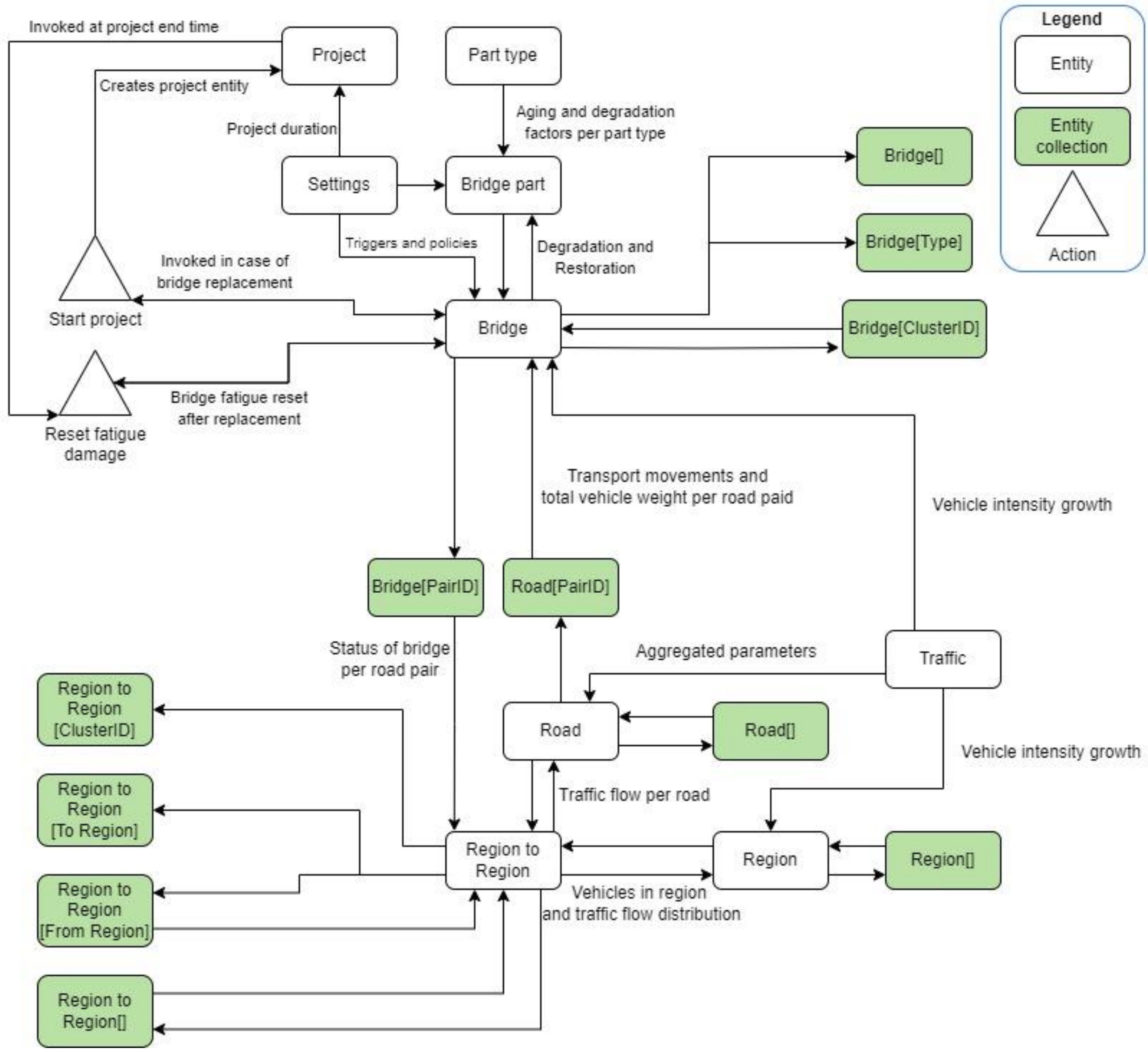

Figure 8: Model map showing relationship between entity types

3.4 Entity types and submodels

In this section, each of the entity types will be elaborated upon. The Entity-based SD model consist of a total of 8 entity types, the elaboration on the Settings, Traffic, Cluster and Part type entity types will be combined in section 3.4.7.

3.4.1 Bridge

Within the first entity type, the bridge entity type, two submodels can be defined. (1) the load capacity submodel for concrete bridges and (2) the fatigue damage submodel for steel type bridges. Firstly, the load capacity submodel determines load capacity of concrete type bridges $C_L(t)$ using a forecast for the load capacity needed to sustain future traffic loads, the initial load capacity of each bridge and the decline of load capacity $d(t)$. The load capacity of a bridge $C_L(t)$ can be expressed as follows:

$$C_L(t) = C_L(t_0) + \int_{t_0}^{t} [\max(R(t), M(t)) - (C_L(t) * d(t))] \, dt, \tag{4}$$

Where $C_L(t_0)$ is a function of the age of the bridge and $\max(R(t), M(t))$ determines the maximum value between the projected need for reinforcement and the planned maintenance works. The projected need for reinforcement is only larger than 0 when the current load capacity $C_L(t)$ smaller than or equal to the current load on the bridge including a safety margin. By default, the safety margin is 5,0%. The decline of load capacity $D(t)$ is defined in the bridge part entity type (See section 3.4.2).

The second submodel is the fatigue damage submodel for steel type bridges. This submodel determines the fatigue damage in percentages of a bridge, and decides if the bridge should be restored or replaced. The fatigue damage $D_F(t)$ of a bridge is expressed as follows:

$$D_F(t) = D_F(t_0) + \int_{t_0}^{t} d_f(t) - r(t) \, dt, \tag{5}$$

Where $D_F(t_0)$ is a function of the age of the bridge. The increase in fatigue damage $d_f(t)$ is determined by the yearly amount of vehicles that pass over a bridge. The yearly restoration $r(t)$ is only larger than 0 if the current fatigue damage level is higher than the fatigue damage threshold, which is determined by a forecast of the fatigue damage including a safety margin. The size of the restoration is determined by a forecast of the yearly fatigue damage multiplied by the desired extra lifetime in years as a results of the restoration. However, if the required restoration size is equal to or greater than the projected fatigue damage threshold, the bridge renovation trigger remains zero. In this event, the bridge gets replaced instead of renovated. Replacing a bridge invokes an action which creates a project entity, this project entity then invokes another 'reset' action, which resets the fatigue damage of the bridge at the specified ending time of the replacement project. As replacing a bridge is invoked by fatigue damage, bridge replacement are only possible for steel type bridges. The focus in this thesis is on concrete type bridges, which leads to 0 replacement and fatigue damage maintenance projects.

The bridge model contains three triggers that determine if a bridge gets maintenance or is replaced. In order to allow for clustered maintenance and replacement works, these triggers are all paired with a secondary cluster trigger. These cluster triggers check, when maintenance or replacement works are triggered, if the bridge is part of a cluster (e.g. a geographical cluster). If true, the cluster trigger is used to signify maintenance or replacement events instead of the singular triggers described above.

The bridge entity type has 5 (sub)collections. Firstly, the bridge collection, allows for access to aggregate values of all the bridges in the model. This collection calculates some of the outcomes that will be used in chapter 0. These are the (1) total projects executed, (2) change in capacity utilization, (3) average load capacity and (4) average fatigue damage. The total number of executed projects is determined by aggregating values from all variables that initiate maintenance or replacement activities, as explained earlier. The change in capacity utilization expresses the percentage change in projects being executed in year *t,* compared to year *t-1*. Lastly, the average load capacity $\overline{C_L(t)}$ and average fatigue damage $\overline{D_F(t)}$ are determined by taking the average value for these two stocks of the entire collection of bridges.

Secondly, the bridge by PairID collection, is used to access the status of bridges for each pair of roads that match the PairID of a bridge. This collection is primarily used to define the variable 'bridge flow', which calculates for each pair of roads if its bridge is open or closed for maintenance or replacement. The variable returns 1 if no maintenance is active, and it returns 0 if the sum of the aggregate maintenance or replacement triggers is larger than 0. The bridge flow variable is used in the Region to Region entity to determine the traffic flow for each road.

Thirdly, the bridge by ClusterID collection, collects information from all bridge entities and aggregates it by ClusterID. This collection is used to facilitate the creation of the cluster triggers mentioned earlier. The built-in count variable allows Ventity to keep track of the amount of bridges in a cluster. The cluster triggers in the bridge entity type use this count variable to determine if there are other bridges that belong to the same cluster. In this thesis, three types of Clusters will be distinguished: (1) Geographical, (2) Construction year and (3) Bridge type. More information on clustering can be found in section 3.6.3.

Lastly, the bridge collections by RoadID and Type are only used to provide some additional information to the model user. The variables defined in these collections are not used anywhere else in the model.

3.4.2 Bridge part

The bridge part entity type defines the condition, degradation and restoration of two types of bridge parts, the construction and the electrical components. This entity type contains two stocks. Firstly, the recovery value of condition $c_{rv}(t)$ captures the declining impact of restoration works on a bridges condition as it ages. It is determined by the initial recovery value of condition $c_{rv}(t_0)$ and a yearly decline in recovery value of condition $d_{rv}(t)$, resulting in equation 7.

$$c_{rv}(t) = c_{rv}(t_0) - \int_{t_0}^{t} d_{rv}(t)\, dt, \tag{7}$$

The initial recovery value of condition is a function of a yearly decline in recovery value factor f_a and the initial age of a bridge. This results in equation 7.1.

$$c_{rv}(t_0) = (1 - f_a)^{age} \tag{7.1}$$

The yearly decline in recovery value of condition $d_{rv}(t)$ is a function of the yearly decline in recovery value factor f_a and the recovery value of condition $c_{rv}(t)$. To ensure that the decline in recovery value is never higher than the recovery value of condition, the minimum between $c_{rv}(t)$ and f_a is taken.

$$d_{rv}(t) = \min\left(c_{rv}(t), f_a\right) \tag{7.2}$$

Secondly, the bridge part entity type is used to calculate the restoration $r_{BP}(t)$ and degradation $d_{BP}(t)$ of bridge parts, which are used to determine the load capacity in the bridge entity type (see equation 4). The bridge condition $c_b(t)$ is a function of the restoration and degradation and can be expressed as follows:

$$c_b(t) = c_b(t_0) + \int_{t_0}^{t} r_{BP}(t) - d_{BP}(t)\, dt, \tag{8}$$

The restoration $r_{BP}(t)$ is calculated using the recovery value of condition $c_{rv}(t)$, and can be expressed as follows:

Where $c_b(t_0)$ is a function of the age of the bridge, and $r_{BP}(t)$ and $d_{BP}(t)$ are expressed as follows:

$$r_{BP}(t) = \ T_{LM}(t) * c_r(t) \tag{8.1}$$

$$d_{BP}(t) = \ \min(c_b(t), a_{BP}) \tag{8.2}$$

In equation 8.1, $T_{LM}(t)$ is a trigger that returns 1 when the bridge is scheduled for large maintenance, and 0 in all other cases. The recovery of condition $c_r(t)$ is a function of the condition of a bridge $c_b(t)$ and the recovery value of condition $c_{rv}(t)$. Equation 8.2 calculates the degradation $d_{BP}(t)$ by taking the minimum between the condition of a bridge $c_b(t)$ and an aging factor a_{BP}. The auxiliary variables f_a and a_{BP} contain different values for the two bridge parts that are distinguished in this entity type. When used in equations 7.1, 7.2 and 8.2, the values of the variables are automatically combined to result in one condition degradation and one decline in recovery value of condition value per bridge.

3.4.3 Project

The project entity type is used to invoke a reset in fatigue damage for bridges that get replaced. This entity type is linked to the bridge entity type via the action ‘create project’. In the bridge entity type, if the required restoration size for a bridge is equal to or greater than the projected fatigue damage threshold, a bridge gets replaced instead of renovated. Replacing a bridge invokes the ‘create project’ which creates a project entity in the project entity type. The project entity inherits the BridgeID from the bridge that is being replaced, and the current model time is assigned as the project start time.

In the project entity, the end time of the replacement project is determined by adding the period required for replacement to the start time of the project. The period required for replacement is a constant, which is assumed to be 10 years. The bridge will only be closed for traffic in the last year of these 10 years, as the period required for replacement refers to the entire project cycle, including planning and designing the replacement project. Once the ending time of the project is reached, the project entity invokes another action called ‘reset fatigue damage’. This action resets the fatigue damage of the bridge corresponding to the BridgeID of the project.

3.4.4 Region

The Region entity type is one of the entity types used to design the spatial component of the model. There are 14 region entities in the model, labeled A through N (see figure 6). The region entity type contains two stocks, the amount of vehicles in a region and the amount of inhabitants in a region. Firstly, the amount of vehicles in a region $V_n(t)$ is a function of the increase in traffic intensity of region n I_n, and the traveling of vehicles between regions n and m $T_{n,m}(t)$. This yields:

$$V_n(t) = V_n(t_0) + \sum_{i=1}^{N} \int_{t_0}^{t} \left[\left(I_n * V_n(t)\right) + T_{m,n} - T_{n,m}\right] dt, \tag{9}$$

Where I_n is a constant, $V_n(t_0)$ is defined in the entity initialization file, and the amount of vehicles from- and to a region $T_{n,m}$ and $T_{m,n}$ are calculated in the Region to Region entity type (see chapter 3.4.5).

Secondly, the population of a region is determined by only one flow, the population growth. Due to the focus of the model being the infrastructure network, the decision has been made to implement a simple population submodel. The population of a region exclusively serves as a determinant for assigning traffic flows to that region. Larger regions receive a proportionately higher share of traffic flow, while smaller regions receive a relatively smaller share. The distribution of traffic flows is determined by the ratio of inhabitants in a region compared to the total population in the model. The population of a region $P_n(t)$ is defined as follows:

$$P_n(t) = P_n(t_0) + \sum_{i=1}^{N} \int_{t_0}^{t} P_n(t) * gp_n \, dt, \tag{10}$$

Where the population growth per region gp_n is a constant, and $P_n(t_0)$ is defined in the entity initialization file. Due to the population growth per region being positive, all the regions see a linear growth in population during a model run. Using the population of a region, we can also define the distribution of traffic flows for a region $df_n(t)$.

$$df_n(t) = \frac{P_n(t)}{\sum_{i=1}^{N} P_n(t)} \tag{10.1}$$

The distribution factor $df_n(t)$ is a normalized value, ensuring that the sum of distribution factors for all regions is equal to 1 (indicating the entire flow is distributed among the regions).

3.4.5 Region to region

The Region to Region entity type is used to facilitate traffic flows from region to region. This submodel uses auxiliaries and stocks defined in the Region and Road entity types as well as the Bridge by PairID subcollection, and several Region to Region subcollections. This section will expand upon section 3.2, which presented the design of the spatial component of the model using the Region, Road and Region to Region entity types. The Region to Region entity type contains a stock-flow structure that allows vehicles to move to another region. A visual representation of a simple version of this stock-flow structure can be seen in figure 7 in section 3.2 . The structure utilizes two references to the amount of vehicles in a region $V_n(t)$ stock from the Region entity type These references are labeled as 'FromRegion' and 'ToRegion', using the attributes assigned to the Region to Region entity type. The labels are used to distinguish the directionality of the traffic flow between regions. Both references to the stock are connected via one flow labeled ‘traveling’, which represents the traveling of vehicles between regions $T_{n,m}(t)$ (see also equation 9). The traveling flow $T_{n,m}(t)$ is defined as follows:

$$T_{n,m}(t) = \max\left(0, \min\left(\frac{C_{n,m}}{f}, \left(\frac{V_n(t) * Dist_{n,m}(t)}{Tt_{n,m}}\right) * \frac{1}{f}\right) * fb_{n,m}(t)\right) \quad (11)$$

Figure 9 shows the stock-flow structure associated with equation 11. The stocks and auxiliaries that contain a green text color indicate that they are defined in a different entity type (e.g., Road capacity is defined in the Road entity type).

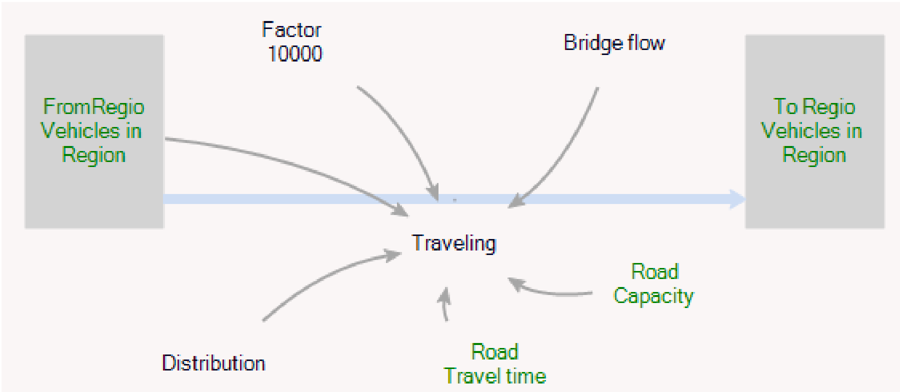

Figure 9: Traveling stock-flow structure

The max and min functions ensure that the travel flow is non-negative and never higher than the capacity of the road connection regions n and m.The min function further calculates the non-restricted traffic flow by multiplying the amount of vehicles in region n with the distribution of vehicles traveling from region n to region m and dividing by the travel time associated with the road from n to m. As mentioned in section 3.2, in order for the Region to Region entity to exhibit expected behavior, the traffic flows are divided by 10.000, which is represented by the constant f in equation 11. Furthermore, the bridge flow variable $fb_{n,m}(t)$ represents the status (1 or 0) of the bridge located on road from n to m. If the bridge is closed due to maintenance ($fb_{n,m}(t) = 0$), the entire term becomes zero, indicating that there is no traffic flow between the regions. For roads that do not have a bridge assigned to them, $fb_{n,m}(t)$ is always 1. The bridge flow variable is defined in the Bridge by PairID subcollection, which leads to the closure of both directions of the road associated with a bridge.

The stock $Dist_{n,m}(t)$ distributes the traffic flows throughout the network. It uses the ratio of inhabitants in a region compared to the total population in the model $df_n(t)$ as the base distribution of traffic flows, $df_n(t)$ is calculated in the Region entity type (see equation 10.1). The allocation of traffic flows for a given road decreases to 0 when the bridge assigned to the road is closed. In the event of a bridge closure, the model assigns the lost traffic flows uniformly to the roads connected to the same origin as the closed road. In the event that a road reopens due to the completion of bridge maintenance, the distribution of all affected roads is set to its base value, which is equal to $df_n(t)$. The distribution for the traffic flow on the road from n to m, $Dist_{n,m}(t)$ can be expressed as follows:

$$Dist_{n,m}(t) = Dist_{n,m}(t_0) + \int_{t_0}^{t} id_{n,m}(t) - \min\left(\left(\left(1 - fb_{n,m}\right) * Dist_{n,m}(t)\right) + o_{n,m}(t), 1\right) dt, \tag{12}$$

Figure 10 shows the stock-flow structure associated with equations 12 and 12.1.

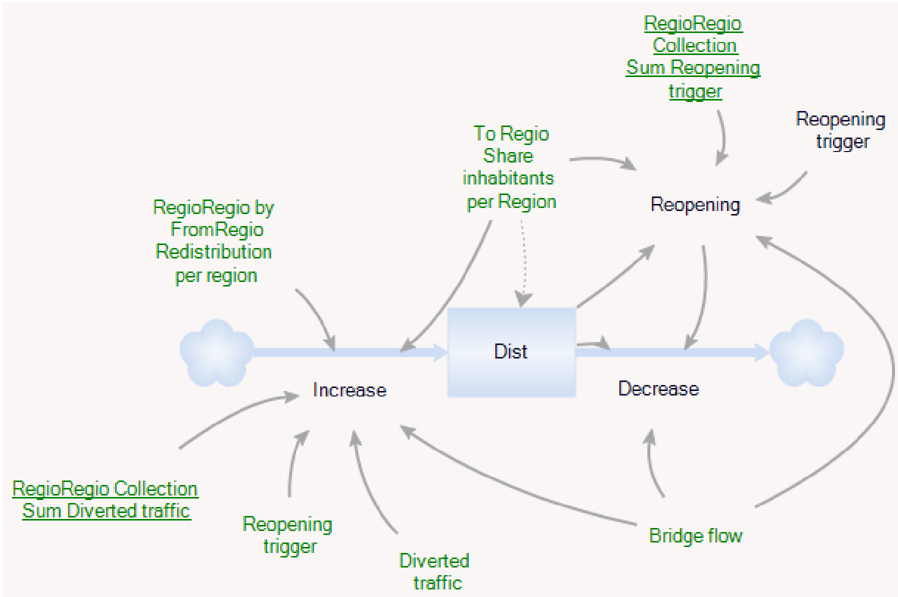

Figure 10: Distribution stock-flow structure

The decrease in distribution for a given road is determined by a min function, that ensures that the decrease does not exceed 1. If a bridge is closed ($fb_{n,m} = 0$), the entire distribution value of the road is set to 0. The reopening of a bridge $o_{n,m}(t)$, calculates the difference between the current value of the distribution of a road and the value it should have based on the base distribution $df_n(t)$. This reopening variable only affects roads that obtained an increased distribution do to a road with the same origin closing down for bridge maintenance. In the event of a bridge reopening, a trigger ensures that the value of the reopening variable $o_{n,m}(t)$ is subtracted for every relevant road. The increase in distribution for a given road $id_{n,m}(t)$ is defined as follows:

$$id_{n,m}(t) = \begin{cases} red_n(t), & div_{n,m}(t) = 0 \text{ and } fb_{n,m} = 1 \text{ and } \sum_{i=1}^{N} div > 0 \\ o_{n,m}(t) * df_n(t), & else \end{cases} \tag{12.1}$$

The increase in distribution $id_{n,m}(t)$ is defined in the model using an IfThenElse statement. Firstly, the function checks if amount of diverted traffic on a road $div_{n,m}(t)$ is equal to 0, the bridge corresponding to that road is open ($fb_{n,m} = 1$), and sum of diverted traffic in the model is larger than 0. The conditions for $div_{n,m}(t)$ and $fb_{n,m}$ are used to ensure that the bridge on a road is not closed. The diverted traffic variable $div_{n,m}(t)$ indicates, in case of the closing of a bridge, how many vehicles would drive over that road if the bridge would have been open. Secondly, $\sum_{i=1}^{N} div > 0$ checks if there is diverted traffic in the model, to ensure that this part of the function will only be valid if there is a closed bridge in the model. If these 3 conditions are true, the function returns $red_n(t)$. This variable is defined in the Region to Region by FromRegion collection, and calculates the distribution that has to be redistributed due to a bridge closing down. This distribution is then redistributed uniformly over roads that hold the same origin (the same FromRegion value) as the road that is closed.

In all other cases, the increase in distribution $id_{n,m}(t)$ returns $to_{n,m}(t) * df_n(t)$. Where $to_{n,m}(t)$ is a trigger that returns 1 when a bridge gets reopened, and 0 in all other cases. The moment of reopening for a bridge is determined by applying a delay of 1 year to the trigger that indicates a bridge closure $fb_{n,m}$. If a bridge reopens, the original base distribution $df_n(t)$ is added to the road again.

Initially, the distribution was determined using an auxiliary. However, to prevent a circularity error in the model, the distribution was changed into a stock-flow structure. The circularity error appeared due to the distribution impacting the degradation of bridges, while the degradation of bridges also impacted the distribution of traffic flows as the closing of a bridge leads to an increased traffic flow allocation for neighboring roads.

The Region to Region entity type has 4 (sub) collections. Firstly, the Region to Region collection allows for access to aggregate values of all the entities in this submodel. This collection is used to compute three aggregate values, the sum of diverted traffic, the sum of reopening triggers and the minimum accessibility for a region. The sum of diverted traffic is used in equation 12.1, while the sum of reopening triggers is used to calculate $o_{n,m}(t)$ in equation 12. Accessibility is defined as the amount of open roads towards a region divided by the total amount of roads heading into a region. The minimum accessibility of a region then takes the minimum value of all the regions in the network at time t. Secondly, the Region to Region by FromRegion collection is used to determine the redistribution for a given region in case of bridge closure $red_n(t)$. This variable is used in equation 12.1. Lastly, the variables defined in the Region to Region collections by ClusterID and ToRegion are not used in any other equations in the model. Instead, these collections provide some additional information to the model user.

3.4.6 Road

The Road entity type is primarily used to provide road specific values to the Region to Region entity type and to provide values to bridges that correspond to certain pairs of roads. This submodel contains 3 stocks, (1) Kilometers driven per road, (2) transport movements, and (3) weight on road. Firstly, the kilometers driven per road $KM_{n,m}(t)$ calculates the total amount of kilometers that have been driven over a road during the simulation time. The stock is only influenced by one flow, the increase in kilometers driven. This yields:

$$KM_{n,m}(t) = KM_{n,m}(t_0) + \int_{t_0}^{t} \left(T_{n,m}(t) * l_{n,m}\right) * f \ dt, \tag{13}$$

Where $KM_{n,m}(t_0) = 0$, $l_{n,m}$ is a constant that represents the length of a road, and f is a factor 10.000. This last factor is added in the equation because the traffic flow $T_{n,m}(t)$ is divided by 10.000 (see equation 11).

Secondly, the total amount of transport movements for a road $TM_{n,m}$ is determined by the annual increase in transport movements. This annual increase is equal to the traffic flow per year divided multiplied by a factor 10.000 f. This yields:

$$TM_{n,m}(t) = TM_{n,m}(t_0) + \int_{t_0}^{t} T_{n,m}(t) * f \ dt, \tag{14}$$

The total amount of transport movement is also used to determine the total time travelled over a road. To obtain the total travel time, the amount of transport movements on a road is multiplied by the average travel time of the road. The total amount of transport movements is used to calculate the fatigue damage of a bridge in the bridge entity type.

Lastly, the weight on a road $W_{n,m}(t)$ is determined by the increase and decrease of the weight on a road, denoted as $wi_{n,m}(t)$ and $wd_{n,m}(t)$. The weight on a road is total cumulative weight on a road in one timestep (i.e., one year). This yields:

$$W_{n,m}(t) = W_{n,m}(t_0) + \int_{t_0}^{t} wi_{n,m}(t) - wd_{n,m}(t) \ dt, \tag{15}$$

Where $wi_{n,m}(t)$ and $wd_{n,m}(t)$ are both a function of the change in vehicle weight on a road $delta\_w_{n,m}(t)$. The change in vehicle weight is defined as the difference between the vehicle weight on a road at time t and time $t-1$. $wi_{n,m}(t)$ and $wd_{n,m}(t)$ are defined as follows:

$$wi_{n,m}(t) = \begin{cases} delta\_w_{n,m}(t), & delta\_w_{n,m}(t) > 0 \\ 0, & else \end{cases} \tag{15.1}$$

$$wd_{n,m}(t) = \begin{cases} delta\_w_{n,m}(t), & delta\_w_{n,m}(t) < 0 \\ 0, & else \end{cases} \tag{15.2}$$

Furthermore, the change in vehicle weight on a road is a function of the traffic flow per year multiplied by the average weight of a vehicle and a factor 10.000. The average weight of a vehicle $w(t)$ is determined by the initial average vehicle weight and a yearly increase in the average vehicle weight w_i. The average weight of a vehicle grows exponentially over the simulation period. This can be expressed as follows:

$$w(t) = w(t_0) * \ (1 + w_i)^t \tag{15.3}$$

Similar to the distribution variable highlighted in the previous section, the weight on a road was initially represented by an auxiliary variable. However, to prevent a circularity error in the model, this variable was also changed into a stock-flow structure. The circularity error appeared due to the weight on a road impacting the degradation of bridges, while the degradation of bridges also impacted the weight on a road as the closing of a bridge leads no vehicles driving over that bridge during that year.

The road entity type has 3 (sub)collections. Firstly, the Road collections aggregates all the data for the entire entity population. This collection is mainly used to calculate the total time travelled, which is used as one of the outcomes of interest in the model (see chapter 3.6.2). The second collection is the Road by PairID. This collection is used to determine two important variables that link the traffic section of the model with the bridge degradation section of the model, these variables are the (1) Road by PairID weight on road, and (2) Road by PairID total amount of transport movements. The aggregate variables use the weight on a road $W_{n,m}(t)$ (equation 15), and the yearly amount of transport movements (equation 14). The Road by PairID collection aggregates the data for roads that match the same PairID, which allows for the use of data for both directions of a road in the Bridge entity type. Lastly, the Road by ClusterID collection is only used to generate some additional insight and validation options for the model user.

3.4.7 Other entity types

This section presents the 4 remaining entity types, (1) traffic, (2) part type, (3) settings and (4) cluster. Firstly, the traffic entity type is a singular entity type used to define the yearly increase in traffic intensity, the yearly growth in the average vehicle weight and the average vehicle weight. A singular entity implies that this entity type is only capable of containing 1 entity, which decreases the work required to use variables defined in this entity type in other entity types. For non-singular entity types, each variable that is used in another entity type has to be matched through attributes. For instance, the travel time per road defined in the Road entity type has to be paired via the RoadID attribute when used in the Region to Region entity type. When using singular entities, this pairing is not necessary as there is only 1 entity that can be paired with. As the yearly increase in traffic intensity and the yearly growth in the average vehicle weight are the same for all the regions and vehicles respectively, the variables are defined in the traffic entity type.

Secondly, the part type entity type contains 3 variables. The yearly decline in recovery value factor f_a (equation 7.1), the aging factor a_{BP} (equation 8.2) and the historical yearly decline in condition. The historical yearly decline in condition is used in combination with the age of the bridge, to determine the initial condition of bridge $c_b(t_0)$ (equation 8). These variables are defined in the entity type so they are able to hold different values for every bridge part that is defined in the entity initialization file. For this thesis, the two bridge parts are the construction and the electrical components.

The settings entity type is another singular entity type, used to define some parameters and triggers used in the model. By defining these parameters and triggers in the settings entity type, it is easy and clear for the model user to change values. Due to the entity type being a singular entity, it is also easy to include the variables defined in the settings entity type in other entity types. Lastly, the cluster entity type is only used to distinguish the possible clusters that bridges and roads can belong to. By adding this last entity type, it becomes possible to create a set of possible clusters (e.g. geographical or by construction year) in the entity initialization file, which can then be used to close bridges in clusters. Moreover, in future research, variables could be added to the cluster entity type to define specific characteristics of certain clusters.

3.5 Model validation

This section will assess whether the model is fit for answering the main research question of this thesis. The goal of the validation process is to increase confidence in the model and determine to what extent the results of the model are useful. There is no single test that can determine the validity of an SD (or Entity-based SD) model. Rather, a set of tests will be used to gradually identify correspondence between the model and empirical reality, and thereby increase confidence in the model (Senge & Forrester, 1980). First, the purpose of this thesis will be discussed to determine if the model is fit-for-purpose. Secondly, the structural validity of the model will be assessed. Lastly, the behavioral validity of the model will be discussed.

3.5.1 Model purpose

The goal of this thesis is to prove that it is possible to construct spatially explicit SD models using Entity-based SD, and to understand the long-term effects of clustering bridge maintenance on the maintenance capacity utilization and performance of the road infrastructure system. In this context, long-term refers to the next 100 years. It is not the purpose of the model to make highly confident forecasts of future traffic behavior or to determine the exact amount of bridge maintenance projects needed in the Netherlands in the coming century. If the former was true, the distribution of traffic flows would have been far more complex than its current version, as the distribution of traffic in the model is only impacted by the size of the regions in the model and the status of bridges.

The purpose of the model was considered when designing the network used in this thesis (see figure 6). The network is an abstract representation of a fictitious network. It is therefore not capable of providing highly confident forecasts for any existing network. Rather, it is designed to support the exploration of the behavior on the system under an array of deeply uncertain futures and policy measures.

3.5.2 Structural validity

In SD, structural validation test include structure-verification, parameter-verification, extreme-condition, boundary-adequacy, and dimensional-consistency tests (Auping, 2018; Senge & Forrester, 1980). The structure-verification test implies comparing the model structure directly with the structure of the real model that the model represents. In order to pass this test, the model should not contradict any of the knowledge about the structure of the real system (Senge & Forrester, 1980). The structure of the bridge replacement and renovation sections of the model was constructed by Copernicos. These submodels (Bridge, bridge type, bridge part, part type and project) capture the degradation, renovation and replacement mechanisms of concrete and steel bridges. The structure of these submodels has been determined and verified with the input from sector experts.

The bridge part entity type captures the degradation and restoration of bridge condition based on the degradation and restoration factors per bridge part. This captures the multi-layered construction of a bridge as different parts have different rates of degradation. Moreover, multiple maintenance strategies are supported in the model, both preventive and corrective maintenance (Sánchez-Silva et al., 2016). Preventive maintenance refers to providing maintenance to make sure that the performance of a structure stays above a certain threshold, while corrective maintenance refers to taking maintenance actions when this performance threshold is reached. In the model, preventive maintenance is modelled through periodic maintenance and corrective maintenance is modelled as just-in-time maintenance. The model does not include any shock-based deterioration, which is deterioration induced by extreme events, such as storms or blasts (e.g. explosions due to accidents) (Sánchez-Silva et al., 2016). Thus, the model is valid under the assumption that no extreme events impact the performance of bridges.

Another assumption of the model is that there is no maximum performance condition for concrete bridges. Where steel bridges have fatigue damage as their condition indicator (ranging from 0 to 1), concrete bridges have carrying capacity as condition indicator. The carrying capacity is not constrained by the initial carrying capacity of a bridge and is therefore able to exceed the initial value during a model run. Hence, the model is only valid if the load capacity of a concrete bridge is able to exceed the initial value of the load capacity of a bridge.

For the spatial section of the model, attempts have been made to resemble reality as close as possible. However, as the objective of this thesis, and therefore the objective of the model, was to prove that it is possible to construct spatially explicit models using Entity-based SD, and to understand the long-term effects of clustering bridge maintenance on the maintenance capacity utilization and performance of the road infrastructure system, certain abstractions have been made. Firstly, the distribution of traffic flows is only influenced by population and bridge status, and the population submodel has been kept highly abstract. In reality, more factors influence the distribution of travel flows, like the economic activity of a region. However, the factors influencing traffic flow distribution in the model are fit for the scope of this thesis, as the impact of bridge closure on traffic flows can be analyzed.

Another abstraction is the lack of traffic jams in the model. As the model is hypothetical, it is assumed that the roads in the model have sufficient capacity to absorb traffic flows from nearby roads that are closed for maintenance, without it impacting the average speed on that road. Thus, the model is only valid for the hypothetical network presented in chapter 3.1.

The parameter-verification test compares the values of model parameters (i.e., constants) against available knowledge of the real system, to determine if these parameters correspond to real life (Senge & Forrester, 1980). In the exploratory modeling approach used in this thesis, parameters are assumed to have a bandwidth of possible values, as determining of a fixed best value is impossible (Auping, 2018). The results of this test can be found in chapter 3.6.1.

The extreme-condition test has two interpretations (Auping, 2018). The first interpretation describes this test as a reality check, meant to assess if the model produces expected behavior in extreme conditions. For instance, if vehicles would seize to drive in the model, this should lead to zero bridge maintenance projects, as degradation would be close to 0. However, if the definition of a variable selected for this test is ambiguous, and the meaning of that variable is therefore misinterpreted, this test becomes problematic (Auping, 2018). The second interpretation of the extreme-condition test is the exploration of conditions under which the model breaks. This interpretation can be well supported by the use of the EMA approach. If wide parameter bandwidths are chosen, the samples taken for the EMA analysis can be considered as extreme-conditions tests.

The model was initially run with the uncertainties and their corresponding ranges presented in table 8 in appendix B. The ranges for most parameters have been set intentionally wide, so that they can provide insight into the conditions under which the model 'breaks'. Figure 11 and figure 12 show the behavior of two outcomes, the total amount of projects executed and the average carrying capacity of all bridges. In case of the total projects executed, the model is assumed to break when there are no projects executed, which is seen to occur for all of the 4 policies. In figure 12, 2 large outliers can be seen that report a far greater average carrying capacity, these are also considered as model breaking. In total, 10.000 of the 20.000 scenarios reported 0 executed projects during the model run. Furthermore, two scenarios were defined as outliers, based on the average carrying capacity. Based on the findings from this test, the ranges of the uncertainty parameters were altered to those presented in table 3.

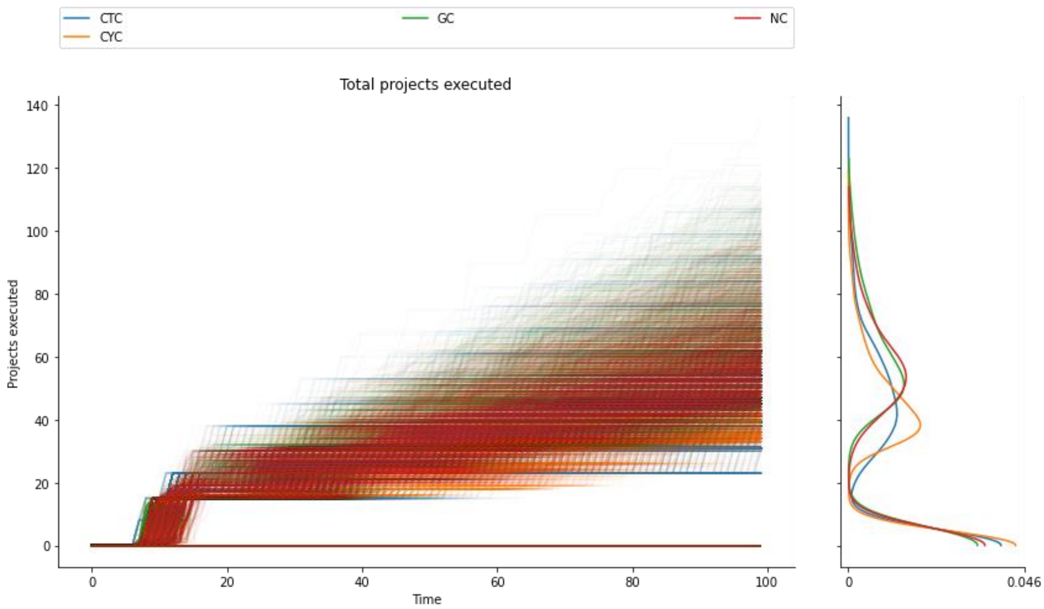

Figure 11: Total projects executed extreme value test

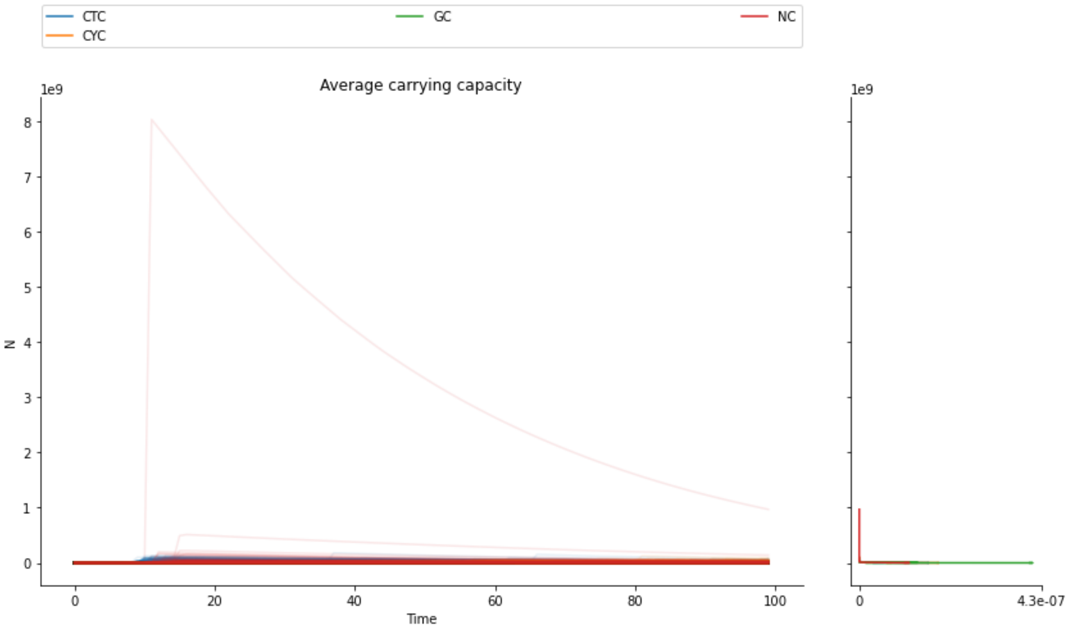

Figure 12: Average carrying capacity extreme value test

Dimensional-consistency can be assessed using the ‘check units’ function in Ventity. This function allows the software to detect any inconsistency in the units used in the equations in the model. If a model fails to pass this test, it is an indication of a defective model structure (Senge & Forrester, 1980). The model constructed in this thesis was found to pass the dimensional-consistency test.

To conclude, the model can be used to prove that it is possible to construct spatially explicit SD models using Entity-based SD, and to understand the long-term effects of clustering bridge maintenance on the maintenance capacity utilization and performance of the road infrastructure system presented in figure 6.

3.5.3 Behavioral validity

For the behavioral validity section, the maintenance projects executed in the model is compared to the prognosis of the Dutch organization for applied scientific research (TNO) (Rasker et al., 2023). The prognosis is determined based on the average expected lifespan of all bridges in the Netherlands. Figure 13 displays this prognosis and shows two clear 'waves' of maintenance projects, the first being around the years 2035 to 2040, and the second being around 2085 to 2090.

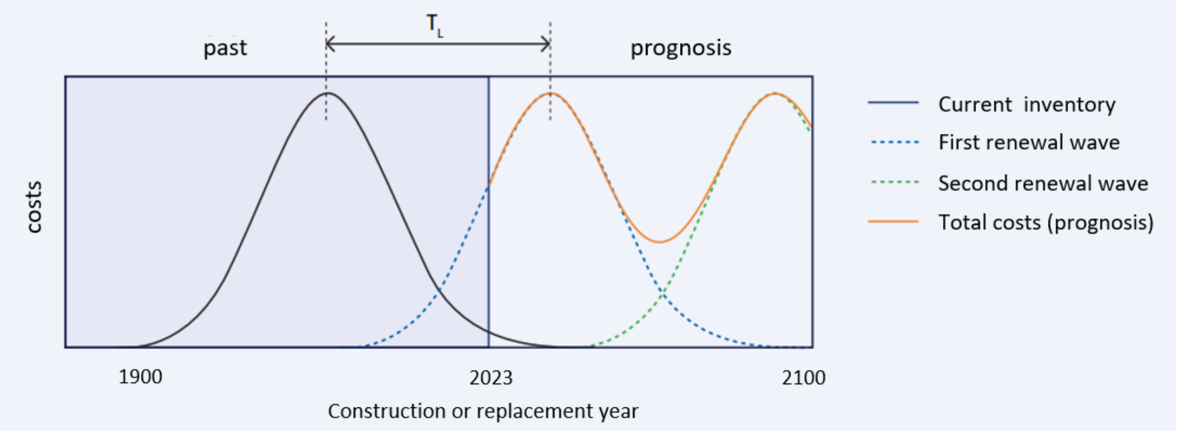

Figure 13: Maintenance wave prognosis (adapted from (Rasker et al., 2023))

Figure 14 presents the cumulative amount of maintenance projects executed over time of one model run, using a just-in-time maintenance strategy and without any active policies. A clear first maintenance wave can be seen around the year 2035, which is consistent with the forecast made by Rasker et al. (2023). Moreover, a steep increase in the amount of maintenance projects can also be seen around the years 2085 to 2090, which indicates that the model corresponds to the rough prognosis in figure 13.

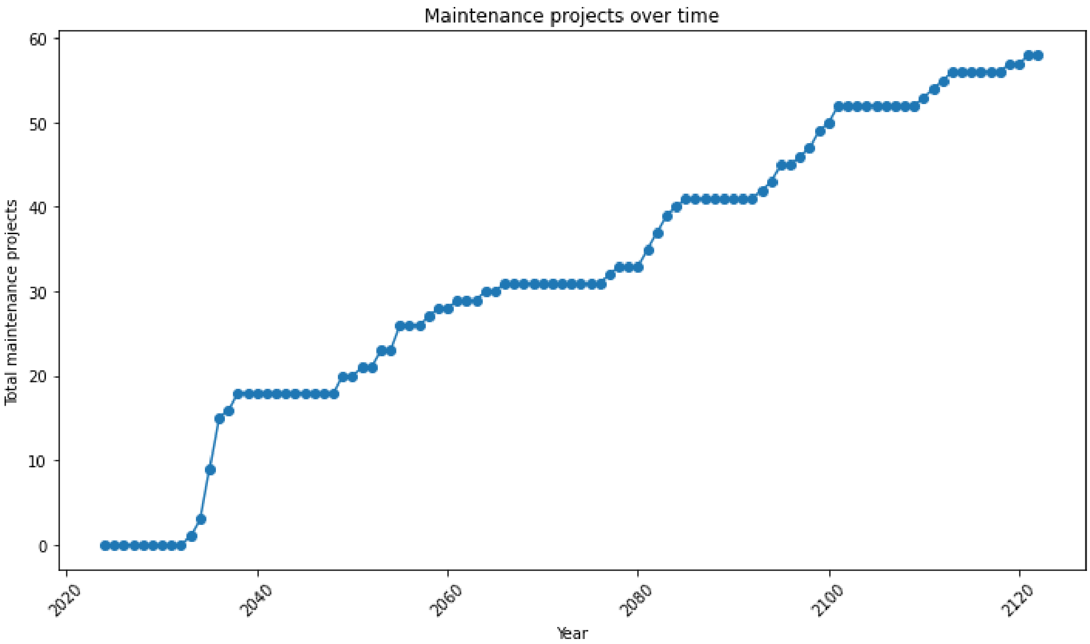

Figure 14: Maintenance projects over time

The model output shows many more maintenance waves, which can be explained by way the set of bridges and the way the model forecasts the required size of reinforcement maintenance. The model creates a forecast, based on a forecast horizon given as a parameter, to determine the size of the reinforcement maintenance. The forecast horizon is given as 25 years in the model corresponding to the data in figure 14. Figure 15 depicts the difference between the total amount of maintenance projects over time for a forecast horizon of 25 and 50 years, to illustrate the impact of this parameter on the maintenance waves. Both scenarios return the same first big maintenance wave around, while also containing a smaller wave around the year 2090.

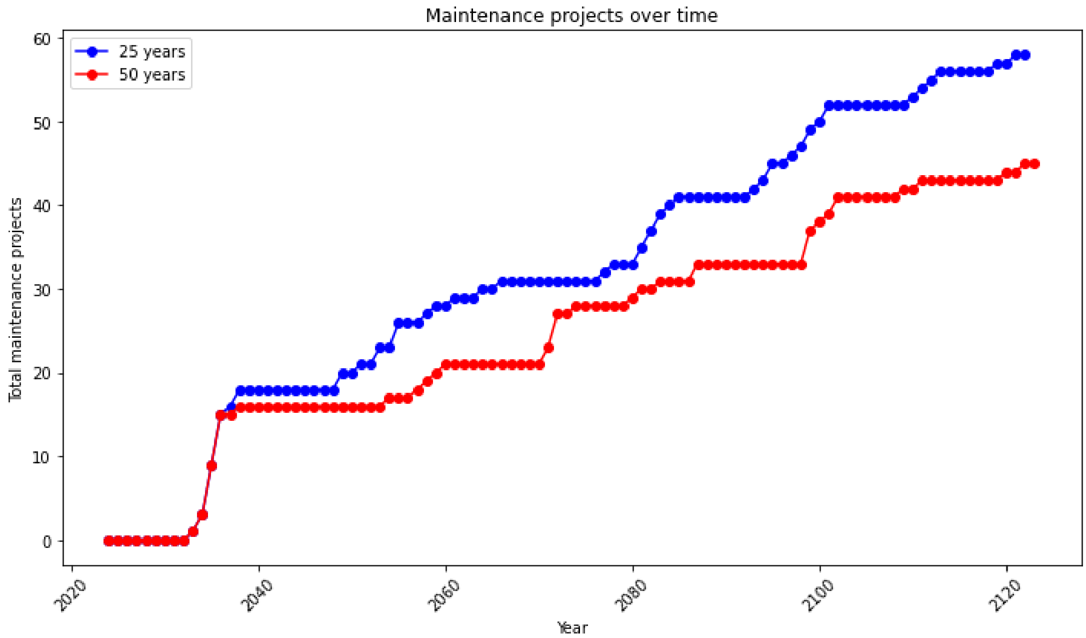

Figure 15: Maintenance projects over time with different forecast horizons

For a second behavioral validation, the relationship between the spatial component and the bridge degradation is presented in figure 16 and figure 17. Firstly, figure 16 shows the bridge load, load capacity and status of bridge b1 (situated on the road between region A and C in the network). The bridge load is determined by the vehicles driving over the bridge and the weight of the deck of the bridge. When the bridge is closed (indicated by the light blue bar) due to maintenance, the capacity increases in the next timestep, indicating that the maintenance is completed. The load on the bridge drops to 0 in the following timestep, as traffic is unable to cross the bridge. Both the capacity and load change 1 timestep later than the bridge status, as both are calculated using stock-flow structures. The stock that holds the relevant information updates the timestep after the maintenance trigger is active.

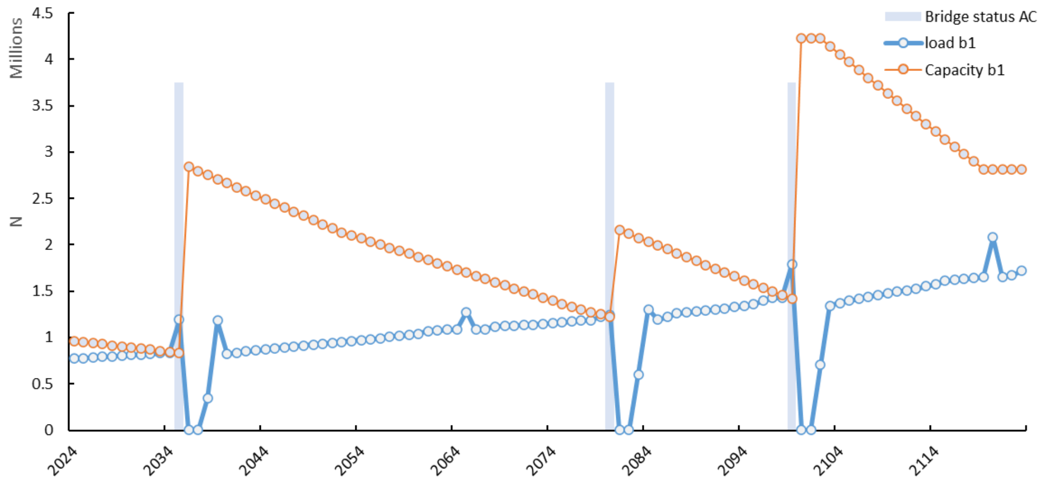

Figure 16: Bridge status, load and capacity

Figure 17 shows the relationship between the traffic flow and the load on bridge b1. An increased traffic flow is the direct result of the closure of another bridge linked to either region A or C, and a decreased (not to 0) traffic flow is the result of the opening of another bridge linked to region A or C. A traffic flow equal to 0 indicates that the bridge on road AC is currently closed. As the figure shows, the load on a bridge moves with the change in traffic flow on the road. As explained above, due to the load on bridge variable being calculated via a stock-flow structure, the load is updated one timestep after the traffic flow.

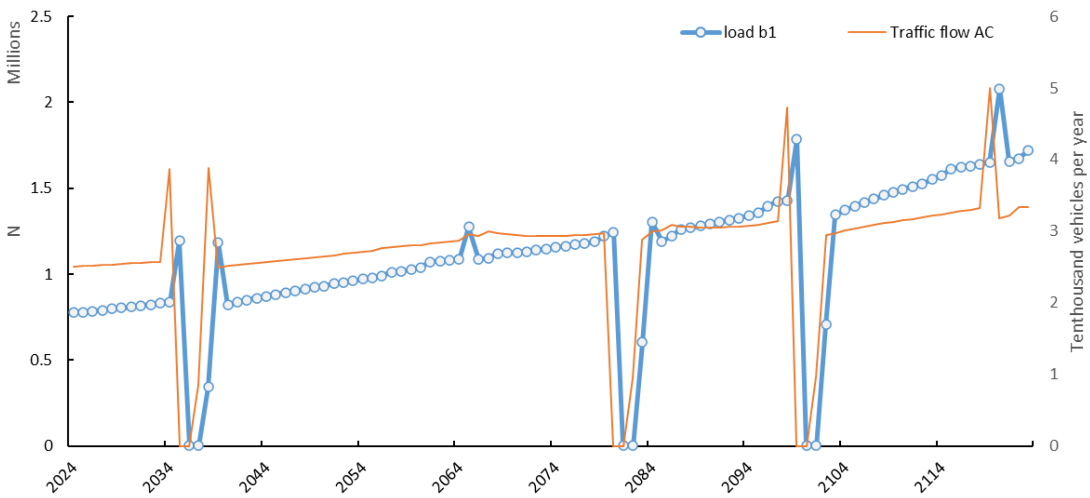

Figure 17: Bridge load and traffic flow

3.6 Experimental setup

The experimental setup is designed with the Robust Decision Making framework (Lempert et al., 2006), which was introduced in chapter 2.4. This implies that the experimental setup contains three steps, (1) scoping, (2) scenario discovery and (3) policy (re)design. Firstly, the scoping of the analysis is determined using the XLRM framework (Lempert, 2003) that was introduced in chapter 2.3.2. The model uncertainties are presented in chapter 3.6.1. Secondly, the outcome metrics, or outcomes of interest are discussed in chapter 3.6.2. Lastly, the policies levers that will be tested in the experiment are presented in 3.6.3.

To run the model, Ventity version 5.0 beta 6 by Ventana Systems was used. For scenario discovery, 5.000 runs are performed using the Latin Hypercube sampling method for each of the policies. This results in a DataFrame of 2.000.000 rows and 68 columns. To measure the performance of the different policies, statistical (or density based) robustness is chosen as robustness metric. The more the distribution of the expected outcomes is skewed or peaked towards the desired region of outcomes, the more robust the policy is considered to be (Kwakkel et al., 2016).

The model is run using the sensitivity analysis function in Ventity, where the same run seed will be used for all the policies. The model is run using a timestep of 1 years, with a simulation time of 100 years. In order to decrease the output file size and the simulation time, a savelist is created in Ventity which ensures that only the variables of interest are exported into the output file. With the savelist active, 20.000 runs (5.000 runs for 4 policies) only take around 3 minutes to complete using an HP Zbook Studio x360 G5 with an Intel Core i7 processor. However, due to the large sizes of the output files, the amount of runs has been limited to 5000 per policy. For the analysis of the model runs, the EMA workbench version 2.5.0 was used in combination with Python version 3.8.8.

3.6.1 Model uncertainties

The model contains a series of exogenous parameters that require a manual data input. The uncertainties that will be sampled over using the EMA Workbench can be seen in table 3, along with the equation that the uncertainties play a role in and their reference (if applicable). The sixth column indicates the type of uncertainty. Two types of uncertainties are distinguished, parametric and structural. Structural uncertainties refer to different possible formulas in the model, which are varied through switch variables. For instance, if the value for the periodic bridge reinforcement is equal to 1, the 'just-in-time' strategy for bridge reinforcement works is turned off, and changed to a periodic strategy instead. As of yet, Ventity does not allow the user to specify that a variable can only hold integers. Therefore, a sensitivity trigger has been added to the model to correctly change the values for periodic bridge maintenance. If the value of the corresponding sensitivity trigger is equal to or greater than 0.5, the uncertainty takes on the value of 1. On the contrary, if the sensitivity trigger is smaller than 0.5, the uncertainty takes the value 0.

Table 3: Model uncertainties

Name	Entity	Unit	Min	Max	Type	Equation	Source
Yearly growth average vehicle weight	Traffic	%	0.35	0.8	Parametric	15.3	(Copernicos Groep, 2018)
Yearly growth in traffic intensity	Traffic	%	0.24	0.36	Parametric	9	(Copernicos Groep, 2018)
Population growth	Settings	%	2.5	5.0	Parametric	10	(Compendium voor de Leefomgeving, 2023)
Average vehicle speed	Traffic	Km/hour	60	100	Parametric	11	Assumption
Safety margin bridge load	Settings	%	1	10	Parametric	4	Assumption
Period between bridge reinforcement works	Settings	Year	10	30	Parametric	N/A	Assumption
Aging factor Construction	Part type	%	0.83	1.25	Parametric	8.2	Assumption
Aging factor E & W	Part type	%	1.12	1.68	Parametric	8.2	Assumption
Factor historical annual deterioration in condition Construction	Part type	%	0.0024	0.0036	Parametric	7	Assumption
Factor historical annual deterioration in condition E & W	Part type	%	0.0040	0.0060	Parametric	7	Assumption
Factor historical annual reduction in condition recovery Construction	Part type	%	0.00064	0.00096	Parametric	7.1	Assumption
Factor historical annual reduction in condition recovery E & W	Part type	%	0.004	0.006	Parametric	7.1	Assumption
Periodic bridge maintenance	Settings	Dimensionless	0	1	Structural	8.1	N/A

3.6.2 Outcomes of interest

For this thesis, 5 outcomes of interest were selected. Firstly, the minimum accessibility for a region, is chosen to be able to monitor if any of the policies result in the total exclusion of a region in the network. This would be an unacceptable result of a clustering policy, as all regions have to be accessible by at least 1 road at all times. Secondly the total travel time is included as one of the outcomes of interest as an indicator of the effect of a clustering policy on the performance of the road infrastructure network. The total projects executed is chosen as it gives an overview of the total maintenance capacity needed over the model simulation time. As an extension to this, the change in capacity utilization represents the percentage change in maintenance projects in each year, compared to the year before. This outcomes is included because it is desirable to obtain a constant and predictable flow of maintenance projects, instead of a select few years where big maintenance ‘bubbles’ have to be processed. Lastly, the average load capacity of all bridges in the model keeps track of the average quality of the bridges in the model. This last outcome is included to provide more insight in the performance of the policy options. For instance, It could be the case that a policy option results in a far lower amount of projects executed and a more stable change in capacity utilization than the other policy options, however, the performance can be placed context if the average quality of the bridges is also considered. Table 4 presents an overview of the outcomes of interest with their corresponding units.

Table 4: Outcomes of interest

Name	Unit
Minimum accessibility for a region	%
Total travel time	Hour
Total projects executed	#
Change in capacity utilization	%
Average load capacity	N

3.6.3 Policy levers

The policy levers in the model represent 4 different maintenance clustering strategies. In the model, these policy levers are modelled as triggers. The bridge model contains three triggers that determine if a bridge gets maintenance. In order to allow for clustered maintenance and replacement works, these triggers are all paired with a secondary cluster trigger. These cluster triggers check, when maintenance or replacement works are triggered, if the bridge is part of a cluster (e.g., a geographical cluster). If true, the cluster trigger is used to signify maintenance events for all bridges in the cluster instead of the singular triggers described above. As the set of bridges only includes concrete bridges, only reinforcement maintenance will be performed during a model run.

Table 5 presents an overview of the policy levers. The no clustering policy contains zero maintenance policies, each bridge gets maintenance individually. The other policies will be compared with this 'no interference' scenario. Three alternative clustering policies are considered, (1) geographical clustering, (2) construction type clustering, and (3) construction period clustering. The selection of clustering policies is motivated by the findings of Assaf and Assaad (2023), which suggest that geographic proximity, similarity in project types and similarity in condition rating of projects are the most important considerations in designing infrastructure project bundling strategies. Firstly, geographic proximity is represented by the geographical clustering policy. Secondly, the similarity in project types will be represented by the construction type clustering policy. Lastly, the condition rating of projects is represented by the construction period clustering policy. As the initial load capacity of a bridge is a function of the age of the bridge (see chapter 3.4.1), bridges with the same age (i.e., the same construction year) will have the same initial condition rating. The rest of this chapter will present the clustering policies in more detail.

Table 5: Policy levers

Name
No clustering
Geographical clustering
Construction type clustering
Construction period clustering

Geographical clustering

The geographical clustering policy will bundle maintenance activities based on the location of bridges in the model. Figure 18 shows a visual representation of the 5 geographical clusters. The figure depicts the initial division of geographical clusters. In chapter 4, the geographical clustering will be further refined based on the first results of the experiments, in line with the RDM methodology.

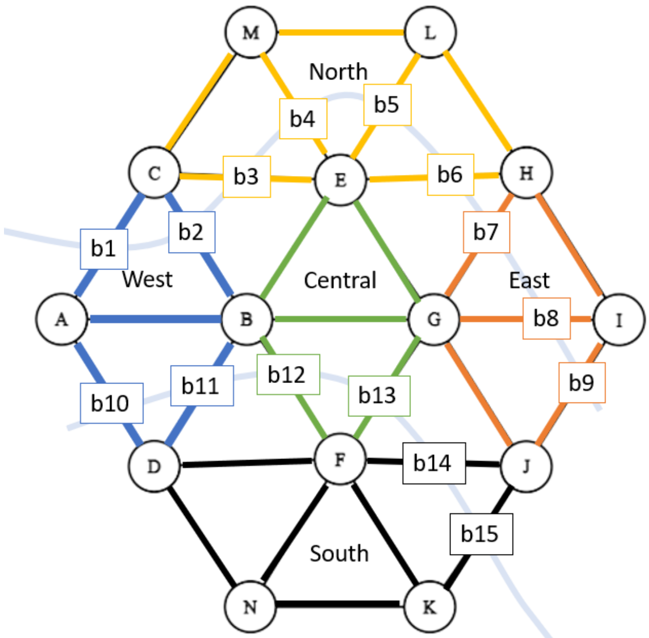

Figure 18: Network with geographical clusters

Construction type clustering

The second clustering policy bundles bridges based on their construction type. Bridges are categorized as either small concrete bridges or big concrete bridges. The characterization is in line with each of the bridges real-life counterpart, and is obtained from the Copernicos bridge database (Copernicos Groep, 2024). Figure 21 shows the construction type of each of the 15 bridges in the model. In total, there are 8 small concrete bridges and 7 big concrete bridges.

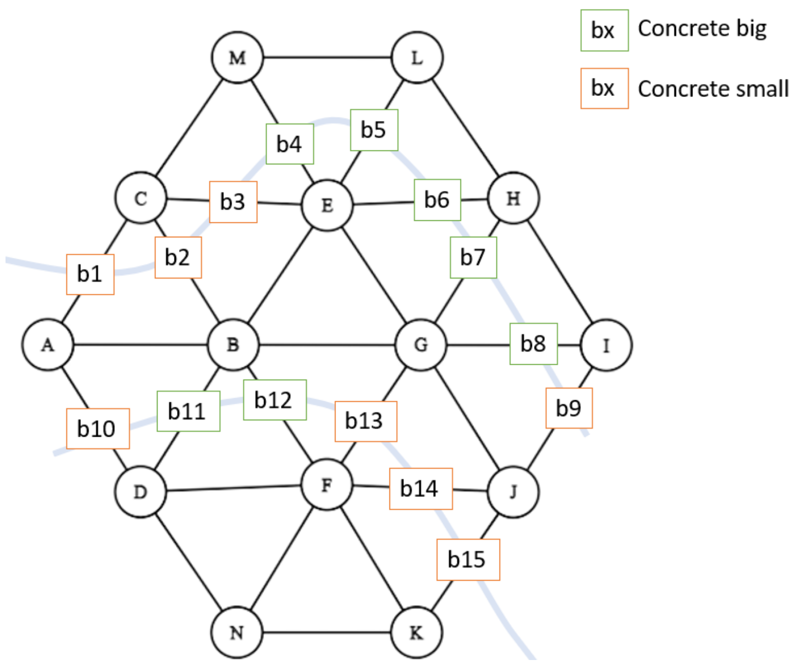

Figure 19: Network with construction type clusters

Construction year clustering

The third and last clustering policy bundles bridges based on the year in which they were constructed. The year of construction is then aggregated to the decade corresponding to the year. Figure 20 shows the distribution of construction years of the bridge set, along with the distribution (in percentages) of the construction years of the national database of which the bridge set is a subset. As shown in the figure, the construction year distribution of both datasets are similar, indicating that a representative subset of bridges (in terms of age) has been chosen for this thesis. Figure 21 shows the bridges and their construction year cluster in the network.

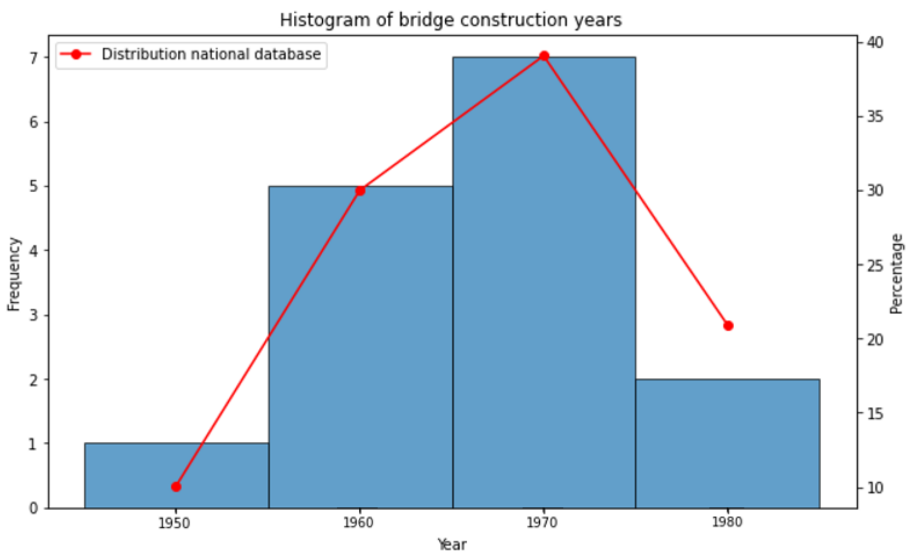

Figure 20: Bridge construction years

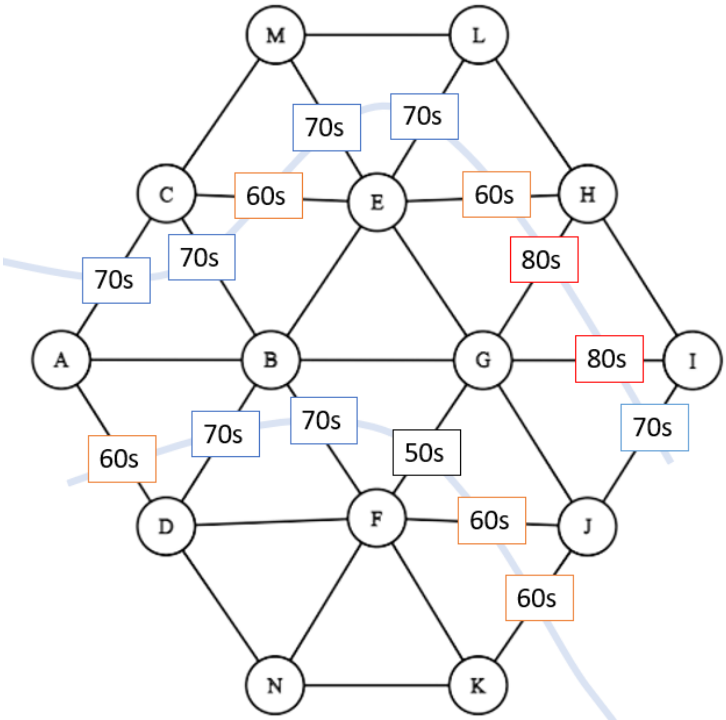

Figure 21: Network with construction years

4 Results

The results in this chapter are based on a homogeneous network, where all regions have an equal population, an equal amount of initial vehicles, and the same distance between all other regions. The results presented in this chapter have been generated and analyzed using a combination of the sensitivity analysis function in Ventity and the EMA Workbench. In order to facilitate the connection between Ventity and the EMA Workbench, the connector presented in section 2.3.2 has been used. The code used to analyze the results can be found here.

Section 4.1 discussed the performance of each of the cluster policies, by analyzing their impact on the behavior of the outcomes of interest. Section 4.2 presents a set of revised geographical clustering policies, and their performance relative to the other policy options. In section 4.3, scenario discovery using a rule-induction algorithm is presented to find regions of interest within the uncertainty space that hold a high concentration of experiments of interest. Lastly, section 4.4 presents an overview of the key drivers of the system.

To increase interpretability, the figures used in this chapter are generated using only 100 runs per policy option, resulting in a maximum of 400 lines per figure. The distributions of expected outcomes for both the 100 runs and 5000 runs per policy are largely consistent, which allows for the interpretation of the figures presented in this chapter. Appendix C contains a side-by-side comparison of the 100 run and 5000 run per policy figures.

Table 6 presents an overview of the abbreviations used in the legends of the figures of this chapter, and their corresponding policies.

Table 6: Policies and abbreviations

Policy name	Abbreviation
No clustering	NC
Geographical clustering	GC
Construction type clustering	CTC
Construction year clustering	CYC

4.1 Clustering policy performance

4.1.1 Capacity utilization

Figure 22 shows an envelope plot of the change in capacity utilization per policy over time. A high value indicates that the capacity utilization increases considerably compared to the year prior. On the contrary, a low value indicates that the capacity utilization remained comparable to the year prior. Consistent low values are considered to be desirable for this outcome, as this indicates that the requested capacity remains consistent, and therefore predictable, over time. The envelope plot displays the maximum and minimum value for a set of runs over time, where a set of runs corresponds to a policy. A small distance between the lowest value and the highest value of a policy indicates that the change in capacity utilization is less variable than policies with larger gaps between the maximum and minimum value. For all policies, the lowest value at any given timestep is 0. The no clustering policy and the geographical clustering policy consistently have the lowest maximum change in capacity utilization over their set of runs.

The period 2030-2040 shows a maximum value of 1 (100%) for the change of in capacity utilization. This is because the first projects in all runs are executed during this time period. The change in capacity utilization is expressed as the percentage change in projects being executed in year *t,* compared to year *t-1*. An increase from 1 to >1 projects therefore returns a change in capacity utilization of 1 (100%).

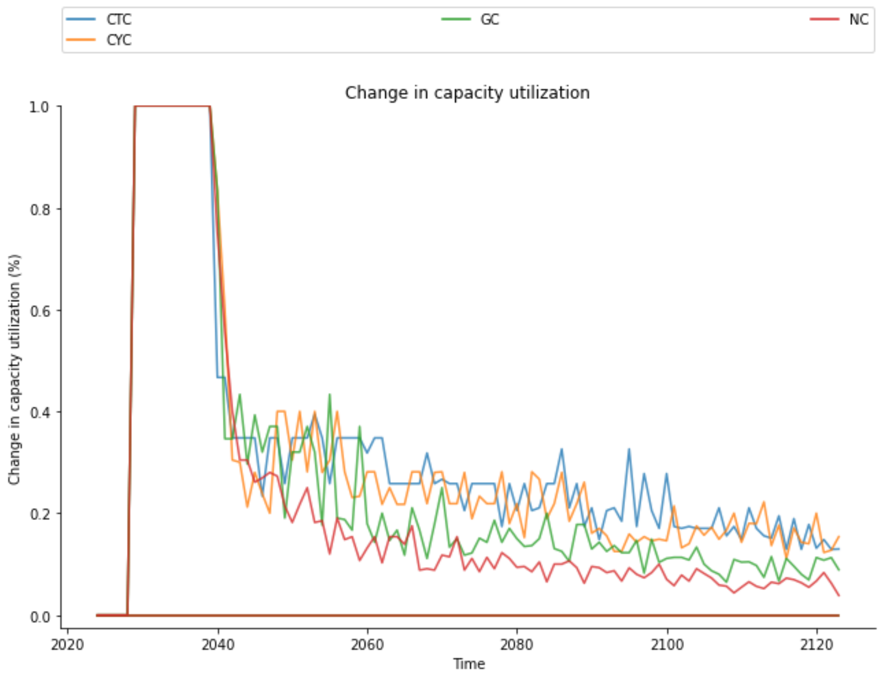

Figure 22: Envelope plot of the change in capacity utilization per policy

No density plot is added to figure 22, as the density plots represent the distribution of values in the outcome space at the final timestep of the model run. The interest with the change in capacity utilization lies in its performance over time. Therefore, figure 23 presents a heatmap plot per policy of the change in capacity utilization, which provides a clearer overview of the density of values over time. A lighter color in the heatmap indicates a higher density of values over all the runs.

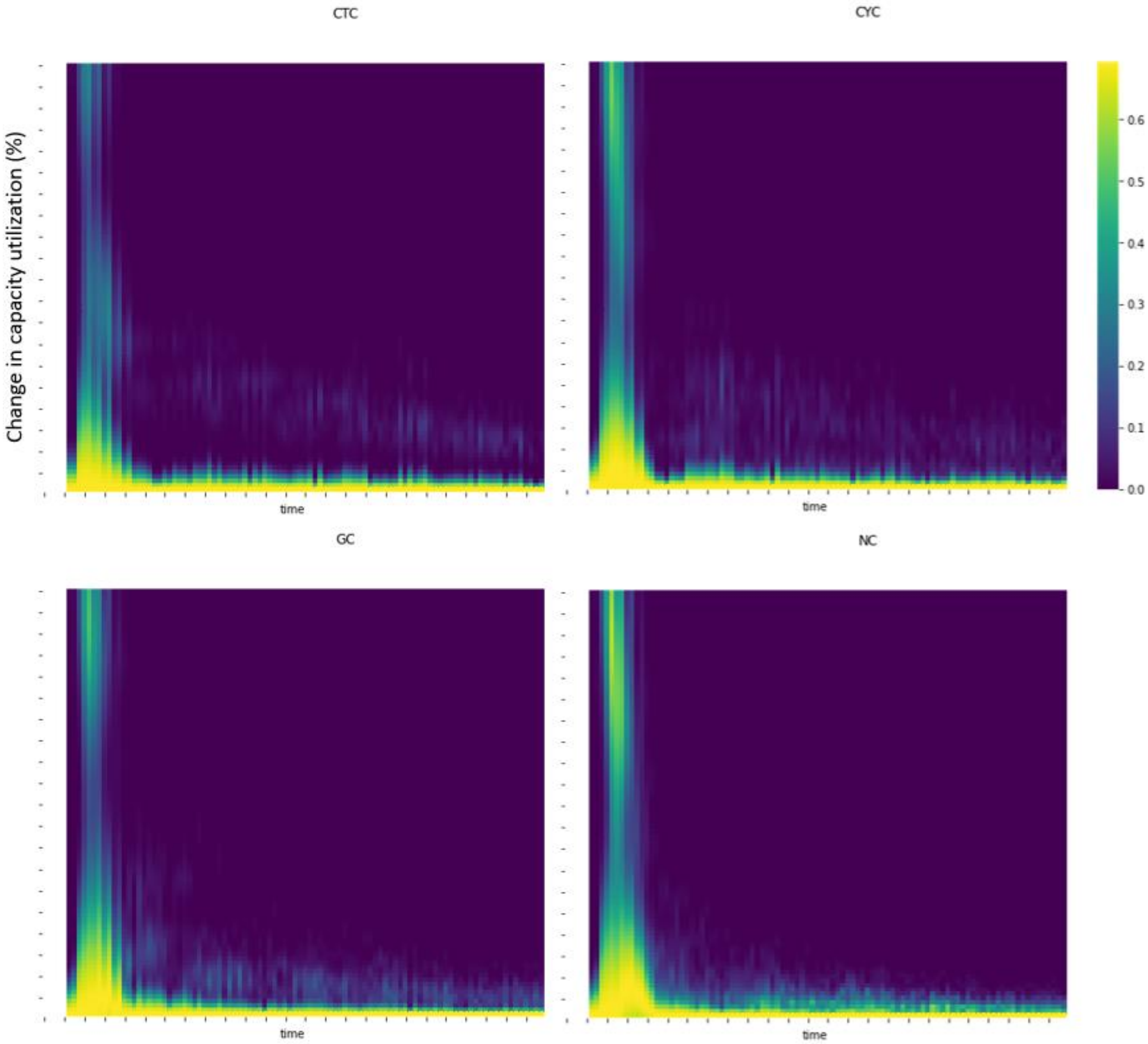

Figure 23: Change in capacity utilization – heatmap per policy

The heatmaps confirm the findings from the envelope plot, as the policies with large clusters (Construction type clustering and construction year clustering) have a higher density of values in the higher sections of the y-axis. This can be explained by the fact that larger clusters lead to larger values for capacity utilization change, as more projects get executed in the same timestep. Furthermore, we can clearly see that the no clustering policy has the highest concentration of density in the lowest section of the y-axis. Thus, the results suggest that in terms of the change in capacity utilization, the no clustering policy is the most robust policy.

4.1.2 Travel time

None of the policy options show significant influence on the behavior of the total travel time. This could be explained by two factors, (1) the assumption that all roads in the network have sufficient capacity at all times and (2) the lack of a destination based traffic flow distribution in combination with a shortest route algorithm. These points are addressed in more detail in chapter 5.

4.1.3 Total projects

The total amount of projects executed exhibits a wide outcome space for all 4 of the policy options, which is visible in Figure 24. Section 4.4 will shed more light on the drivers behind this wide outcome space. An interesting observation is that the policy options that utilize larger clusters (Construction type clustering and construction year clustering) have a higher density of outcomes in the lower values. This becomes more apparent when considering the 5.000 run kde plot in figure 39, where the construction type clustering policy has a relatively high and concentrated density of expected outcomes in the lower section of the outcome space. However, as the clusters of the construction type clustering policy are very big (around 50% of the bridge set), the variation of possible expected outcomes is limited.

On the contrary, the distribution of expected outcomes of the geographical clustering policy, which has smaller clusters than the construction type and construction year cluster policies, and the no clustering policy is skewed towards higher total project values. Furthermore, the geographical clustering policy has a distribution of expected outcomes that is relatively high in the highest values of the outcome space. Interestingly, regardless of the policy and scenario, the first maintenance wave can be clearly seen in the line plot.

The results suggest that performing maintenance on larger clusters of bridges can result in a lower amount of maintenance projects executed in total. More specifically, the best performing policy is the construction year clustering policy. However, when considering the total amount of maintenance projects, it is also important to consider the performance of the bridge population in the network. Although it is desirable to have a lower amount of projects executed, the interpretation of this finding can be significantly different if the performance of the bridge population is lower than in other policies.

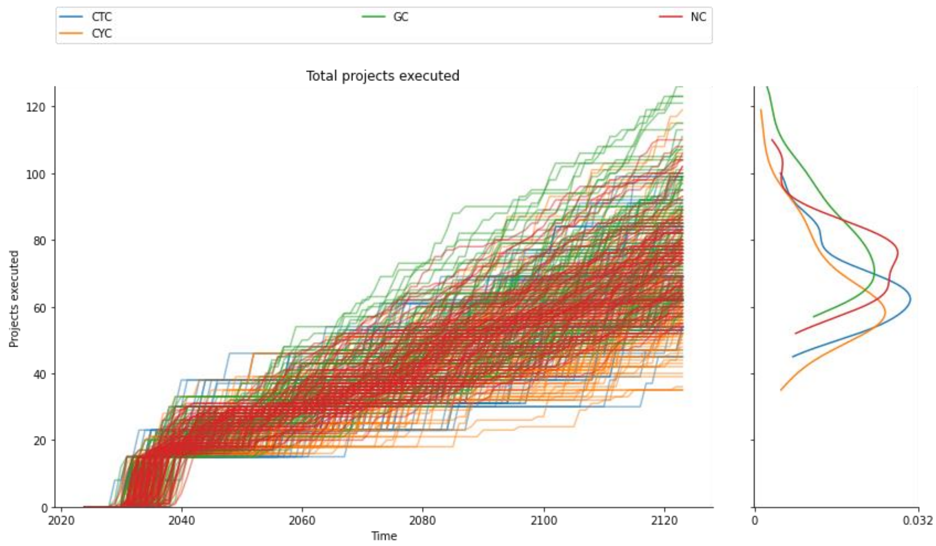

Figure 24: Line plot of the total amount of projects executed per policy (left) and a kde plot (right)

4.1.4 Average load capacity

Figure 25 shows a similar performance of policies, in terms of the density of expected outcomes, as figure 24 in the previous section. Policies that performed better in the previous section (i.e., construction type clustering and construction year clustering), also perform better on the average load capacity outcome. This shows the relationship between the two outcomes, as the average load capacity increases, the expected amount of projects decreases, and vice versa. Policy options with larger clusters (construction type clustering and construction year clustering) perform more preventive maintenance than the other policy options, as maintenance is performed on bridges in clusters that are still above their corrective maintenance threshold. The determination of the size of the maintenance (in N) does not differ between reactive and preventive maintenance projects, leading to higher average carrying capacities for policies with larger clusters.

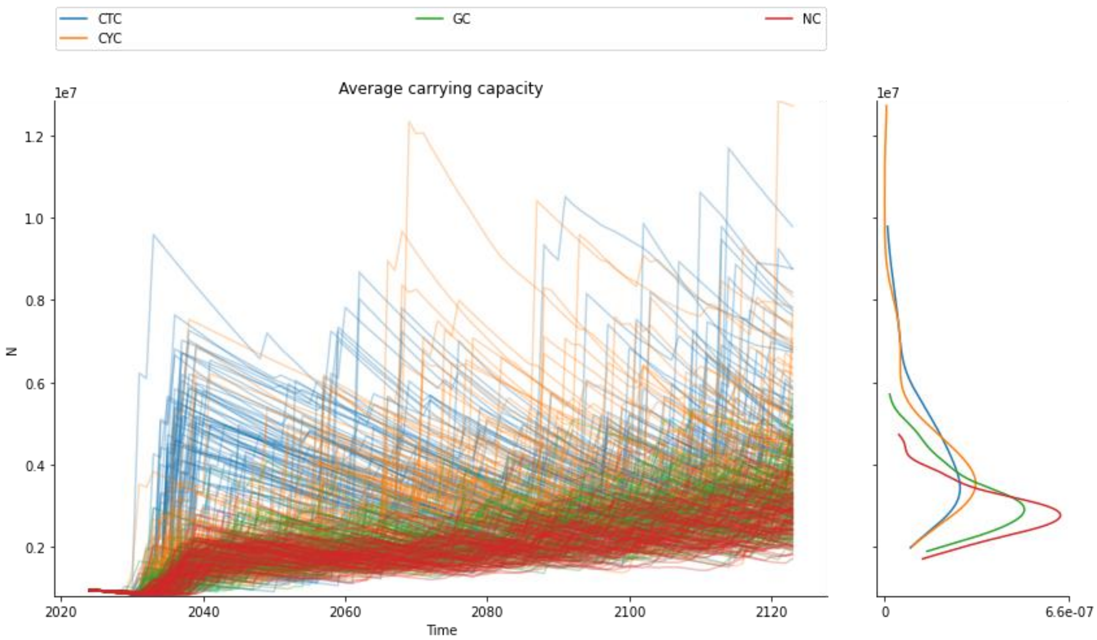

Figure 25: Line plot of the average carrying capacity per policy (left) and a kde plot (right)

4.1.5 Accesibility

The minimum accessibility envelop plot shows that none of the policies result in the exclusion of a region in the network. This was an expected finding, as this is a direct result of the design of the network (see figure 6). None of the regions in the network contain bridges on all of their connected roads. Moreover, all of the policy options display the same minimum value over their set of runs. From the violin plot, it becomes clear that the three clustering policies construction type, construction year, and geographical clustering, have a higher density of values in the lower accessibility values. This is expected behavior, as these clustering policies result in more simultaneous bridge closures, which in turn impacts the accessibility of a region.

Conversely, the no clustering policy holds the lowest density in the 100% (1.0) accessibility section. This indicates that there are more instances over time where the accessibility of the network gets affected. This is explained by the fact that each bridge gets maintenance individually, leading to more maintenance occurrences.

The results indicate that clustered maintenance leads to less frequent, but more impactful, decrease in accessibility. On the contrary, a no clustering maintenance strategy leads to a more frequent, but less impactful, decrease in accessibility.

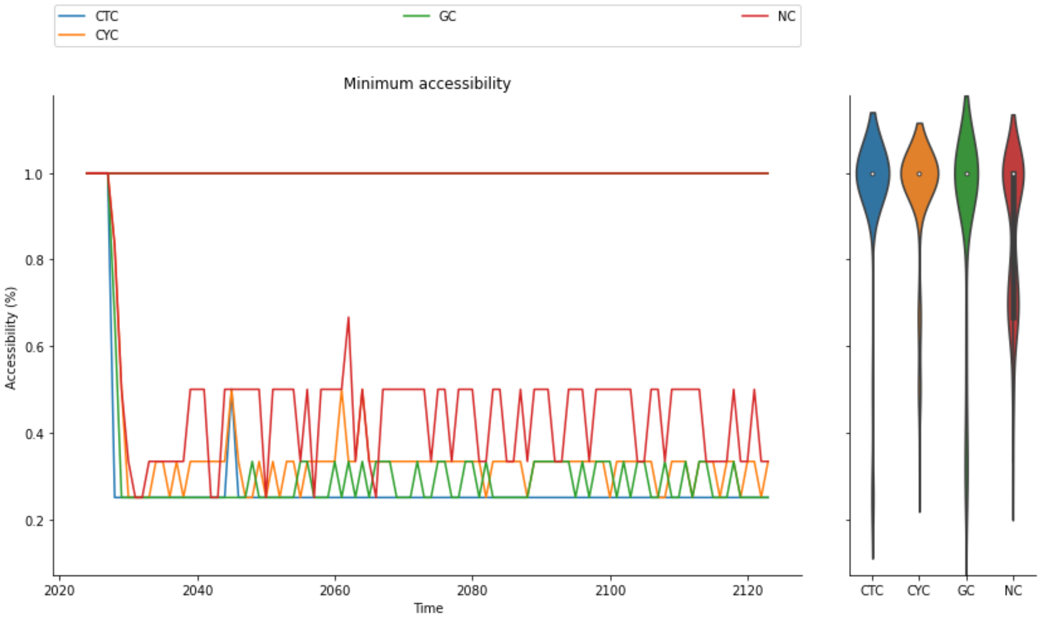

Figure 26: Envelope plot of the minimum accessibility per policy (left) and a violin density plot (right)

4.2 Revised policy performance

Using the results obtained from the previous sections, two new revised variations of the geographic clustering policy have been designed. Firstly, based on the findings from the capacity utilization analysis, a smaller geographic clustering policy has been analyzed. This policy contains 8 clusters, with an average of 1.9 bridges per cluster. In comparison, the original geographical clustering policy contained 5 clusters with an average of 3 bridges per cluster. Secondly, based on the findings from the analyses of the total projects executed and the average load capacity, a larger geographic cluster policy has been added. This policy contains 4 clusters with an average of 3.75 bridges per cluster. The new policies will be denoted in figures as GC small and GC big, respectively. See figure 27 for a visualization of the revised policies. For the clarity of the figures uses in the analyses in this chapter, the new policies will only be compared to the best performing policies and the no clustering policy on the chosen outcomes of interest.

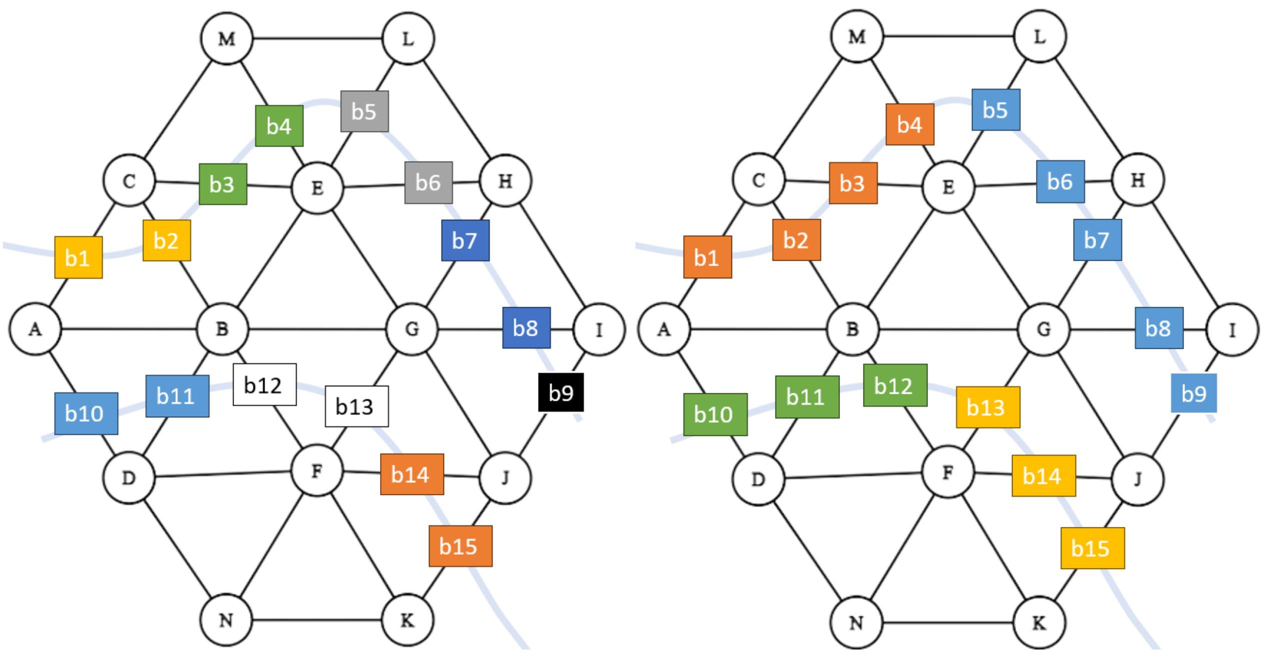

Figure 27: Revised geographic clustering policies. Smaller clusters (left) and bigger clusters (right)

Firstly, the performance of the revised policies on the change in capacity utilization over time. Figure 28 displays the heatmaps of 5000 runs of the two revised policies along with the no clustering and original geographic clustering policies. A lighter color in the heatmap indicates a higher density of values over all the runs of that policy. The heatmaps confirm the findings from the analysis in section 4.1.1, larger clusters lead to a higher density of values in the higher sections of the y-axis. This can be seen when comparing the geographical clustering policy and big geographical clustering policy in figure 28. Interestingly, the smaller geographic cluster from the small geographical clustering policy result in a relatively stable distribution in the density of values over time. When compared to the no cluster policy, the density follows a more stable pattern over time. Furthermore, the maintenance wave between 2030 and 2040 holds a higher density in the lower section of the y-axis for the geographically clustered policies than for the no cluster policy.

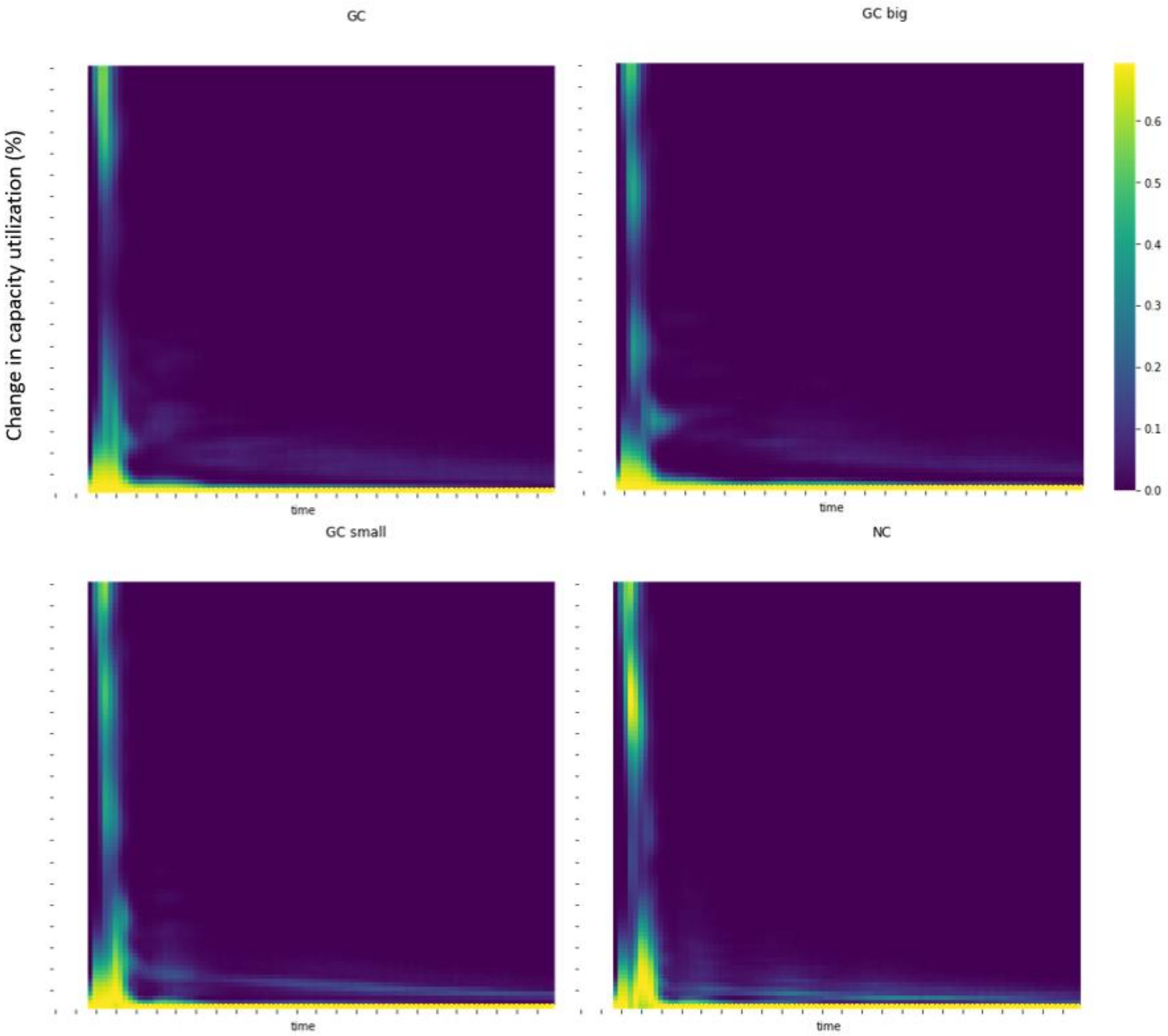

Figure 28: Revised policies change in capacity utilization heatmaps

Secondly, figure 29 shows the total amount of projects executed for the revised policies, along with the no cluster policy and the construction type clustering and construction year clustering policies. The figure remains consistent with the findings presented in 4.1.3. When comparing the two revised policies, the big geographical clustering policy has a slightly higher density of expected outcomes in the lower region of the expected outcomes. Compared to the no cluster policy, both revised policies prove to be slightly more robust, as their densities peak more towards the desired region of outcomes. Compared to the construction year clustering and construction type clustering policies however, both the revised policies prove to be less robust.

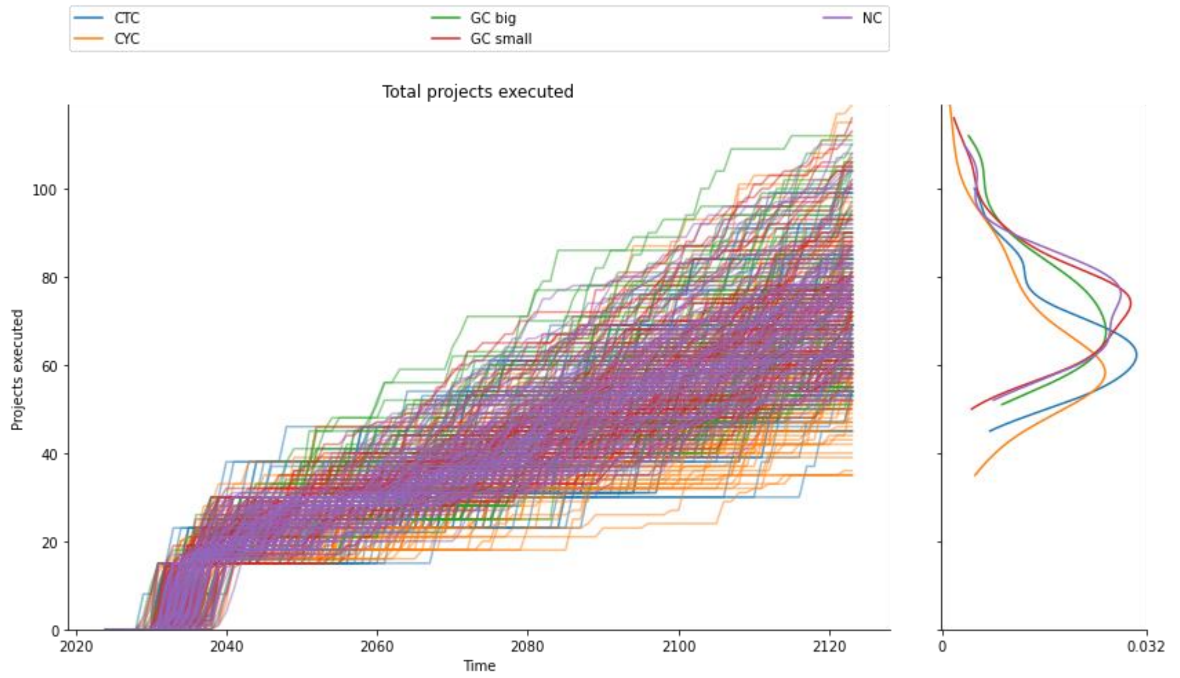

Figure 29: Revised policies total projects executed line plot (left) and kde plot (right)

Lastly, figure 30 displays the average carrying capacity for the revised policies, along with the no cluster policy and the construction year clustering and construction type clustering policies. Similar to the results of the total projects executed, the distribution of expected outcomes for both revised policies are skewed more towards the desired region of outcomes than the no cluster policy. Compared to the larger clusters of the construction year clustering and construction type clustering policies, there is less density in the higher region of expected outcomes.

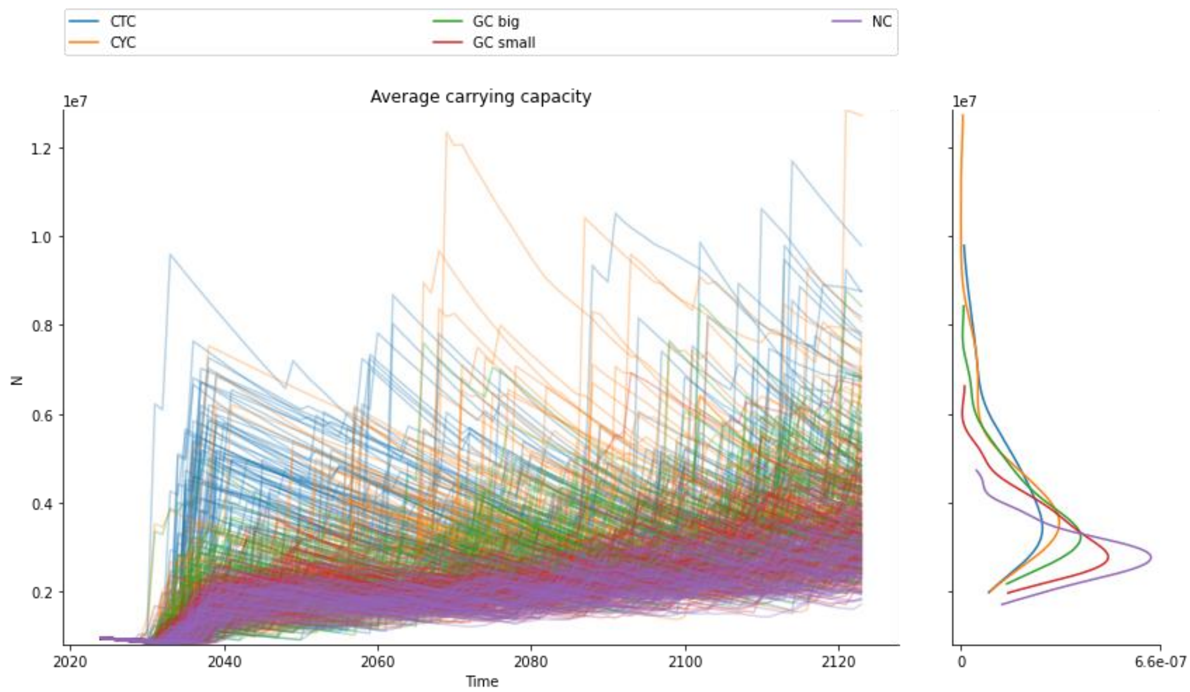

Figure 30: Revised policies average carrying capacity line plot (left) and kde plot (right)

4.3 Scenario discovery

Now that the general model behavior over the uncertainty space and policies has been explored, this chapter will perform scenario discovery through the Patient rule induction method (PRIM). The algorithm has been applied to two outcomes of interest, the total amount of projects executed and the average load capacity. Firstly, it is interesting to understand which values of input variables in combination with policies result in a low amount of projects executed. Therefore, we are interested in cases within the set of 30.000 experiments (5.000 experiments for the 4 base policies and the 2 revised policies) where the total amount of project executed is lower than 60. Figure 31 displays the boxes found by the PRIM algorithm that satisfy the threshold of 60 projects executed or less. The minimum coverage threshold that a box should meet is set to 80%.

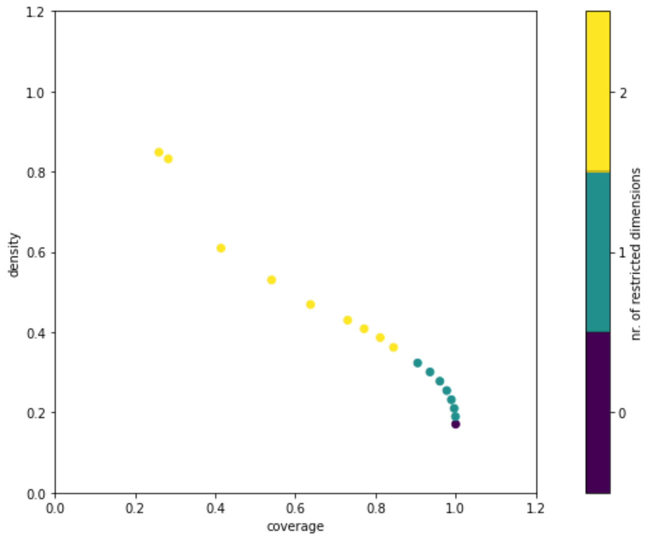

Figure 31: PRIM – Total projects executed trade-off

Figure 31 displays the trade-off between coverage, density and interpretability. Firstly, the density refers to the amount of cases in the box (a box is represented by a dot in the figure) are of interest (i.e., < 60 projects). The coverage refers to the amount of cases of interest, compared to the total amount of cases of interest, that are covered in a box. Lastly, the interpretability refers to the amount of dimensions that need to be restricted (i.e., how many uncertainties are described in the box). Within the EMA framework, a density of at least 80% is customary for the identification of boxes of interest. As such, box 15 (counted from the bottom right-most point up) is chosen for closer inspection. The details of box 15 are displayed in figure 32.

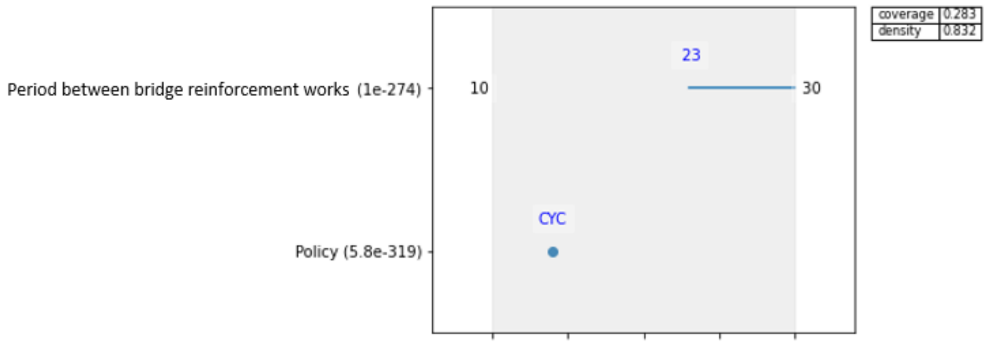

Figure 32: PRIM – Total projects executed box 15

Box 15 has a density of 83,2%, but simultaneously only covers 28,3% of the cases of interest. The two restrictions that confine the box are displayed on the y-axis. The values in brackets behind the names are p-values that assess the statistical significance of their respective restriction. A p-value below 0.05 is deemed to indicate statistical significance. Both the Policy and Period between bridge reinforcement works are therefore deemed statistically significant at causing a total amount of projects below 60. The blue line (and dot) indicates the subrange of values for the restrictions that are captured in the box. Thus, a period between bridge reinforcements between 23 and 30 years and the construction year clustering policy. As the chosen box only covers 28,3% of the cases of interest, a second PRIM iteration was applied to the data to find a second set rules that could explain a part of the remaining cases of interest. Unfortunately, a second set of rules could not be found as the second PRIM analysis could not meet the minimum coverage threshold of 80%.

A secondary analysis will be done to understand which values of input variables in combination with policies result in a high average load capacity. Therefore, we are interested in cases where the average load capacity is higher than 4.000.000 N. Figure 33 displays the boxes found by the PRIM algorithm that satisfy the threshold. The minimum coverage threshold that a box should meet is again set to 0.8.

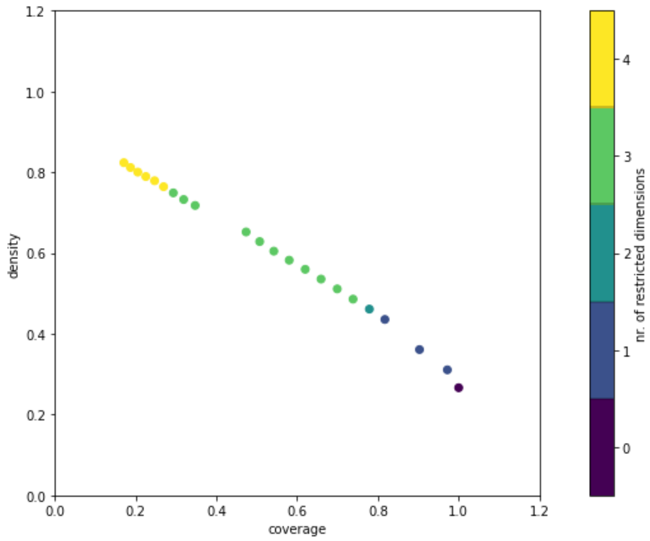

Figure 33 PRIM – Average load capacity trade-off

From the trade-off visualization in figure 33, we choose the 19th box (counted from the bottom right-most point up) for further investigation. This box is characterized by 4 restrictions, of which 3 are statistically significant. The period between bridge reinforcement works is considered to be statistically insignificant as its p-value is larger than 0.05. The top right table of figure 34 indicates that this box has a density of 80%, but only covers a small part of the cases of interest at 20.5%. This 20.5% of cases, where the average load capacity is greater than 4.000.000 N can be explained by the average vehicle speed, the yearly growth in average vehicle weight and the policy.

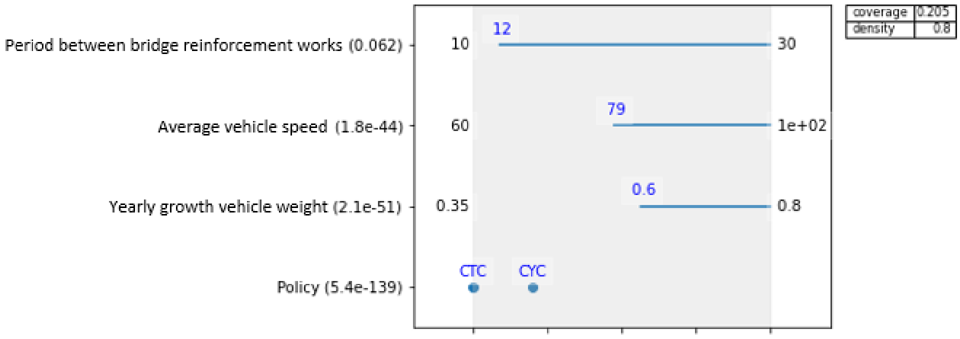

Figure 34: PRIM – Average load capacity box 19

As the chosen box only covers 20,5% of the cases of interest, a second PRIM iteration was applied to the data to find a second set rules that could explain a part of the remaining cases of interest. Unfortunately, for this outcome of interest, a second set of rules could also not be found as the second PRIM analysis could not meet the minimum coverage threshold of 80%.

4.4 Identifying key drivers in the system

To gather some additional information on the functioning of the system, a feature scoring algorithm has been applied to the set of 30.000 experiments to identify the key drivers in the system. The algorithm uses the last available datapoint of each outcome, which is the datapoint in the year 2123. It then scores each of the input variables based on how much of the variance in each of the outcomes that input variable causes. The following outcomes of interest have been excluded from this analysis: (1) the change in capacity utilization and (2) the minimum accessibility of a region. Our interest in these outcomes lies in their behavior over time, not in their ending state values. As such, the information obtained from the inclusion of these variables in the feature scoring analysis would have little value for this thesis.

From figure 35 we can see that the total travel time is mainly driven by the yearly growth in traffic intensity. This is expected, as a greater growth in traffic intensity leads to more vehicles in the model, which in turn will lead to a higher aggregate travel time. Interestingly, none of the other uncertainties or policies have a significant influence on the total travel time, which is consistent with the findings in section 4.1.2.

The total projects executed is primarily driven by the period between bridge reinforcement works, and to a lesser extent by the aging factor E & W and the active policy. This is not unsurprising, as the a smaller period between scheduled bridge reinforcements works will lead to a larger amount of projects executed during the simulation time. Moreover, we have seen in chapter 4.1.4 that the active policy has an impact on the density of expected outcomes for the total projects executed.

The average load capacity is primarily impacted by the active policy. As we have seen in chapter 4.1.4, policies with larger clusters have a higher density in expected outcomes for the higher load capacity values. Interestingly, the inclusion of period bridge maintenance in the model seems to have only a minimal impact on each of the outcomes of interest included in this analysis.

Figure 35: Feature scoring

As the change in capacity utilization has been excluded from the feature scoring analysis presented in figure 35, an additional temporal feature scoring analysis has been performed. Figure 36 shows the analysis, where the algorithm scores each of the input variables based on how much of the variance in the change in capacity utilization that input variable causes, at the timestamps on the x-axis. Over all the reported years, the active policy has the most steady impact on the change in capacity utilization. The impact of the period between bridge reinforcement works and the aging factor E & W gradually decline over the simulation period. Interestingly, none of the variables seem to have consistently high impact on the change in capacity utilization in the reported years. The aging factor E & W does explain a significant part of the variance in the year 2034. On the contrary, the active policy has barely any influence in 2034. This last observation is consistent with earlier findings however, as all policies seem to have a similar density of expected values in the years 2030 to 2040.

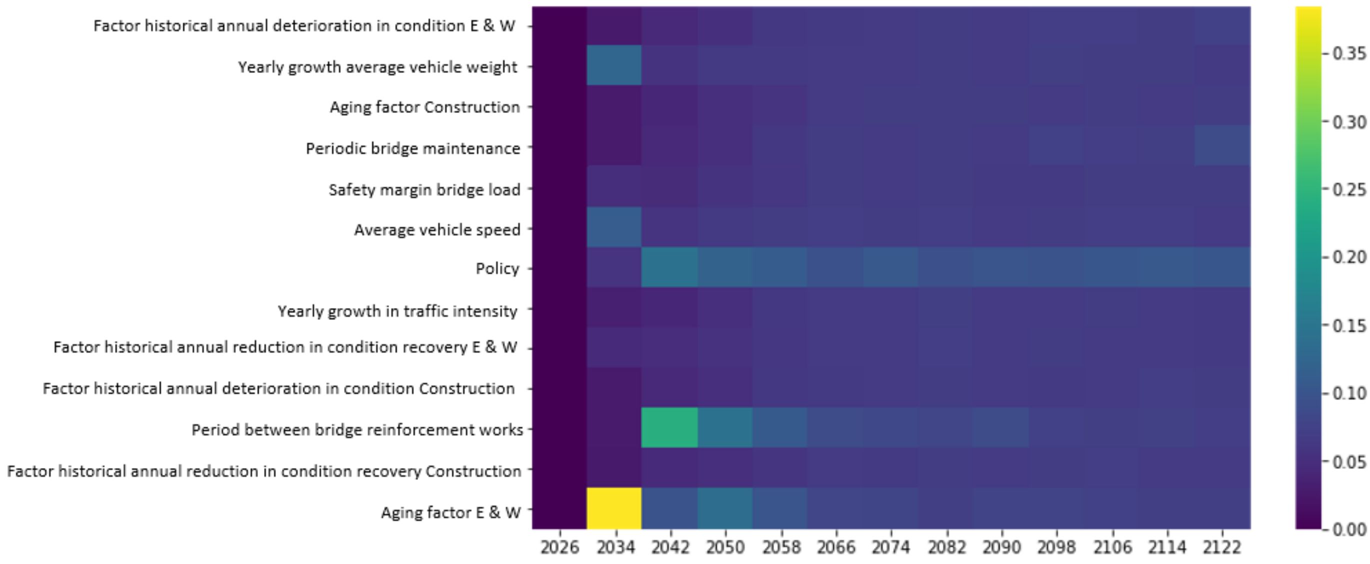

Figure 36: Temporal feature scoring change in capacity utilization

5 Discussion

In this thesis, a spatially explicit Entity-based System Dynamics (SD) model has been presented. The spatial component designed for this thesis is based on the network structure components of network theory (Quimpo & Wu, 1997) and the model structure of the GOM GIS 2 Ventity model constructed by Ventana Systems (Ventana Systems, 2022). Combined, they allow for the modeling of infrastructure components, such as roads and regions, their relative position in the network and their dynamic relationships with other model components. An abstract network was constructed using these infrastructure components to assess the feasibility of the spatial modeling approach. Firstly, in chapter 5.1, the added value brought by the spatially explicit Entity-based SD approach will be discussed by comparing it to other network modeling approaches. Secondly, in chapter 5.2, the advantages and limitations of the EMA-Workbench-Ventity connector will be discussed. Lastly, the model results will be reflected upon and compared to existing literature, and the limitations and future recommendations for the model will be highlighted in chapter 5.3.

5.1 The added value of spatially explicit Entity-based SD

5.1.1 A comparison with System Dynamics

When compared to existing attempts at spatially explicit System Dynamics (SD) models, such as those presented by Benaich and Pruyt (2015), BenDor and Metcalf (2006) and Fallah-Fini et al. (2013), the approach presented in this thesis provides a number of advantages that can be used to appraise its usefulness over traditional SD modeling. These advantages have been divided into 2 categories, (1) replicability and (2) computational requirements.

First, the replicability of the spatial component. As stated in chapter 3.2, the focal consideration when designing the spatial component was ensuring a high degree of replicability, which was achieved by making use of 4 Entity-based SD specific features, (1) entity types, (2) attributes, (3) references and (4) external network initialization data. Because entity types can be independently defined, infrastructure components can be individually modeled in as much or as little detail as is appropriate for the modeler. As stated by Shepherd (2014), SD models that use spatial elements through subscripts or arrays, such as the model presented by Fallah-Fini et al. (2013), quickly lose their 'white box model' status as the communicability and the computational power required get strongly affected as the network in the model gets larger. Through the use of multiple model views, one for each defined entity type, the communicability of the spatial Entity-based SD model to stakeholders remains at a high level, as there are no 'hidden' variables present (i.e., subscripts).

Furthermore, entity types are defined and saved individually to the folder containing the Ventity model, which allows for the easy reuse of pre-made entity types in other models. As such, the Region to Region, Road Region entity types constructed for the model presented in this thesis can be integrated into any existing Ventity model. The only remaining difficulty here is to identify through which references and variables these entity types, which jointly comprise the spatial component, the connection to the rest of the model should be made.

Through the externalization of the network (or entity) initialization data, the spatial Entity-based SD approach is able to introduce a new dimension of replicability to spatial SD modeling. This implies that all the relevant network data, such as the length, direction and capacity of roads and the identification of all regions (nodes) in the network, are not modeled in the Ventity model. Rather, this data is captured in an Excel file and is read by Ventity upon a model run (see table 2). The spatial SD models presented by Benaich and Pruyt (2015) and Fallah-Fini et al. (2013), require the modeler to manually alter the subscripts (i.e., individual roads or regions) in case the modeler wants to expand or change the network that is used in the model. While this is not necessarily a problem when modeling a small network, the modeling and verification of large networks can become complex and time-consuming (Benaich & Pruyt, 2015). By separating the dynamics of infrastructure components and the network specification data, components can be altered individually without the need to alter the other. This also plays a large role in the scalability of the presented approach, as the only addition necessary would be the expansion of the datapoints in the external Excel file. A first exploration of the scalability of the approach was performed during the modeling process, as the initial network used for testing the dynamics of the individual entity types was scaled up to the network used in the results section of this thesis. During this test, the amount of nodes (regions) in the network were increased from 3 to 14, the amount of links (roads) increased from 6 to 58, and the amount of bridges increased from 3 to 15. The upscaling of the network, performed by only editing the network initialization file, required no further work in the Ventity model, as all the dynamics of the entity types were correctly transferred to the new roads, regions and bridges. The increased network size also did not result in a noticeable drop in model run speed.

Second, the computational requirements of the spatial Entity-based SD approach is limited compared to traditional SD models. As reported by Ouyang (2014), for infrastructure modeling, SD is considered to be a medium computational complexity approach. This indicates that a single model run takes between several seconds to several minutes. Moreover, Benaich (2015) states that the subscript-driven spatial SD approach is not computationally efficient, and is unsuitable for modeling larger networks. In comparison, the spatial Entity-based SD model constructed in this thesis takes a fraction of a second to complete one model run, which would place it in the small computational complexity category in the framework presented by Ouyang (2014). Also, as stated before, the upscaling of the network used in the model did not result in any noticeable increase in required computational power, which is a first indication that the findings of Benaich (2015) do not hold true for this spatial Entity-based SD approach. However, as only one upscaling exercise was attempted, and the network used in this thesis is still limited in size, additional research will be needed to confirm if the spatial Entity-based SD approach will remain computationally efficient even when modeling increasingly larger networks.

Another important consideration is the computational requirements of the approach when pairing it with exploratory modeling, as the computational costs of exploratory modeling are significant due to the large ensembles of runs (Auping, 2018). The 30.000 experiments that were run for the results section of this thesis were performed using the sensitivity analysis function within Ventity. Using an HP Zbook Studio x360 G5 with an Intel Core i7 processor, the total time needed to run these 30.000 experiments was less than 5 minutes. In comparison, van Opstal (2023) reports a run time of 32 hours to run 15.000 experiments for an SD model where the runs are being performed in the EMA Workbench. One important sidenote has to be made here, as the speed of the model run, and the size of the output files is heavily dependent on the savelist chosen by the modeler. A savelist allows the modeler to specify which variables get saved into output files during the sensitivity analysis runs. The savelist used for the generation of experiments in this thesis was limited to only the uncertainties and outcomes of interests specified in chapter 3.6. Moreover, all variables are defined in singular entities or (sub-)collections of entities. In case variables are added in the savelist that are defined and saved for each individual entity within an entity type, for example, the amount of vehicles in a region (see equation 9), the computational costs increase steeply. As such, the advantage in terms of the computational costs when performing a large ensemble of runs is only valid when the modeler defines uncertainties and outcomes of interest that refer to singular entities and/or (sub-)collections of entities.

5.1.2 A comparison with non-SD network modeling methodologies

Comparing the spatial Entity-based SD approach to other non-SD network modeling methodologies, such as network modeling and agent-based modeling (ABM), provides some further interesting insights into the added value of the approach. Firstly, as the spatial Entity-based SD approach is an extension of the SD modeling methodology, it provides a holistic approach to infrastructure modeling (Benaich, 2015; Sterman, 2002). This is a fitting angle to infrastructure modeling (Abbas & Bell, 1994; Shepherd, 2014), as it allows for not only the modeling of the infrastructure network, but also the system that the infrastructure network is a part of. Thus, although not accounted for in the model constructed for this thesis, external effects caused by (changes in) traffic flows such as pollution and economic activity, can be accounted for in the spatial Entity-based SD approach. Moreover, unlike ABM and network modeling, Entity-based SD can account for nonlinearity, time delays and feedback loops, such as the feedback loop between supply and demand in transportation.

A second advantage compared to non-SD network modeling methodologies is the modeling interface. Due to the clear structure utilized by the model presented in this thesis, visualized in the form of stocks, flows and causal links, the model communicability is high. This is considered to be an added value of the approach as group model building along with stakeholders and the communicability of model results to stakeholders come very natural to approaches within the SD paradigm.

Compared to network-modeling approaches specifically, the spatial Entity-based SD approach has two additional key advantages, (1) computational costs and (2), EMA Workbench support. Although flow-based network modeling approaches offer a higher degree of detail to the modeler, this comes at an expense of computational costs (Ouyang, 2014). As mentioned before, the computational costs of the approach introduced in this thesis are limited. Secondly, due to the Ventity-EMA Workbench connector constructed for this thesis, Entity-based SD can now be combined with exploratory modeling. This allows for the exploration of the consequences of deep uncertainty in the models created within the Entity-based SD methodology.

However, spatial Entity-based SD should not be seen as replacement for the alternative non-SD spatial modeling approaches. It provides valuable advantages in terms of the holistic approach, the communicability and the computational costs, but there are also limitations that decrease the applicability of this approach in certain contexts. Firstly, the Entity-based SD methodology offers limited documentation, as the maturity (i.e., the development level) of the approach is low. This low maturity has had a direct effect on the process of creating the model presented in the previous chapters. The documentation incorporated in the Ventity software is helpful at times, but rather incomplete in other instances. As an example, while designing the distribution component of the model (see equation 12), the initial plan was to use an allocation action to distribute traffic flows from and to regions. However, as the documentation on the allocation function is limited and as of yet, these actions only allow for the allocation of fixed quantities, another approach had to be introduced. Moreover, similar to ES, the Entity-based SD approach is not meant to generate precise forecasts (Sterman, 2002). As such, if this is the objective of the modeler or stakeholder, Entity-based SD should not be considered as a candidate approach.

5.2 EMA-Workbench-Ventity connector

For the analysis of model results, the EMA-Workbench-Ventity connector constructed for this thesis provides some interesting insights. As stated in section 2.3.2, the EMA Workbench connector developed for this study is not a conventional connector and is therefore not alike to any of the connectors that are currently in use. Rather, it is a data processing tool that utilizes the built-in sensitivity analysis capabilities of Ventity and processes the data into a format that is readable and useable for the EMA Workbench. The first insight is that the use of a connector that utilizes the API of the modeling software, such as the EMA-Workbench-Vensim connector, should always be preferred. Although the connector presented in this thesis does generate the requested results, a set of EMA Workbench functionalities are lost because the workbench and the modeling software are not explicitly linked. For instance, because the execution of model runs is not performed within the EMA Workbench, but in the modeling software, it is not possible for the EMA Workbench to track convergence. More specifically, none of the functions present in the optimization module are compatible with the connector presented in this thesis. Therefore, to obtain full functionality of the EMA Workbench, the development of a EMA-Workbench-Ventity connector that utilizes the Ventity API is encouraged.

A second insight is that the connector presented in this thesis is a functional placeholder that can be used in anticipation of a connector that uses the API of the modeling software. As presented in chapter 4, the connector is able to facilitate the use of the core functionalities of the EMA Workbench in combination with Ventity. Moreover, the presented connector can be used as a framework for the development of other connectors of the same kind for modeling software that are currently not directly supported by the EMA Workbench. As the connector only requires knowledge about the format of data that gets exported by the modeling software, and the required input data for the EMA Workbench, EMA Workbench analyses can be performed without the access to the extensive documentation of the API of the modeling software.

The combination of Entity-based SD with the Exploratory Modeling and Analysis methodology is considered to have added value for analyzing the bridge maintenance system described in this thesis. Through the coupling with the EMA Workbench, this thesis was able to obtain a deeper understanding of the bridge maintenance system than would have been possible without the EMA methodology. Furthermore, through the use of EMA, stakeholders and decisionmakers can be informed more comprehensively about the dynamics of the system and the performance of policies.

5.3 Model results, limitations and recommendations

The model results of this study show that larger clusters lead to more change in capacity utilization, while smaller clusters lead to more expected projects executed in total. In terms of the performance of the set of bridges, measured by the average load capacity, larger clusters lead to a higher expected average load capacity, which can be primarily attributed to the increased amount of preventive maintenance works. An important notion is that network configuration is a key consideration in studies that model maintenance clustering of structures (Sánchez-Silva et al., 2016). In line with this finding, Qiao et al. (2019) found that for more efficient maintenance, the optimal size for bridge clusters varies strongly based on the network that is considered. However, for bridge maintenance, a small cluster was found to be consistently more efficient when compared to single bridge clusters and larger clusters. Similarly, section 4.2 shows that policies with larger cluster sizes outperform the no cluster policy on all outcomes of interest, apart from the change in capacity utilization. As the change in capacity utilization is the most important outcome of interest however, the overall performance of the larger cluster policies is diminished significantly. The GC small policy however, consisting of an average of 1.9 bridges per cluster, results in a more stable change in capacity utilization than the no cluster policy, while simultaneously performing slightly better on the other outcomes of interest presented in section 4.2. These results corroborate the findings presented in Qiao et al. (2019).

Another important finding is that the model presented in this thesis is not fit to analyze the impact of bridge maintenance clustering policies on travel time. This can be attributed to 2 factors, (1) the assumption that all roads in the network have sufficient capacity at all times and (2) the lack of a destination based traffic flow distribution in combination with a shortest route algorithm. The road capacity assumption was made to decrease the complexity of the Region to Region entity type, as exceeding the capacity of a road would lead to traffic jams, which in turn should impact the average speed on the road and the distribution of traffic in proximity of the road. Secondly, the distribution of traffic is only impacted by the status of bridges and the population of regions in the network (see equation 12). This is another assumption that was made with the aim to decrease the complexity of the Region to Region entity type. As an unintended consequence however, these assumptions led to closing of a bridge not causing any significant impact on the travel time in the model. In the event of a bridge closure, an equal proportion of the diverted traffic is allocated to nearby roads, which all have enough capacity to absorb the diverted traffic. Since the model does not allocate a specific destination to each traffic flow however, the diverted traffic does end up at the same destination it would have had before the closure of a bridge. Rather, the other regions connected to a region with a closed bridge all receive more traffic, but after arriving at the new region the distribution remains unchanged. An improvement here could be to add a vehicle entity to the model, which allows each vehicle to decide their own destination. This could be modelled using an allocate action in the vehicle entity, which ranks the possible destinations in the model for each timestep based on a set of weighted criteria (such as economic activity and inhabitants).

A further improvement for the model would be the inclusion of more external effects, such as economic and environmental effects. Due to the focus of this thesis being the development of a spatial Entity-based SD method and capturing the effects of bridge maintenance on capacity utilization and road network performance, the decision was made to limit the amount of external effects that were included in the model. However, to further increase system understanding, the inclusion of additional external effects is important.

Two suggestions for further research are (1) the inclusion of project costs and (2) vehicle emissions. Firstly, the inclusion of costs allows for additional insights in the performance of bridge maintenance clusters. As found by Qiao et al. (2019), Qiao et al. (2018) and Assaf and Assaad (2023), clustered bridge maintenance can also be used to optimize project cost efficiency. Secondly, the inclusion of vehicle emissions can shed a light on the environmental effects of various maintenance cluster policies. If a certain policy leads to a relative strong increase in the amount of diverted vehicles, which in turn leads to an increase in the amount of kilometers driven, this also leads to more emissions.

Furthermore, the inclusion of a finite yearly maintenance capacity would be an important addition to the model. Currently, the model assumes that an infinite amount of bridges can be maintained in any timestep. However, in reality the capacity of bridge maintenance works (in terms of personnel and material resources) is limited. As an extension, the size of maintenance projects should also have a finite size. As mentioned in 3.5.2, the model assumes that bridges can be strengthened to levels that exceed their initial load capacity, whereas the maximum performance that a bridge can achieve after maintenance is usually equal to or smaller than its initial performance (Sánchez-Silva et al., 2016). Moreover, since bridge replacement is a function of fatigue damage, bridge replacement are only possible for steel type bridges. Another suggestion for improvement of the model is to incorporate a separate bridge replacement mechanism for concrete bridges.

A limitation for the model is the chosen timestep. The bridge part of the model, which was originally constructed by Copernicos in 2018, was modelled with a timestep of 1 and a time unit of years. When designing the spatial component of the model the decision was made to change the timestep to 0.125 years or less. Unfortunately, the smaller timestep led to the malfunctioning of the replacement & renovation part of the model, as this part was designed to function with a timestep of 1. As of writing this thesis, Ventity does not support more than one integration method so the influence of other methods on this issue cannot be discussed. In order to solve the issue, the model timestep was set back to 1, and the traffic flows were divided by a factor of 10.000 to obtain flows of traffic per 10.000 vehicles. Through this decrease in traffic flow values, both sides of the model now showed their expected behaviors. However, the used timestep has some consequences in the rest of the model. The distribution of traffic flows is changed 1 timestep later than the closing of a bridge, due to the distribution being calculated using stock-flow structures. This leads to traffic being unable to pass a bridge 2 timesteps in a row. During the first timestep, traffic cannot pass a bridge because the bridge flow is set to 0 due to maintenance (see equation 11), while traffic will not pass the bridge because the distribution on that road is changed to 0 in the second timestep. A smaller timestep would have decreased the impact of this limitation, as traffic would only have been stopped for a fraction of a year too long. Moreover, this limitation also emphasizes the suggestion of changing the structure by which the distribution of traffic flows is calculated mentioned earlier in this section.

6 Conclusion

This thesis set out to develop and reflect upon a novel spatially explicit Entity-based System Dynamics (SD) modeling method to analyze the effect of bridge maintenance cluster policies on maintenance capacity demand. In this thesis, it has been shown that it is possible to create a replicable spatially explicit Entity-based SD model through the use of attributes, references and externalized entity initialization data. The spatial component designed for this thesis is based on the network structure components of network theory and the model structure of the GOM GIS 2 Ventity model. Combined, they allow for the modeling of infrastructure components, such as roads and regions, their relative position in the network and their dynamic relationships with other model components. The abstract network used for the model consists of 14 regions, 58 roads, and 15 bridges. The model exhibits expected behavior for the impact of spatially distributed traffic flows on the degradation of bridges in a network.

With the model, six different maintenance cluster policies have been tested, three variations of geographical clustering (small, medium, and large), construction type clustering, construction year clustering, and a no clustering policy. The model results indicate that the choice of maintenance clustering policy has a significant impact on the outcomes of interest. Policies that utilize larger cluster sizes lead to more fluctuations in the change in capacity utilization, and therefore are not effective at facilitating a steady and predictable maintenance capacity demand. Conversely, policies with larger cluster sizes do lead to a lower expected amount of projects executed and a higher average performance of the bridges during the model run time. Both of these findings can be explained by the higher degree of preventive maintenance performed when these policies are active. Policies with small cluster sizes, such as the no cluster policy and the small geographic cluster policy significantly outperform their larger cluster counterparts in terms of the change in capacity utilization. Notably, the small geographical clustering, consisting of an average of 1.9 bridges per cluster, policy provides a more steady and predictable maintenance capacity demand over time than all other policy options. An important consideration, however, is that the optimal cluster sizes vary based on network considerations such as the size of the network or the share of roads that contain bridges.

A further consideration of the model outcomes reveals that the model has some limitations, as the model proves to be unfit for analyzing the impact of bridge maintenance clustering policies on travel time. Two factors contribute to this limitation. Firstly, the assumption that all roads in the network always have sufficient capacity hinders the model's ability to simulate traffic jams resulting from exceeding road capacity. This assumption was made to simplify the Region to Region entity type. Secondly, the absence of a destination-based traffic flow distribution, combined with a shortest route algorithm, affects the model's response to bridge closures.

Based on the modeling process and analysis results, this thesis concludes that the novel spatially explicit Entity-based SD approach offers added value in analyzing spatially explicit bridge maintenance cluster policies. Due to the model being organized into smaller components, in the form of entity types, the approach is able to achieve a high degree of replicability compared to other infrastructure modeling approaches. Additionally, the ability to externalize network initialization data allows for the quick and easy altering of the network composition, without the need to alter the dynamics of the model. A second advantage is the low computational requirement of the approach. Moreover, the holistic perspective of the model enables consideration of external effects caused by changes in traffic flows, providing a comprehensive understanding of the impact of maintenance policies on spatial dynamics. Lastly, due to the combination of the Entity-based SD approach with Exploratory Modelling, the approach is able to explore the consequences of deep uncertainty on the model behavior. This is especially valuable as infrastructure modeling is a field characterized by deep uncertainty and complexity.

While the spatially explicit Entity-based SD approach offers distinct advantages, it should not be viewed as a replacement for alternative spatial modeling approaches. As of yet, the approach has limitations, most notably in documentation due to its low maturity level. This impacted the modeling process, requiring alternative approaches due to incomplete documentation, such as in the design of the distribution component. Furthermore, the approach is not suitable for generating precise forecasts, aligning more with the qualitative understanding focus of System Dynamics. If precise forecasting is a primary objective, other modeling approaches may be more suitable.

6.1 Recommendations

Future recommendations for the modeling of the performance of maintenance clustering are to include more external effects into the model, to test the performance of clustering strategies on economic or environmental factors. Two specific suggestions for further research are (1) the inclusion of maintenance project costs and (2) vehicle emissions. Secondly, the inclusion of a finite yearly maintenance capacity would be an important addition to the model to align it closer to reality. Thirdly, for more accurate bridge renovation and replacement, it is encouraged to introduce a finite bridge strengthening size and a separate mechanism for the replacement of concrete bridges. Lastly, the spatial component of the model can be enhanced further by coupling the model with a GIS approach (Geographic Information System), which allows for the visualization of model results in an animated map of the network. Ventity supports the use of GIS in the program itself, removing the need to connect Ventity with external software. To make use of GIS in Ventity, the entity initialization data file that holds the network initialization data needs to be saved as a .dbf file. Furthermore, a shapefile (.shp) needs to be added to Ventity that holds the geometric locations of the network components. After both files are correctly initialized and saved, the model results can be visualized using the 'Visualization" section of Ventity.

Under the network considerations of the network presented in this thesis, small maintenance clusters aid in smoothing out the capacity demand of bridge maintenance over time. Policymakers should implement policies that encourage the formation of small maintenance clusters, which can lead to more efficient utilization of maintenance resources. However, the optimal size for bridge maintenance clusters may vary based on the network configuration. Hence, policymakers should adopt a flexible approach, considering the specific characteristics of the infrastructure network when formulating maintenance clustering policies. Emphasizing the importance of understanding the network configuration and its impact on maintenance efficiency can guide policymakers in making informed decisions for optimizing bridge maintenance.

This thesis has served as a first investigation into a novel Entity-based SD approach to infrastructure modeling. To further enhance the applicability and effectiveness of the Entity-based SD methodology, there is a need for improvements in documentation and the maturity of the approach. This includes developing comprehensive guides and resources to facilitate modelers in utilizing the approach for infrastructure modeling. Another interesting point of further research is discovering if the computational requirements of the approach remain low when increasingly larger networks are used as basis for the model. Furthermore, it is recommended to apply the spatially explicit Entity-based SD method to other types of infrastructure systems, such as water, energy, or communication networks. This can help to test the generalizability and scalability of the method. Lastly, modelers and practitioners adopting the approach should also consider collaborating to create a knowledge-sharing platform to exchange best practices, improving the overall understanding and utilization of Entity-based SD.

References

Abbas, K. A., & Bell, M. G. (1994). System dynamics applicability to transportation modeling. *Transportation Research Part A: Policy and Practice*, *28*(5), 373-390. https://doi.org/https://doi-org.tudelft.idm.oclc.org/10.1016/0965-8564(94)90022-1

Assaf, G., & Assaad, R. H. (2023). Key Decision-Making Factors Influencing Bundling Strategies: Analysis of Bundled Infrastructure Projects. *Journal of Infrastructure Systems*, *29*(2), 04023006. https://doi.org/10.1061/jitse4.Iseng-2225

Auping, W. (2018). *Modelling uncertainty: Developing and using simulation models for exploring the consequences of deep uncertainty in complex problems* [Dissertation, Delft University of Technology]. https://doi.org/10.4233/uuid:0e0da51a-e2c9-4aa0-80cc-d930b685fc53

Auping, W., Pruyt, E., & Kwakkel, J. H. (2015). Societal Ageing in the Netherlands: A Robust System Dynamics Approach. *Systems Research and Behavioral Science*, *32*(4), 485-501. https://doi.org/10.1002/sres.2340

Bankes, S. (1993). Exploratory modeling for policy analysis. *Operations research*, *41*(3), 435-449. https://doi.org/https://doi-org.tudelft.idm.oclc.org/10.1287/opre.41.3.435

Benaich, H. (2015). *Towards Flow Propagation Modeling with System Dynamics? Application on the Ring of Brussels* TU Delft]. http://resolver.tudelft.nl/uuid:224789d3-cf44-4054-bae3-868fac95ff28

Benaich, H., & Pruyt, E. (2015). Exploring Traffic and Congestion Policies: An Entity-Based Micro-Macro System Dynamics Approach. Proceedings of the 2015 International System Dynamics Conference, Cambridge, MA, USA,

BenDor, T. K., & Metcalf, S. S. (2006). The spatial dynamics of invasive species spread. *System Dynamics Review: The Journal of the System Dynamics Society*, *22*(1), 27-50. https://doi.org/https://doi-org.tudelft.idm.oclc.org/10.1002/sdr.328

Bernhardt, K. (2007). Agent-based modeling in transportation. *Artificial Intelligence in Transportation*, 72-80. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=5f8b41b984d1b127ebc082f0cff618d62e135b4e#page=78

Bleijenberg, A. (2022). *Position paper t.b.v. rondetafelgesprek Achterstallig onderhoud infrastructuur d.d. 30 maart 2022*. https://www.tweedekamer.nl/kamerstukken/detail?id=2022Z04282&did=2022D08769

Bomey, N. (2023). EVs are much heavier than gas vehicles, and that's posing safety problems. https://www.axios.com/2023/04/28/evs-weight-safety-problems

Bonabeau, E. (2002). Agent-based modeling: methods and techniques for simulating human systems. *Proc Natl Acad Sci U S A*, *99 Suppl 3*(Suppl 3), 7280-7287. https://doi.org/10.1073/pnas.082080899

Calvi, G. M., Moratti, M., O'Reilly, G. J., Scattarreggia, N., Monteiro, R., Malomo, D., Calvi, P. M., & Pinho, R. (2019). Once upon a time in Italy: The tale of the Morandi Bridge. *Structural Engineering International*, *29*(2), 198-217. https://doi.org/https://doi.org/10.1080/10168664.2018.1558033

Chester, M. V., Allenby, B., Iles, A., & Chang, M. E. (2019). Infrastructure as a wicked complex process. *Elementa: Science of the Anthropocene*, *7*. https://doi.org/10.1525/elementa.360

Compendium voor de Leefomgeving. (2023). *Bevolkingsgroei, 2018-2023*. https://www.clo.nl/indicatoren/nl2102-bevolkingsgroei-nederland-#:~:text=De%20bevolking%20van%20Nederland%20is,maar%20in%20weinig%20gemeenten%20voor.

Copernicos Groep. (2018). *Bruggenmodel*. In *Ventity*

Copernicos Groep. (2024). *Bruggenbestand RWS*.

Copernicos Groep. (n.d.). *Bruggen: hoe kan systeem-dynamisch modelleren ons helpen in het zoeken naar strategieën voor versnelling en duurzaamheid?*

Daulat, S., Rokstad, M. M., Klein-Paste, A., Langeveld, J., & Tscheikner-Gratl, F. (2022). Challenges of integrated multi-infrastructure asset management: a review of pavement, sewer, and water distribution networks. *Structure and Infrastructure Engineering*, 1-20. https://doi.org/https://doi.org/10.1080/15732479.2022.2119480

European Commission. (2019). Discussion paper—'State of infrastructure maintenance'. In: European Commission Brusells, Belgium.

Fallah-Fini, S., Rahmandad, H., Chen, H. J., Xue, H., & Wang, Y. (2013). Connecting micro dynamics and population distributions in system dynamics models. *Syst Dyn Rev*, *29*(4), 197-215. https://doi.org/10.1002/sdr.1508

Federal Highway Administration. (2022). *Awarding a single contract for several preservation, rehabilitation, or replacement projects helps agencies reduce costs and achieve program goals*. https://www.fhwa.dot.gov/innovation/everydaycounts/edc_5/docs/project-bundling-factsheet.pdf

FIEC. (n.d.). *Infrastructure Maintenance*. https://www.fiec.eu/priorities/infrastructure-maintenance

Fontoura, W. B., & Ribeiro, G. M. (2021). System dynamics for sustainable transportation policies: A systematic literature review. *urbe. Revista Brasileira de Gestão Urbana*, *13*, e20200259. https://doi.org/https://doi.org/10.1590/2175-3369.013.e20200259

Friedman, J. H., & Fisher, N. I. (1999). Bump hunting in high-dimensional data. *Statistics and Computing*, *9*(2), 123-143. https://doi.org/10.1023/a:1008894516817

G20. (2021). *G20 Policy Agenda on Infrastructure Maintenance.* http://www.g20.utoronto.ca/2021/G20-Policy-Agenda-on-Infrastructure-Maintenance.pdf

Godau, R. I. (1999). The changing face of infrastructure management. *Systems Engineering*, *2*(4), 226-236. https://doi.org/https://doi.org/10.1002/(SICI)1520-6858(1999)2:4%3C226::AID-SYS5%3E3.0.CO;2-8

Gómez, C., Sanchez-Silva, M., Dueñas-Osorio, L., & Rosowsky, D. (2013). Hierarchical infrastructure network representation methods for risk-based decision-making. *Structure and Infrastructure Engineering*, *9*(3), 260-274. https://doi.org/10.1080/15732479.2010.546415

Grafius, D. R., Varga, L., & Jude, S. (2020). Infrastructure interdependencies: Opportunities from complexity. *Journal of Infrastructure Systems*, *26*(4), 04020036. https://doi.org/https://doi.org/10.1061/(ASCE)IS.1943-555X.0000575

Hasan, S., & Foliente, G. (2015). Modeling infrastructure system interdependencies and socioeconomic impacts of failure in extreme events: emerging R&D challenges. *Natural Hazards*, *78*(3), 2143-2168. https://doi.org/https://doi.org/10.1007/s11069-015-1814-7

Helmrich, A. M., & Chester, M. V. (2020). Reconciling complexity and deep uncertainty in infrastructure design for climate adaptation. *Sustainable and Resilient Infrastructure*, *7*(2), 83-99. https://doi.org/10.1080/23789689.2019.1708179

Ibanez, E., & McCalley, J. D. (2011). Multiobjective evolutionary algorithm for long-term planning of the national energy and transportation systems. *Energy Systems*, *2*(2), 151-169. https://doi.org/10.1007/s12667-011-0031-z

Jifeng, W., Huapu, L., & Hu, P. (2008). System dynamics model of urban transportation system and its application. *Journal of Transportation Systems engineering and information technology*, *8*(3), 83-89. https://doi.org/https://doi-org.tudelft.idm.oclc.org/10.1016/S1570-6672(08)60027-6

Kompeer, J., & Schellevis, J. (2021, August 23, 2021). 'Babyboomerbruggen' toe aan groot onderhoud, files en kosten verwacht. *NOS*. https://nos.nl/artikel/2394865-babyboomerbruggen-toe-aan-groot-onderhoud-files-en-kosten-verwacht

Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling & Software*, *96*, 239-250. https://doi.org/10.1016/j.envsoft.2017.06.054

Kwakkel, J. H., Eker, S., & Pruyt, E. (2016). How Robust is a Robust Policy? Comparing Alternative Robustness Metrics for Robust Decision-Making. In *Robustness Analysis in Decision Aiding, Optimization, and Analytics* (pp. 221-237). Springer International Publishing. https://doi.org/10.1007/978-3-319-33121-8_10

Kwakkel, J. H., & Pruyt, E. (2015). Using system dynamics for grand challenges: the ESDMA approach. *Systems Research and Behavioral Science*, *32*(3), 358-375. https://doi.org/https://doi-org.tudelft.idm.oclc.org/10.1002/sres.2225

Lempert, R. J. (2003). Shaping the next one hundred years: new methods for quantitative, long-term policy analysis.

Lempert, R. J., Groves, D. G., Popper, S. W., & Bankes, S. C. (2006). A general, analytic method for generating robust strategies and narrative scenarios. *Management science*, *52*(4), 514-528. https://doi.org/https://doi-org.tudelft.idm.oclc.org/10.1287/mnsc.1050.0472

Liu, M., & Frangopol, D. M. (2005). Time-Dependent Bridge Network Reliability: Novel Approach. *Journal of Structural Engineering*, *131*(2), 329-337. https://doi.org/10.1061/(asce)0733-9445(2005)131:2(329)

Liu, M., & Frangopol, D. M. (2006). Optimizing Bridge Network Maintenance Management under Uncertainty with Conflicting Criteria: Life-Cycle Maintenance, Failure, and User Costs. *Journal of Structural Engineering*, *132*(11), 1835-1845. https://doi.org/doi:10.1061/(ASCE)0733-9445(2006)132:11(1835)

Mattioli, G. (2019). What Caused the Genoa Bridge Collapse—And the End of an Italian National Myth. *The Guardian*. https://www.theguardian.com/cities/2019/feb/26/what-caused-the-genoa-morandi-bridge-collapse-and-the-end-of-an-italian-national-myth

Maxwell, T., & Costanza, R. (1997). A language for modular spatio-temporal simulation. *Ecological modelling*, *103*(2-3), 105-113. https://doi.org/https://doi-org.tudelft.idm.oclc.org/10.1016/S0304-3800(97)00103-8

Ministerie van Algemene Zaken. (2023). *Inkomsten en uitgaven van het Rijk*. https://www.rijksoverheid.nl/onderwerpen/prinsjesdag/inkomsten-en-uitgaven-van-het-rijk#:~:text=De%20totale%20uitgaven%20van%20het,die%20mensen%20en%20bedrijven%20betalen.

Ministerie van Infrastructuur en Waterstaat. (2018, October 16, 2018). Samen aan de bak voor de grootste onderhoudsopgave ooit. https://www.magazinesrijkswaterstaat.nl/zakelijkeninnovatie/2018/04/workshop-vervanging-en-renovatie

Ministerie van Infrastructuur en Waterstaat. (2023). *Nieuwe wegprojecten op pauze, geld en menskracht naar groot onderhoud*. https://www.rijksoverheid.nl/actueel/nieuws/2023/06/23/nieuwe-wegprojecten-op-pauze-geld-en-menskracht-naar-groot-onderhoud

Nava Guerrero, G., Schwarz, P., & Slinger, J. (2016). *A recent overview of the integration of System Dynamics and Agent-based Modelling and Simulation.* Proceedings of the 34th International Conference of the System Dynamics Society, Delft, Netherlands.

NOS. (2019, January 17, 2019). *'Merwedebrug was bijna ingestort, Nederland aan ramp ontsnapt'*. https://nos.nl/artikel/2267818-merwedebrug-was-bijna-ingestort-nederland-aan-ramp-ontsnapt

Nurre, S. G., Cavdaroglu, B., Mitchell, J. E., Sharkey, T. C., & Wallace, W. A. (2012). Restoring infrastructure systems: An integrated network design and scheduling (INDS) problem. *European Journal of Operational Research*, *223*(3), 794-806. https://doi.org/10.1016/j.ejor.2012.07.010

Organisation for Economic Co-operation and Development. (2021). *Building Resilience: New Strategies for Strengthening Infrastructure Resilience and Maintenance*. OECD Publishing. https://www.oecd.org/publications/building-resilience-354aa2aa-en.htm

Oughton, E. J., Usher, W., Tyler, P., & Hall, J. W. (2018). Infrastructure as a complex adaptive system. *Complexity*, *2018*, 1-11. https://doi.org/https://doi.org/10.1155/2018/3427826

Ouyang, M. (2014). Review on modeling and simulation of interdependent critical infrastructure systems. *Reliability engineering & System safety*, *121*, 43-60. https://doi.org/https://doi-org.tudelft.idm.oclc.org/10.1016/j.ress.2013.06.040

Parlikad, A. K., & Jafari, M. (2016). Challenges in infrastructure asset management. *IFAC-PapersOnLine*, *49*(28), 185-190. https://doi.org/https://doi-org.tudelft.idm.oclc.org/10.1016/j.ifacol.2016.11.032

Qiao, Y., Fricker, J. D., & Labi, S. (2019). Influence of Project Bundling on Maintenance of Traffic Costs across Highway Project Types. *Journal of Construction Engineering and Management*, *145*(8), 05019010. https://doi.org/10.1061/(asce)co.1943-7862.0001676

Qiao, Y. J., Fricker, J. D., Labi, S., & Mills, T. (2018). Bundling Bridge and Other Highway Projects: Patterns and Policies. *Transportation Research Record: Journal of the Transportation Research Board*, *2672*(12), 167-178. https://doi.org/10.1177/0361198118797804

Quimpo, R. G., & Wu, S.-J. (1997). Condition Assessment of Water Supply Infrastructure. *Journal of Infrastructure Systems*, *3*(1), 15-22. https://doi.org/10.1061/(asce)1076-0342(1997)3:1(15)

Rasker, P. (2023, November 14, 2023). *Forse renovatie-opgave infrastructuur vraagt inzicht en samenwerking van beheerders*. https://www.tno.nl/nl/newsroom/insights/2023/11/renovatie-opgave-infrastructuur/

Rasker, P., Bletsis, A., Brongers, B., Vervuurt, A., & Verweij, E. (2023). Vernieuwingsopgave infrastructuur.

Rijkswaterstaat. (n,d.). *Roadmap Bruggen*. https://rwsinnoveert.nl/focuspunten/vervanging-renovatie/roadmap-bruggen-0/

Rittel, H. W. J., & Webber, M. M. (1973). Dilemmas in a general theory of planning. *Policy Sciences*, *4*(2), 155-169. https://doi.org/10.1007/bf01405730

Sánchez-Silva, M., Frangopol, D. M., Padgett, J., & Soliman, M. (2016). Maintenance and Operation of Infrastructure Systems: Review. *Journal of Structural Engineering*, *142*(9), F4016004. https://doi.org/10.1061/(asce)st.1943-541x.0001543

Schwarz, P., & Pruyt, E. (2016). Modelling and simulation the Zika Outbreak under Deep Uncertainty: A Multi-Method Multi-Resolution Approach. 34rd International System Dynamics Conference,

Senge, P. M., & Forrester, J. W. (1980). Tests for building confidence in system dynamics models. *System dynamics, TIMS studies in management sciences*, *14*, 209-228.

Shepherd, S. (2014). A review of system dynamics models applied in transportation. *Transportmetrica B: Transport Dynamics*, *2*(2), 83-105. https://doi.org/https://doi.org/10.1080/21680566.2014.916236

Smits, J. (2016). Fiber-reinforced polymer bridge design in the Netherlands: Architectural challenges toward innovative, sustainable, and durable bridges. *Engineering*, *2*(4), 518-527. https://doi.org/https://doi-org.tudelft.idm.oclc.org/10.1016/J.ENG.2016.04.004

Snijder, H., & Hesselink, B. (2018). Repair, strengthening and upgrading of steel bridges in The Netherlands. 39th IABSE Symposium in Vancouver 2017: Engineering the Future: Engineering the Future,

Sterman, J. (2002). System Dynamics: systems thinking and modeling for a complex world. http://hdl.handle.net/1721.1/102741

Süsser, D., Ceglarz, A., Gaschnig, H., Stavrakas, V., Flamos, A., Giannakidis, G., & Lilliestam, J. (2021). Model-based policymaking or policy-based modelling? How energy models and energy policy interact. *Energy Research & Social Science*, *75*, 101984. https://doi.org/https://doi-org.tudelft.idm.oclc.org/10.1016/j.erss.2021.101984

The World Bank. (2021). *Well Maintained: Economic Benefits from more Reliable and Resilient Infrastructure.* https://ppp.worldbank.org/public-private-partnership/library/well-maintained-economic-benefits-more-reliable-resilient-infrastructure

van Opstal, L. (2023). Understanding long-term labour market dynamics under deep uncertainty: A system dynamics approach for a labour market system. http://resolver.tudelft.nl/uuid:3bdba271-7ab2-4b3f-872b-ebeda2338cdb

Ventana Systems. (2022). *GOM GIS 2*. In *Ventity*

Walker, W. E., Haasnoot, M., & Kwakkel, J. H. (2013). Adapt or Perish: A Review of Planning Approaches for Adaptation under Deep Uncertainty. *Sustainability*, *5*(3), 955-979. https://www.mdpi.com/2071-1050/5/3/955

Xiong, Y., Fricker, J. D., & Labi, S. (2017). Bundling or Grouping Pavement and Bridge Projects: Analysis and Strategies. *Transportation Research Record: Journal of the Transportation Research Board*, *2613*(1), 37-44. https://doi.org/10.3141/2613-05

Yeager, L., Fiddaman, T., & Peterson, D. (2014). Entity-based system dynamics. Proceedings of the international system dynamics conference, Delft,

Appendices

A. Symbol overview

Table 7 shows an overview of the symbols used in the equations presented in this thesis along with their definition.

Table 7: Symbol overview

Symbol	Definition
$D_F(t)$	Fatigue damage of a bridge at time t.
$Dist_{n,m}(t)$	Distribution of traffic flows for a road from n to m.
I_n	Traffic intensity of region n.
$KM_{n,m}(t)$	Total amount of kilometers driven on a road at time t.
$P_n(t)$	Population of region n at time t.
$T_{LM}(t)$	Trigger for large maintenance.
$TM_{n,m}(t)$	Total amount of transport movements on a road a time t.
$T_{n,m}(t)$	Traveling of vehicles between regions n and m at time t.
$V_n(t)$	Amount of vehicles in region n at time t.
$W_{n,m}(t)$	Weight on a toad at time t.
$c_b(t)$	Bridge condition.
$c_{rv}(t)$	Recovery value of condition for bridge parts.
$d_{BP}(t)$	Degradation of bridge parts.
$delta\_w_{n,m}(t)$	Change in vehicle weight on a road.
$d_f(t)$	Increase in fatigue damage.
$df_n(t)$	Distribution factor for traffic flows in region n at time t.
$div_{n,m}(t)$	The amount of diverted traffic on a road at time t.
$d_{rv}(t)$	Yearly decline in recovery value of condition.
$fb_{n,m}(t)$	Bridge flow variable for the road from n to m.
gp_n	Population growth factor for region n.
$id_{n,m}(t)$	Increase in distribution for a road at time t.
$o_{n,m}(t)$	The difference between the current value of the distribution of a road and the value it should have based on the base distribution.
$r_{BP}(t)$	Restoration of bridge parts.
$red_n(t)$	Distribution that has to be redistributed to region N due to a bridge closing down at time t.
$wd_{n,m}(t)$	Decrease in weight on a road at time t.
w_i	Yearly increase in the average vehicle weight.
$wi_{n,m}(t)$	Increase in weight on a road at time t.
$C\_L(t)$	Load capacity of a bridge at time t.
$D(t)$	Decline of load capacity.
$M(t)$	Planned maintenance works.
$R(t)$	Projected need for reinforcement.
$r(t)$	Yearly restoration.
$w(t)$	Average weight of a vehicle at time t.

B. Initial set of uncertainties

Table 8 shows the initial set of uncertainties and their respective ranges of values used in the validation section of this thesis. The ranges for the parameters had been set intentionally wide, so that they can provide insight into the conditions under which the model 'breaks'.

Table 8: Initial uncertainty ranges

Name	Entity	Unit	Min	Max	Type	Equation	Source
Yearly growth average vehicle weight	Traffic	%	0.35	0.8	Parametric	15.3	(Copernicos Groep, 2018)
Yearly growth in traffic intensity	Traffic	%	0.24	0.36	Parametric	9	(Copernicos Groep, 2018)
Population growth	Settings	%	2.5	5.0	Parametric	10	(Compendium voor de Leefomgeving, 2023)
Average vehicle speed	Traffic	Km/hour	60	100	Parametric	11	Assumption
Safety margin bridge load	Settings	%	0	10	Parametric	4	Assumption
Load capacity average forecast horizon	Settings	Year	1	5	Parametric	4	Assumption
Period between bridge reinforcement works	Settings	Year	10	50	Parametric	N/A	(Copernicos Groep, 2018)
Aging factor Construction	Part type	%	0.83	1.25	Parametric	8.2	Assumption
Aging factor E & W	Part type	%	1.12	1.68	Parametric	8.2	Assumption
Factor historical annual deterioration in condition Construction	Part type	%	0.0024	0.0036	Parametric	7	Assumption
Factor historical annual deterioration in condition E & W	Part type	%	0.0040	0.0060	Parametric	7	Assumption
Factor historical annual reduction in condition recovery Construction	Part type	%	0.00064	0.00096	Parametric	7.1	Assumption
Factor historical annual reduction in condition recovery E & W	Part type	%	0.004	0.006	Parametric	7.1	Assumption
Periodic bridge reinforcement	Settings	Dimensionless	0	1	Structural	4	N/A
Periodic bridge maintenance	Settings	Dimensionless	0	1	Structural	8.1	N/A

C. Figure comparison 100 and 5000 runs

To increase interpretability, the figures used in the results chapter were generated using only 100 runs per policy option, resulting in a maximum of 400 lines per figure. The figures in this appendix show each of these figures with their 5000 run counterpart. The distributions of expected outcomes for both the 100 runs and 5000 runs per policy are largely consistent, which allows for the interpretation of the figures presented in the results chapter.

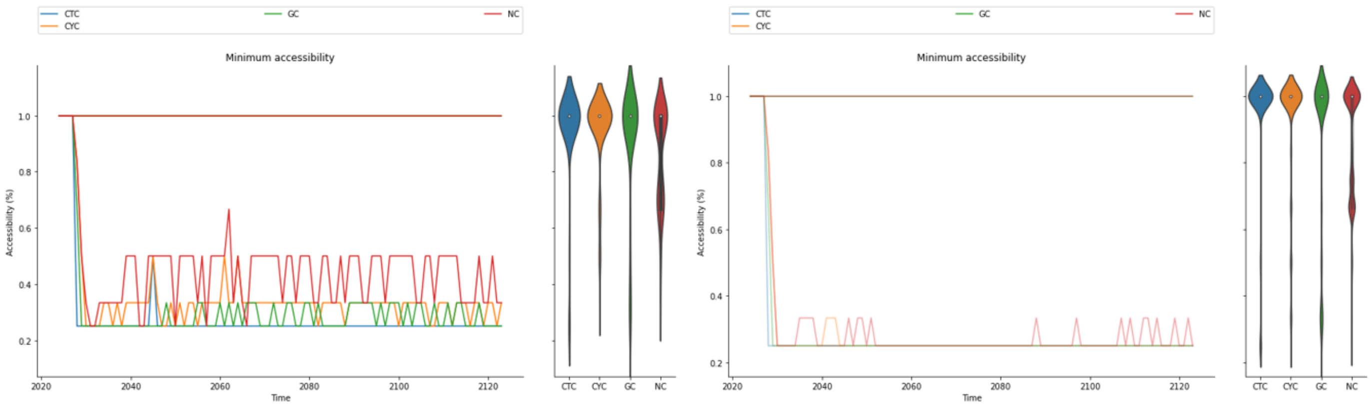

Figure 37: Minimum accessibility 100 runs per policy (left) and 5000 runs per policy (right)

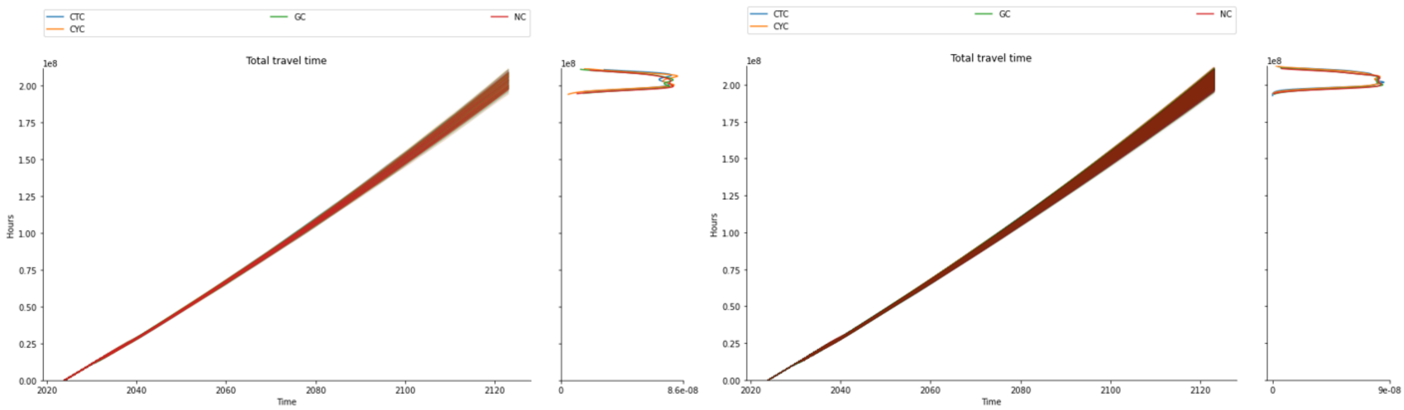

Figure 38: Total travel time 100 runs per policy (left) and 5000 runs per policy (right)

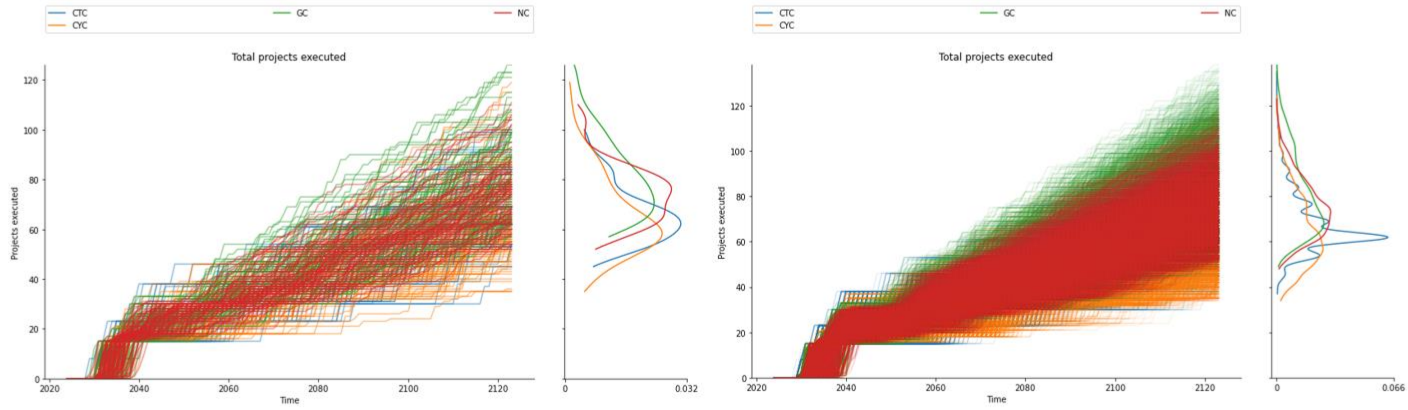

Figure 39: Total projects executed 100 runs per policy (left) and 5000 runs per policy (right)

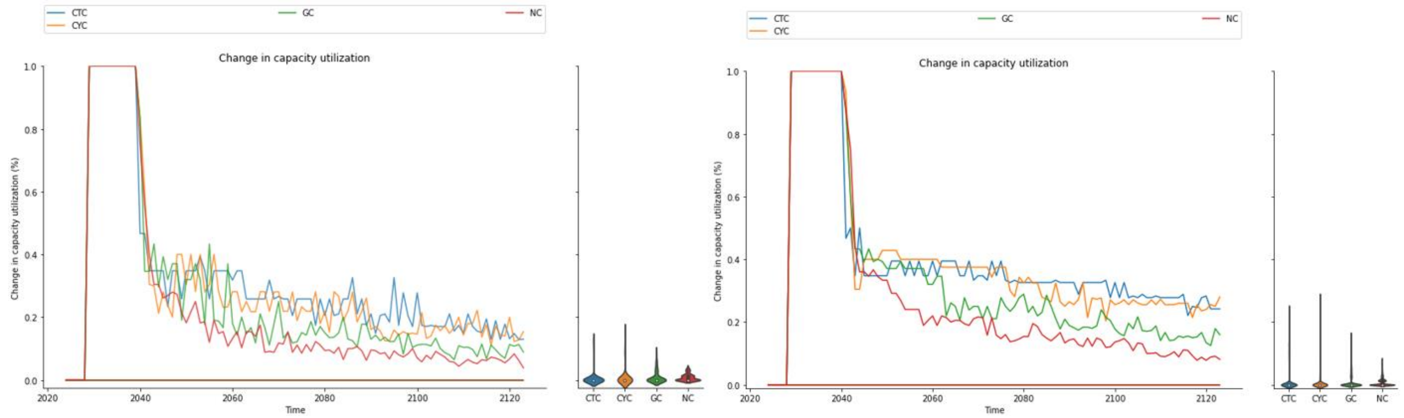

Figure 40: Change in capacity utilization 100 runs per policy (left) and 5000 runs per policy (right)

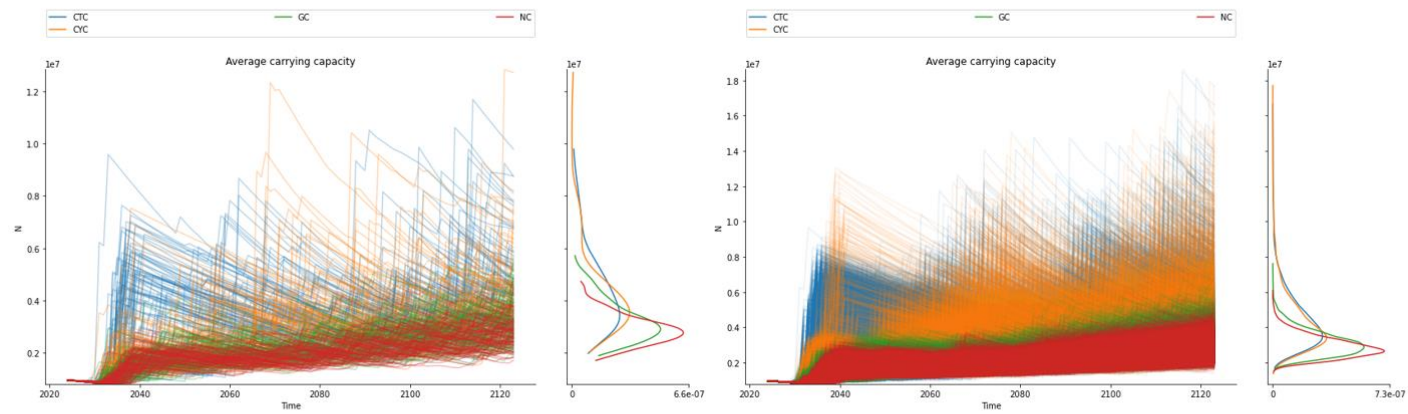

Figure 41: Average carrying capacity 100 runs per policy (left) and 5000 runs per policy (right)