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Building Climate Energy Management in Smart Thermal Grids via Aquifer Thermal Energy Storage Systems☆

Vahab Rostampour[a,*], Marc Jaxa-Rozen[b], Martin Bloemendal[c,d], Tamás Keviczky[a]

[a] *Delft Center for Systems and Control, Delft University of Technology, Mekelweg 2, 2628 CD, Delft, The Netherlands*
[b] *Faculty of Technology, Policy and Management, Delft University of Technology, Jaffalaan 5, Delft 2628 BX, The Netherlands*
[c] *Faculty of Civil Engineering and Geosciences, Delft University of Technology, Stevinweg 1, 2628 CN Delft, The Netherlands*
[d] *KWR Watercycle Research Institute, Groningenhaven 7, 3433 PE Nieuwegein, The Netherlands*

Abstract

This paper proposes a building energy management framework, described by mixed logical dynamical systems due to operating constraints and logic rules, together with an aquifer thermal energy storage (ATES) model. We develop a deterministic model predictive control strategy to meet building thermal energy demand. At each sampling a mixed integer quadratic optimization problem is formulated. We then provide a simulation study using an agent-based model and a geohydrological simulation environment (MODFLOW) to illustrate the performance of the framework.

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1. Introduction

Worldwide energy consumption has been increasing over the past decades due to increasing population and economic growth [1]. Taking into account the increasing energy demand, there has been a growing interest in energy saving technologies. A less well-known sustainable energy storage technology is ATES which is used to store large quantities of thermal energy in aquifers enabling the reduction of energy usage and CO_2 emissions of the heating and cooling networks in buildings. An ATES system is considered as a heat source or sink, or as a storage for thermal energy. This is achieved by injection and extraction of water into and from saturated underground aquifers. ATES systems are suitable for heating and cooling networks of utility buildings such as offices, hospitals, universities, musea and greenhouses.

Demand for ATES is increasing due to energy saving ambitions and cost. Therefore it is required to intensify and optimize the use of aquifers. However, Intensified use of the subsurface may result in mutual interaction between warm

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* Corresponding author. Tel.: +31-15-27-85056 ; fax: +31-15-27-86679.
E-mail address: v.rostampour@tudelft.nl

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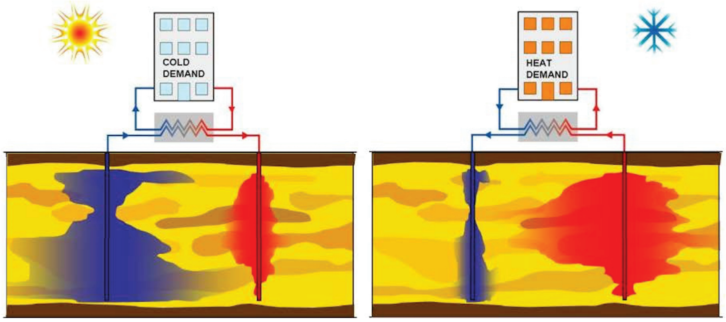


Fig. 1: Operational modes of an ATES system during warm (left) and cold (right) seasons. Figure is taken from [3].

and cold wells. To manage/prevent negative interactions it is needed to organize the use of the subsurface efficiently. The interactions between ATES systems are dynamically time-varying and plagued by uncertainty due to the absence of detailed underground models and cooperation between operators regarding the influence of nearby systems. ATES systems interact via the aquifer in a way comparable to how distributed sources and sinks of electricity are interacting via the electricity smart grid [2]. In a smart grid setting, every agent represents a building with its heating and cooling networks connected to an ATES system.

Each agent has a potential to contribute to local thermal energy balance of the grid and every agent is linked to the neighboring agents via their connections to the aquifer that is represented by a single ATES system. An ATES system consists of two wells and operates in a seasonal mode. One well is used for the storage of cold thermal energy, the second for the storage of heat thermal energy. In warm seasons, cold water is extracted from the aquifer using the cold storage well and through a heat exchanger to provide cooling to a building. This heats up the water, which is subsequently injected back into the aquifer via the warm storage well. This procedure is reversed during cold seasons where the flow direction is reversed such that the warmer water is extracted from the warm well to provide heating to a building. Figure 1 depicts the operational modes of an ATES system for a single building.

In this paper, we develop a simple thermal storage model for an ATES system. We describe an ATES system for control design purposes using a single electrical battery model that has charging, discharging and storing modes. A heat pump model is also incorporated in the system description during cold seasons. A building thermal energy demand profile, with respect to the building desired thermal comfort limits, is assumed to be known a-priori. We propose a building energy management framework described by mixed logical dynamical systems due to operating constraints and logic rules. We then formulate an optimal control problem to determine optimal pump flow rates of the ATES system to meet building thermal energy demand. This formulation leads to mixed-integer quadratic programing. To illustrate the performance of our thermal storage model together with the propose control framework, we provide a simulation study using an agent-based model and MODFLOW, a geohydrological simulation environment.

The structure of this paper is as follows. Section 2 proposes a simple mathematical model for an ATES system together with a deterministic model predictive control strategy. In Section 3, we describe our agent-based model simulation framework and the results of an idealized case study. Section 4 concludes this paper.

2. Aquifer Thermal Energy Storage: A Seasonal Energy Storage System

In this section we present a control-oriented thermal storage model for an ATES system. Each ATES system consists of warm and cold wells to store warm water during warm season and cold water during cold season, respectively. It can be thought of as a single thermal energy storage where the amount of stored energy is proportional to the stored water temperatures difference. Typically, stored energy from the last season is going to be used for the current season and so forth. An ATES system can be characterized by some physically meaningful parameters such as the amount of thermal energy content and with different operating modes. The operations of an ATES system is addressed with three different modes that are as follows: charging, discharging and storing modes. The charging and discharging modes correspond to injection and extraction of the thermal energy into or from the wells, respectively. The storing mode refers to input and simply keeping the stored thermal energy inside wells. Parameters that we use to describe an ATES system are defined as maximum and minimum energy content, maximum and minimum charge flow rate with discharge flow rate, and coefficient of losses.

$Q_{b,k} > 0$	Cold Season - HP is on	$s_{n,k} = 0, s_{h,k} = 1$
$Q_{b,k} = 0$	Storing mode	$s_{n,k} = 0, s_{h,k} = 0$
$Q_{b,k} < 0$	Warm Season - HP is off	$s_{n,k} = 1, s_{h,k} = 0$

Table 1: Operation modes of an ATES system based on the corresponding seasons.

2.1. Mathematical Model Description

Consider an ATES system to be a black box model having as input the energy request, as output the energy drawn and as state the energy content where the flow rate of a pump is defined as a manipulated variable. Denote with $k \in \{1, 2, \cdots, N\}$ each sampling time instance of a finite horizon optimal control problem [4]. Following this description, one can proceed with an autoregressive exogenous model $ARX(1, 1)$ as follows:

$$Q_{s,k+1} = A\ Q_{s,k} + Q_{aq,k}\ , \tag{1}$$

where $A \in [0, 1)$ is introduced as a lumped coefficient of losses, $Q_{s,k} \in \mathbb{R}$ represents the amount of stored energy and $Q_{aq,k} \in \mathbb{R}$ corresponds to the inlet or outlet energy according to its sign at a certain sampling instance k, respectively. $Q_{aq,k}$ is formulated with the following equation:

$$Q_{aq,k} = \int_{k\tau}^{(k+1)\tau} q_{aq}(t)\ dt \cong q_{aq}(k)\ \tau\ , \tag{2}$$

where τ is a sampling period and $q_{aq}(k) = \rho_w c_w u_k \Delta T_{aq}$ is the thermal energy of the aquifer at each sampling time. ρ_w and c_w are related to the water density and water volumetric specific heat capacity, respectively. ΔT_{aq} is defined as the temperature difference between warm and cold wells. It is assumed that the average water temperature difference in warm and cold wells is constant. The manipulated variable is pump flow rate that is represented by u_k. By substituting all defined variables into a single ATES system model (1), one can end up with the following equation in terms of $Q_{s,k}$ and u_k:

$$\begin{aligned} Q_{s,k+1} &= A\ Q_{s,k} + B\ u_k\ , \\ Q_{th,k} &= \left(\alpha_{hp,k}\ s_{h,k} + s_{n,k}\right)\ Q_{s,k}\ , \end{aligned} \tag{3}$$

where $B = \rho_w c_w \Delta T_{aq} \tau$ represents the coefficient of control variable, and $Q_{th,k} \in \mathbb{R}$ is an output performance of the proposed ATES system model (1) that contains the amount of thermal energy of all operating modes. The symbols $s_{h,k}, s_{n,k} \in \{0, 1\}$ are binary variables that correspond to the status of heat pump and the normal operation, respectively. In cold season $s_{h,k} = 1$ and ATES system is working in discharging mode together with a heat pump, whereas during warm season $s_{n,k} = 1$ and ATES system is working in charging mode. ATES system is in storing mode when $s_{h,k} = 0, s_{n,k} = 0$. In order to achieve an overall system energy balance, the requested thermal energy should be equal to the reserved thermal energy in an ATES system as it is shown in Figure 2.

2.2. Control Problem Formulation

The amount of thermal energy requested by the building is $Q_{b,k} \in \mathbb{R}$ that takes into account the overall building effects, e.g. zones, walls, humans and non-human thermal energy sources. The operating mode of an ATES system is determined based on the sign of $Q_{b,k}$ at each sampling time. $Q_{b,k}$ can be a positive scalar representing the building energy demand for the heating system and that the operating mode of ATES system is discharging and working with heat pump. An ATES system is charging whenever $Q_{b,k}$ has a negative value that corresponds to the building surplus thermal energy, which can be stored. If $Q_{b,k}$ is zero, an ATES system is in the storing mode. All operation modes are summarized in Table 1 based on the operational seasons.

We define a vector of continuous decision variables as $\boldsymbol{u} := [u_0, u_1 \cdots, u_{N-1}] \in \mathbb{R}^n$ and a vector of integer decision variables as $\boldsymbol{y} := [s_{h,0}, s_{n,0}, s_{h,1}, s_{n,1}, \cdots, s_{h,N-1}, s_{n,N-1}]$. Consider c_1, c_2, c_3 to be cost coefficients for the required thermal energy, electricity of heat pump, and pump of the ATES system, respectively. The total electricity demands that are used to operate the ATES system and the heat pump are $P_{s,k} = \eta_p h_p \tau\ u_k$ and $P_{hp,k} = \frac{1}{\text{COP}-1}\ Q_{s,k}$, respectively. The efficiency of the pump to deliver one cubic meter of aquifer water is η_p and h_p is the length of filter screen.

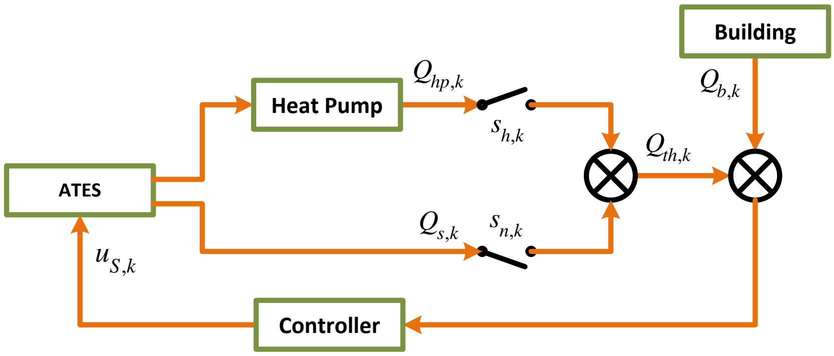


Fig. 2: Control system block diagram.

We formulate the optimization problem over a finite future time horizon N as follows:

$$\underset{\boldsymbol{u},\boldsymbol{y}}{\text{minimize}} \quad \sum_{k=1}^{N} c_1(Q_{b,k}+Q_{th,k})^2 + c_2(P_{hp,k}\ s_{h,k})^2 + c_3 P_{s,k}^2 \tag{4a}$$

$$\text{subject to} \quad \begin{cases} Q_{s,k+1} = A\ Q_{s,k} + B\ u_k \\ Q_{th,k} = \left(\alpha_{hp,k}\ s_{h,k} + s_{n,k}\right)\ Q_{s,k} \end{cases}, \tag{4b}$$

$$\begin{cases} -Q_{b,k} + (M-\epsilon)\ s_{h,k} \geq -\epsilon \\ Q_{b,k} - (m+\epsilon)\ s_{n,k} \geq -\epsilon \\ Q_{b,k} + (\epsilon - m)\ (1-s_{h,k}) \geq \epsilon \\ Q_{b,k} - (\epsilon + M)\ (1-s_{n,k}) \leq -\epsilon \end{cases}, \tag{4c}$$

$$Q_{\min} \leq Q_{s,k} \leq Q_{\max}\ , \tag{4d}$$

$$(s_{n,k}+s_{h,k})\ u_{\min} \leq u_k \leq u_{\max}\ (s_{n,k}+s_{h,k})\ , \tag{4e}$$

where $\alpha_{hp} = \text{COP}(\text{COP}-1)^{-1}$ corresponds to a function of coefficient of performance of the heat pump. Equation (4a) refers to the finite predictive control horizon objective which consists of two parts: a reference tracking part, and an economical part that represents the costs of total electricity that is used to operate an ATES system with a heat pump. Equation (4b) is related to the dynamics of ATES system, and constraint (4e) denotes upper and lower bounds for the pump flow rate of an ATES system, whereas (4d) represents upper and lower bounds for the energy content of ATES system. The binary variables represent the modes of operation via (4c), where $M = \max(Q_{b,k})$, $m = \min(Q_{b,k})$ and $\epsilon = 10^{-6}$ a positive constant. This formulation in (4c) corresponds to transform mixed logical dynamical facts involving continuous variables into linear inequalities [5].

It is assumed that the entire state vector $[Q_{s,1}, Q_{s,2}, \cdots, Q_{s,n}]$ of the system is known at each time instant, given the initial state value $Q_{s,0} = x_0$. The proposed optimization problem (4) is a multistage mixed-integer quadratic program, whose stages are coupled by the discrete-time dynamical ATES system equation (4b). The proposed MPC framework is summarized in Algorithm 1.

Algorithm 1 Model Predictive Control (MPC)

1: Initialize the state $Q_{s,0} = x_0$
2: Solve optimization program (4) and determine an optimal solution $\boldsymbol{u}^\star$.
3: Apply the first element of optimal solution $u_k := u_0^\star$ to the system (3)
4: Measure the state $Q_{s,k}$, and the building energy demand trajectory $\{Q_{b,k}\}_{k=1}^{N}$
5: Go to step 2.

Description	Symbol	Dimension	Value
water density	ρ_w	[kg m^{-3}]	1000
water specific heat capacity	c_w	[J(kg.K)$^{-1}$]	4200
temperature difference of warm and cold wells	ΔT_{aq}	[K]	10.0
sampling period	τ	[h]	168
coefficient of state loss	A	-	0.65
coefficient of control input	B	[MJ.h m^{-3}]	7056
number of pumps of an ATES system	n_p	-	1
length (filter screen)	h_p	[m]	20
pump efficiency	η_p	[kW h m^{-3}]	0.15
coefficient of performance	COP	-	4

Table 2: Detailed model parameters with their symbols and values.

2.3. Simulation Results

We simulate the proposed MPC strategy with a prediction horizon $N = 45$ and weekly-based sampling time. The simulation environment is MATLAB together with YALMIP which is a toolbox [6] for formulating the proposed optimization problem (4) in MATLAB and a quadratic programming solver (QUADPROG). Maximum, minimum pump flow rate is $5[m^3h^{-1}]$, $-5[m^3h^{-1}]$ and maximum, minimum energy content of an ATES system is $10^6[J]$, $-10^6[J]$, respectively. The Table 2 contains all detailed information of the model parameters and symbols with their corresponding values. The simulation has been done for the proposed optimization problem (4) in an open-loop (optimizing over the control input sequence). We assumed an artificial demand energy profile that represents the requested thermal energy of building for heating and cooling system. The building demand profile has positive and negative values that has the following interpretation. When it is a positive value that means the building requested thermal energy for the heating network during a cold season and when it is a negative value that corresponds to a warm season when the building has an extra amount of thermal energy (surplus) and wants to store in ATES system.

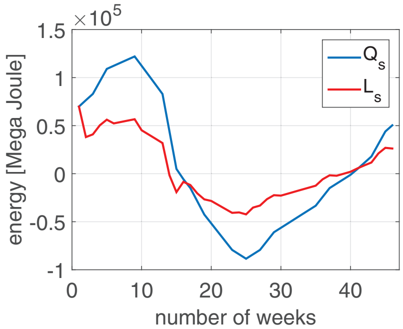
Figure 3 illustrates the results of our simulation study. Figure 3a depicts the amount of stored thermal energy in ATES system with 'blue' line and the amount of thermal energy at each sampling time in charging or discharging phase with 'red' line. Whereas, the amount of thermal energy content in an ATES system (red line) with negative sign and the amount of demand thermal energy of the building (blue line) at each sampling time is presented in Figure 3b to demonstrate the gap between thermal energy demand of the building for heating and cooling system and the stored thermal energy in ATES system. In Figure 3c the gap between thermal energy demand (blue line) and the provided thermal energy from ATES system (red line) is shown. Finally, the optimal pump flow rate of ATES system at each sampling time is shown in Figure 3d.

As it is clearly shown in Figures 3b and 3c, building thermal energy demand with positive values represents building heat demand during cold season for heating purpose, whereas, its negative values show cold demand during warm season for cooling purpose. During warm seasons the thermal energy demand is perfectly matched with the provided heat from ATES system Q_s and Q_{th}, due to the fact that $Q_s = Q_{th}$ and we do not use heat pump during warm seasons. The counterpart is the cold season where in Figure 3b, the gap is not zero. This gap will be zero by using a heat pump to make warmer water for heating system of the building as it is shown that the provided thermal energy from ATES system $Q_{th,k}$ in Figure 3c is almost zero. However, there exists a small gap during cold season in Figure 3c. The reason is that it is considered to have only the ATES system as a thermal energy source for the building. This small gap can be completely zero if we could consider to have an extra thermal energy source such as a boiler.

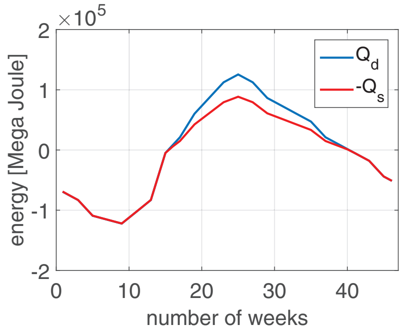
3. Simulation Environment using Agent-Based Model Framework

3.1. Description of Simulation Environment

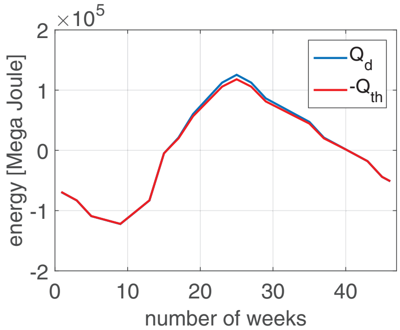
The performance of ATES systems is dependent on the geohydrological properties of the aquifer layer used for energy storage, and ATES operation can in turn have a significant impact on local conditions such as temperature



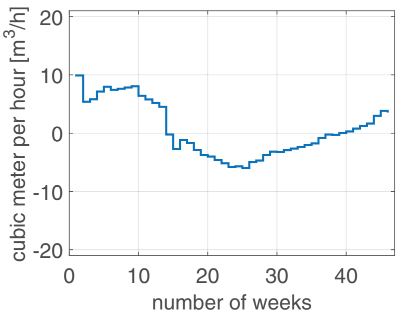
(a) Level of thermal energy in ATES system Q_S demand and the amount of thermal energy at each sampling time in charging or discharging phase, $L_s = Bu_s$.



(b) Building thermal energy demand Q_d versus the level of thermal energy in ATES system Q_s (with negative sign) at each sampling time.



(c) Building thermal energy demand Q_d versus the amount of supplied thermal energy Q_{th} (with negative sign) at each sampling time.



(d) Optimal pump flow rate of ATES system. with respect to the optimal objective at each sampling time.

Fig. 3: Simulation results of the proposed model predictive control framework in Algorithm 1.

distributions. On a broader scale, the adoption and operation of ATES technology is influenced by factors such as technical and economic performance; building owners will be more likely to invest in ATES if they can expect a return on their investment which is competitive with other energy-efficient technologies. This adoption will then increase demand for subsurface resources in urban areas. An accurate assessment of these interactions thus requires a simulation approach which accounts for geohydrological dynamics, as well as building-level ATES operation and adoption.

From this perspective, this section relies on a coupled simulation architecture which interfaces the previously-described MATLAB control system with the MODFLOW/SEAWAT geohydrological models, and with the NetLogo agent-based platform. MODFLOW [7] is a standard code for the simulation of steady and transient flow in confined or unconfined aquifers, using a finite-difference approach to solve the three-dimensional groundwater flow equations. It allows for the simulation of heterogeneous conductivities and transmissivities, as well as external stresses such as flows through wells and drains. Additionally, the SEAWAT version [8] can simulate variable-density groundwater flow and multi-species transport. In parallel, NetLogo [9] is an open-source environment for the design and testing of agent-based models, which includes a range of functions and methods to support the rapid development of spatially-explicit agent-based models. The coupled architecture is implemented in the Python object-oriented language and allows for the exchange of information across the different model components. The basic data exchanges are illustrated in Figure 4.

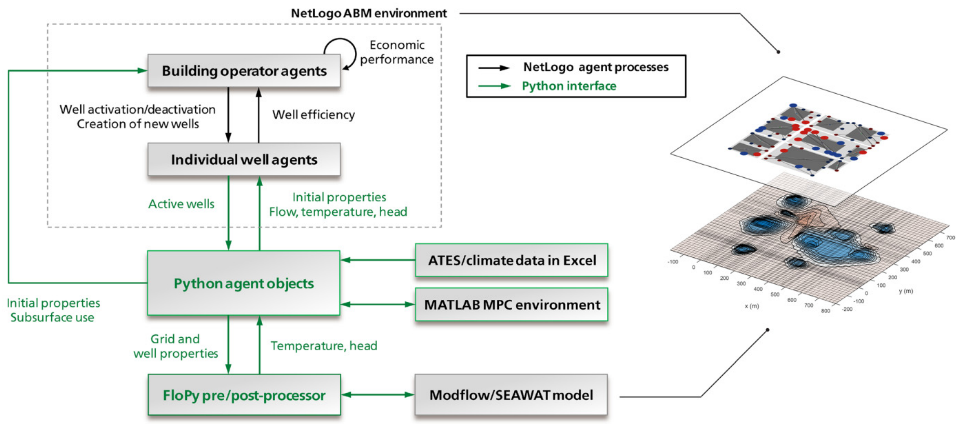


Fig. 4: Coupled Simulation Architecture

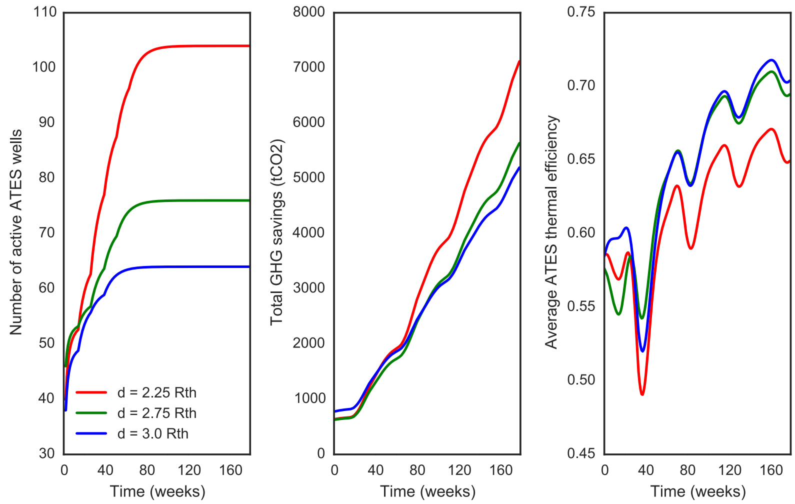


Fig. 5: Coupled Simulation Results

3.2. Idealized Case Study Results

The developed coupled simulation architecture was previously used for an idealized case study of urban ATES adoption and operation (described in more detail in [10]), which used a simpler control component for the calculation of ATES well flows. This case study evidenced several issues which should be acknowledged for the planning of ATES systems; in particular, regulations for the allowed density of ATES wells lead to a trade-off between the individual efficiency of ATES systems, and the collective energy savings which can be obtained within a given area.

The following results extend the case study discussed in [10], by including the control component described in Section 2. The models are parameterized to represent an idealized $1000m \times 1000m \times 20m$ confined aquifer, with 10 simulated building agents. These agents can build new ATES wells at random locations, within policy constraints for the minimum distance between wells of opposite temperatures; this distance is defined as a multiplier d of the average thermal radius R_{th} of the wells. The injection and extraction rates of the ATES wells are then computed with the approach described in Section 2. Figure 5 illustrates selected indicators for three well distance policies, $d \in \{2.25, 2.75, 3\} * R_{\mathrm{th}}$, over a simulated time frame of 180 weekly periods.

In Figure 5 the leftmost panel illustrates the number of active ATES wells over time. As could be expected, the policies which allow for a smaller distance between wells lead to a greater number of wells within the simulated $1000m \times 1000m$ area, whereas the $d = 3R_{\mathrm{th}}$ policy (representative of current design guidelines in the Netherlands) could potentially lead to inefficient use of subsurface space. As shown in the middle panel, the greater well densities allowed by the $d = 2.25R_{\mathrm{th}}$ and $d = 2.75R_{\mathrm{th}}$ policies also yield higher total reductions in greenhouse gas (GHG) emissions relative to conventional building energy systems. However, as indicated in the rightmost panel, the collective reductions in GHG emissions should be balanced against individual efficiency: for this latter indicator, the $d = 3R_{\mathrm{th}}$ policy performs better, by minimizing adverse thermal interactions between neighboring systems. As such, the trade-off illustrated in [10] remains present with a more detailed representation of ATES operation.

4. Conclusions and Future Works

In this paper we developed a simple control-oriented thermal storage model for ATES systems similar to a single electrical battery model that has charging, discharging and storing modes. A heat pump model is also involved together with the thermal storage model during cold seasons to meet the building thermal energy demand. We proposed a building energy management framework described by mixed logical dynamical systems due to operating constraints and logic rules. A model predictive control problem using a mixed-integer quadratic optimization problem formulation is solved at each sampling time and a simulation study using an agent-based model and MODFLOW is provided. This simulation study was used to evaluate the effects of the MPC approach on ATES system performance under different spatial planning policies. The results point towards a general trade-off between individual and collective ATES performance. This supports the results that had been observed for a simplified case of ATES control in [10]. The coupled simulation approach will be used in further work to compare the technical and economic performance of ATES under different control approaches, including hierarchical coordination.

A practical issue in smart thermal grids of ATES systems is that the sum of charging and discharging thermal energy amounts over all sampling time has to be equal to zero, in order to sustain the ATES system and to reduce negative effects to the environment. This condition is imposed by law and can be met within longer periods of time (once in each five years). The integration of this constraint into the developed framework is an interesting future research direction. Our current research direction is to incorporate the developed ATES system dynamics into our proposed thermal grid framework in [11].

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