Control strategies for a residential property with solar building, thermal and electricity storages

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Abstract

We study the control of an advanced energy system for a residential building. The system includes solar thermal and PV/T collectors, heat storages, a shallow geothermal system with a heat pump and a battery. Two control strategies are evaluated with simulation experiments: a rule-based one and model-predictive control. The rule-based strategy performs quite well in warmer seasons whereas MPC outperforms it in wintertime.

Keywords: solar buildings, energy storage, system simulation, model predictive control, control strategy

1. Introduction

Global awareness of consequences of climate change, of greenhouse gas emission and of its connection with the energy consumption is driving society to find more energy efficient and clean energy solutions. The EU Energy Performance of Buildings Directive requires all new buildings to be nearly zero-energy by the end of 2020 and the new research H2020 stream on energy building solutions are supporting the development of innovative smart energy management systems (European Commission, 2010, 2018). With the Strategic Energy Technology plan, the EU aims to aims to accelerate the development and deployment of low-carbon technologies, boosting the penetration of new zero-emissions energy technologies into market (European Commission, 2017). These comprises also renewable energy technologies. The intermittent intrinsic nature of these technologies generates a mismatch between energy production and consumption paving the way to technologies or solutions that are capable of shifting either energy demand or production.

The first section of the paper explores the literature review about building energy system controls in general and, in more detail about model predictive approaches. The second section focuses on the research methodology, emphasizing the approach considered by authors for assessing the performance of the proposed control strategies. The third section introduces the case studied, giving exhaustive detail about main system components and functionalities of the control strategies. Finally, the fourth section presents and discusses the results. The last part of the paper draws the conclusion of the research.

2. Research background

As regards demand shifting solution, demand-side management, defined as modification of energy consumption patterns through a behavioural change of end users, has gained some popularity. However, the needed communication infrastructure is not always available and the incentive systems to enable people engagement and proper participation are not mature yet (Pasini, Reda and Häkkinen, 2017). Besides this type of energy management system through behavioural change, another promising approach is to adopt active control of devices by means of actuators and sensors. This energy management approach is supported by the increasing number of smart devices deployed in buildings (Mohammadi *et al.*, 2018). Tools that enable this energy management approach process energy consumption and generation profiles information to manage energy generation and storage, to curtail and/or to shift energy demand in order to meet specific objectives, usually decrease the energy cost (Beaudin and Zareipour, 2015).

Among different active control methods, a recent review identifies model predictive control (MPC) as an appealing approach from many control techniques, due to advancement in processor speed and ability to adapt to

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many applications, including energy management of large PV or wind plant equipped with a battery system (Sultana *et al.*, 2017). MPC application to single building also showed a great potential. E.M. Wanjiru et al. estimated a potential energy saving of 32.24% during a day when MPC is adopted to control a heat pump and instantaneous shower heater powered using integrated wind and PV energy systems located in South Africa (Wanjiru, Sichilalu and Xia, 2017).

Model predictive control is an advanced control method originally developed in the 1970s and 1980s (Morari and Lee, 1999). The controlled system is modelled as an optimal control problem

$$\begin{aligned} \min_u J(u) &:= \int_0^{t_h} r\big(x(t), u(t)\big)\,\mathrm{d}t + g\big(x(t_h)\big) \quad \text{such that} \\ \dot{x} &= f(x, u), \\ x(0) &= x_0. \end{aligned} \tag{1}$$

x and u are functions of time that respectively represent the state of the system and the control input. This is a finite horizon problem, optimising the behaviour of the system up to some time t_h. The state x of the system is subject to dynamics, which also depends on the control input u that is chosen to minimize an objective consisting of costs accumulated over time and another term that evaluates the state that the system is left at the end of the horizon. The second term serves to prevent myopic behaviour, e.g., by assigning value to stored energy in order to prevent MPC from draining storages. There may also be constraints on x and u (not shown). This problem is discretised in time, yielding a finite-dimensional optimisation problem, which is solved numerically with the current state of the system as the initial condition. The control values for the first time step are applied to the actual system. The rest of the solution is discarded: one time step later new optimal controls are computed starting from the state at that time, for time t_h ahead (rolling horizon). Thus the procedure repeats.

Problem (1) must allow for reasonably quick solution, much quicker than the time step used, which should be short enough to capture the relevant dynamics. Traditionally this required linear dynamics and a linear or quadratic objective, yielding a linear or quadratic optimisation problem. Compared with classical linear control, such MPC has the advantage of being able to handle constraints. Impressive performance improvements of computer hardware and optimisation algorithms now allow application of MPC also to more complex models.

Since the cost of energy is the main driver in energy saving applications, recently there appeared a notion of an economic MPC (EMPC), which considers the dynamic character of energy prices. The idea is to use an economic objective for MPC directly as opposed to the more traditional process industry approach of first finding an economically optimal steady state, then tracking it with MPC (Zong *et al.*, 2017). A recent study compared the EMPC control with a rule-based control for managing an air conditioner, a water heater, an electric vehicle, a PV system and a battery in a residential building. One year simulation results showed that residential buildings could achieve cost savings up to 26% under three time of use pricing scheme, 42% under real time price scheme, and 17% under hourly pricing scheme, compared to traditional on/off controls (Mirakhorli and Dong, 2018).

In all the above-mentioned studies that focused on EMPC for renewable energy in buildings only solar energy technology was investigated. Up to the authors' knowledge, only one paper has investigated the use of PV and solar collectors (Khakimova *et al.*, 2017). Results of this study are relevant for what concerns the heating season, while cooling has not been considered. Heat pumps, especially ground-source heat pumps, coupled with solar energy technologies are considered one of the most efficient heating and cooling systems (Reda *et al.*, 2015). Solar-assisted heat pump (SAHP) is a relevant choice for achieving high energy performance of buildings and deserves more research on operational control systems in this field. The contribution of this paper is to investigate application of such an EMPC to a more complex system and optimize several solar energy technologies (PV/T and vacuum collectors) connected to energy storages (battery, seasonal and short-term thermal storages) and to a ground source heat pump. The analysed system configuration is in line with the concept of positive energy building (a building that produces more energy than consumes over a timespan of one year), which lately received an increased attention because of the new EU energy 2030 targets (European Commission, 2014).

3. Methodology

In this study, the objective of the MPC was to minimize operational costs of the system, which would otherwise be controlled using a set of pre-determined rules. To evaluate the two strategies, we carry out simulation experiments using a detailed model of the energy system and compare the resulting operational costs. In both cases we make sure that the model, loads, ambient and initial conditions are the same, and energy demands as well as temperature requirements of heat loads are met at all times. The conceptual scheme of the study is presented on Figure 1.

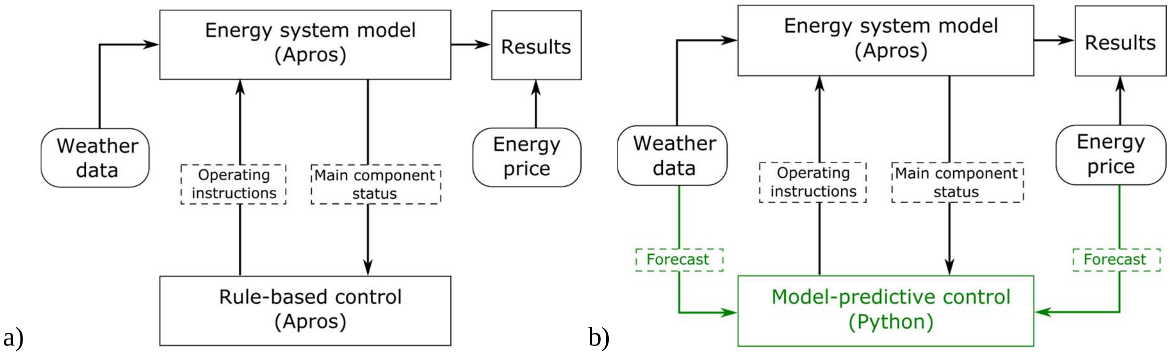

Figure 1 - Conceptual scheme of the study and information flow with rule-based control (a) and model-predictive control (b)

The weather data consists of outdoor air temperature and total solar irradiance incident on the planes of panels of solar energy generation systems. In this study, we used three weeks of a year, determined from one-year weather data for energy simulations as seven consecutive days with the highest, median and lowest values of mean daily outdoor air temperature.

The simulation of the system operation was carried out using the modelling software Apros (*Apros*, 2018). The detailed model consists of energy generation devices, storages as well as thermal and electrical loads. The most important details of hydraulic system, such as flow capacity values of valves, characteristics of circulation pumps are also modelled in order to take into account pumping costs. The electrical phenomena were not subject of the study and for this reason were not modelled in detail. Instead, the model estimates the electrical loads of equipment controlled by the control system: circulation pumps, heat pump and battery. The thermal and electrical loads associated with demands of the building were pre-simulated using TRNSYS software (*TRNSYS Transient System Simulation Tool*, 2017) and were considered in the model as independent external inputs. The initial conditions for the test weeks were the same for both rule-based and model-predictive control systems, and were determined from state of the system at the beginning of these weeks during the second consecutive year of simulation using the rule-based control system. More information about the modelled system is provided in Section 4.

The energy system model reports main component status to the control system. This includes temperature measurements in different parts of the system, including thermal storages, as well as battery state of charge. The control system sends operating commands, which include states of pumps and valves, heat output of heat pump, charging or discharging power of the battery.

The rule-based control system operates continuously using measured temperature levels at every time step to identify directions of possible heat transfer and aims to direct heat flows from heat sources to heat loads using a set of rules. The electric power flows is directed using state of charge of the battery and imbalance between the on-site electricity generation and load.

The model-predictive control system operates with one-hour time step, which is significantly larger than that of the rule-based system. The MPC uses the same weather and price data as the simulation model it controls, i.e. we assume that the forecasts are always correct and this allows us to exclude the factors related to forecast inaccuracy when analysing the results. The model-predictive control system uses its own simplified model of the energy system, which differs from the more detailed simulation model. The integrand r of the objective in (1) is the net electric energy cost. Although it is not possible to sell power into the grid at the actual site, we put a small sell price in the MPC model to avoid frivolous power use during excess. In contrast, it is not clear what the final time term g should be. The only externally given price is that of electricity. We valued stored energy at fixed fractions of the electricity price. The fractions depended on the storage and sometimes season (no value for the space heating tank during summer) but were chosen rather arbitrarily. Further simplifications in the model used by MPC are described in Section 4.

The heat system of the site consists of heat sources and storages connected with heat exchangers to circulating fluid loops that transfer heat between them. Heat transfer is proportional to temperature differences and can also be controlled with the circulating fluid flow (the whole loop can be turned off by stopping the pump and there are also bypass valves for essentially every component). This is surprisingly difficult to optimise. Assuming complete control, the heat transferred by a heat exchanger is

$$Q = Cz\Delta T, \tag{2}$$

where ΔT is the temperature difference, say, between inlets, C is the maximum heat transfer coefficient achievable and $z \in [0,1]$ can be chosen at will. Generally, this is a non-convex constraint. Only if nothing else depends on z and the sign of ΔT is fixed, e.g., greater or equal to zero, we can eliminate z and replace (2) with $0 \leq Q \leq C\Delta T$. But for storages the sign of ΔT cannot be fixed.

To get a solvable model we assumed that z is binary (for most cases in the actual system it is). We then replaced (2) with a convex hull relaxation, obtaining a mixed integer linear program (Rubin, 2010). The relaxation is tight when x is binary but allows unphysical heat transfer for fractional x that occur during solution. The MILP was solved with IBM ILOG CPLEX, an advanced branch & cut solver. It is generally impossible to solve anything but the tiniest MILP to optimum in reasonable time. However, suboptimal but fairly good solutions are often found somewhat quickly. Our model used a one hour time step, which may be long for short-term storages, but fine for the other heat storages, which have vastly larger heat capacity. We gave CPLEX two minutes for solving the MILP and used the best solution it had found in that time. In real time, we could spend a bit longer without wasting a significant part of the one-hour time step, or we could use a shorter time step. However, we want the simulation to run significantly faster than real time. The rolling horizon was 24 hours ahead.

The optimisation model was implemented in Pyomo (Hart *et al.*, 2017), an optimisation modelling library for the Python programming language. Pyomo is a rather high-level framework; a dynamic model can be defined by differential equations and discretized with a transformation from the library. We used the implicit Euler method because it is simple and stable: the optimization problem is solved for all time steps at once, hence an implicit method introduces no additional complexity.

The most important metric should agree with the optimization objective and therefore includes the total cost of electricity from grid during test week:

$$C_{elec} = \int_{t1}^{t2} P_{elec}(t)\ W_{elec}(t)\, \mathrm{d}t \tag{3}$$

where C_{elec} - is the total cost of purchasing electricity from grid during the test week period (t1, t2), $P_{elec}(t)$ - is the price of electricity during hour t, and $W_{elec}(t)$ - is the power drawn from grid during hour t. This corresponds to the term *r* of the optimization objective (1).

When comparing the two control systems and for further agreement with the optimization objective, there is a need to correct for difference in final states of energy storages, to obtain the operation cost reduction (OCR):

$$OCR = C_{elec}^{mpc} - C_{elec} + \sum_i P_i \left(E_i^{mpc,t2} - E_i^{t2}\right) \tag{4}$$

where C_{elec}^{mpc} and C_{elec} are the total costs of grid electricity with MPC and rule-based control systems, P_i - is price of energy stored in energy storage *i*, $E_i^{mpc,t2}$ and E_i^{t2} - are the amounts of remaining energy in energy storage *i* at the end of the test week.

The last summand in (4) corresponds to the term g of the optimization objective in (1), which purpose is to reflect the value of stored energy. We can value energy in the battery at the grid price or some fraction thereof but for the various heat storages value is difficult to quantify.

In addition to operational energy cost savings, we also estimate on-site energy fraction (OEF) and on-site energy matching (OEM) to give a more comprehensive picture of the system performance under the two control approaches. The OEF gives an estimation of the portion of final energy consumption covered by the produced on-site renewable energy. OEM gives an estimation of the portion of the produced on-site renewable energy directly consumed (Cao, Hasan and Sirén, 2013). These indicators have been stated as:

$$OEF_e = \frac{\int_{t1}^{t2} \mathrm{Min}[G_{elec}(t) - ES_{on}(t); L_{elec}(t)]\mathrm{d}t}{\int_{t1}^{t2}[L_{elec}(t)]\mathrm{d}t}, \qquad 0 \leq OEF_e \leq 1 \tag{5}$$

$$OEM_e = \frac{\int_{t1}^{t2} \mathrm{Min}[G_{elec}(t); L_{elec}(t) + ES_{on}(t)]\mathrm{d}t}{\int_{t1}^{t2}[G_{elec}(t)]\mathrm{d}t}, \qquad 0 \leq OEM_e \leq 1 \tag{6}$$

where $\mathrm{d}t$ is the differential time step, G_{elec} is on-site electricity generation, L_{elec} - total electrical loads, and ES_{on}- electric power to the battery (negative when flow is from the battery).

4. Case study and modelling

The simulation study is based on the data and configuration of the EU Story research project demonstration site located in Belgium. The site has a small-scale but rather complex energy system being in implementation phase at a residential property. The system represents a combination of on-site solar heat and electricity generation, long and short-term thermal storages as well as energy conversion (heat pump, PV/T), linking the thermal and electrical subsystems. There is a very well insulated single-family house. Optimal joint operation of equipment installed on site calls for an advanced control method. The main equipment installed on site as well as possible directions of energy transfer are shown on Figure 2.

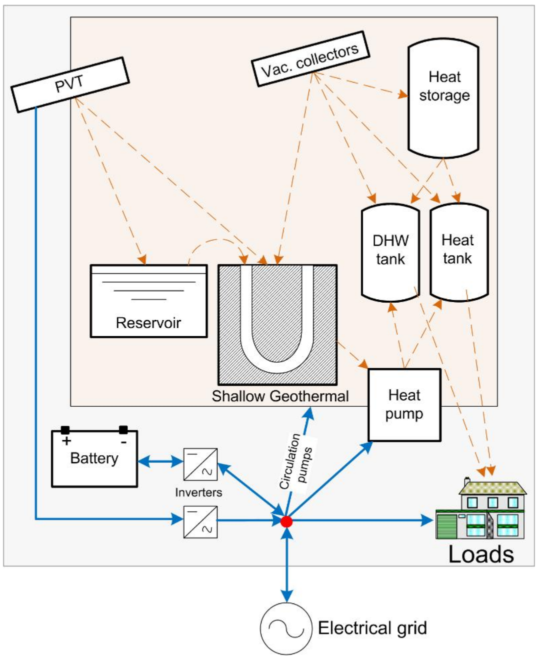

Figure 2 - Main equipment installed on site and paths of possible heat (brown) and electricity (blue) transfer.

The on-site heat generation equipment includes vacuum collectors and a PV/T system. The heat produced by the PV/T system is used to warm up a swimming pool water, which cools down the PV/T panels to increase their electrical efficiency; this part of the thermal system has the most significant circulation pump power. The site has a battery system for electricity storage and a bi-directional connection to a local electricity distribution network. The seasonal heat storage consists of two relatively large water tanks buried in the ground. The main sources of heat for the seasonal and short-term heat storages are vacuum solar collectors and a heat pump. The shallow geothermal system represents twelve thermally activated building foundation piles, each 6.5 meters deep. The main technical parameters of the equipment are presented in Table 1.

Table 1 - The main technical characteristics of the equipment of the case study

System	Main characteristic
PV/T system	10 kWp,/ 24.3 kW
Vac. collectors system	3.8 kW
Seasonal heat storage	2 x 12 m³
Short-term heat storage	2 x 0.2 m³
Heat pump	1.53 kW / 5.8 kW
Reservoir	42 m³
Shallow geothermal	312 m³ of activated soil
Battery (SoC 30-100%)	32.2 kWh

A detailed model of the energy system was implemented in the simulation software Apros. The model takes into account the dynamics of the hydraulic system on the heating side with water tanks and circulation pumps. The data for the simulation model included technical data sheets of manufacturers, interviews with the owners as well as online measurement data made available through a cloud service. A hydraulic diagram of the thermal part of the system is shown on Figure 3.

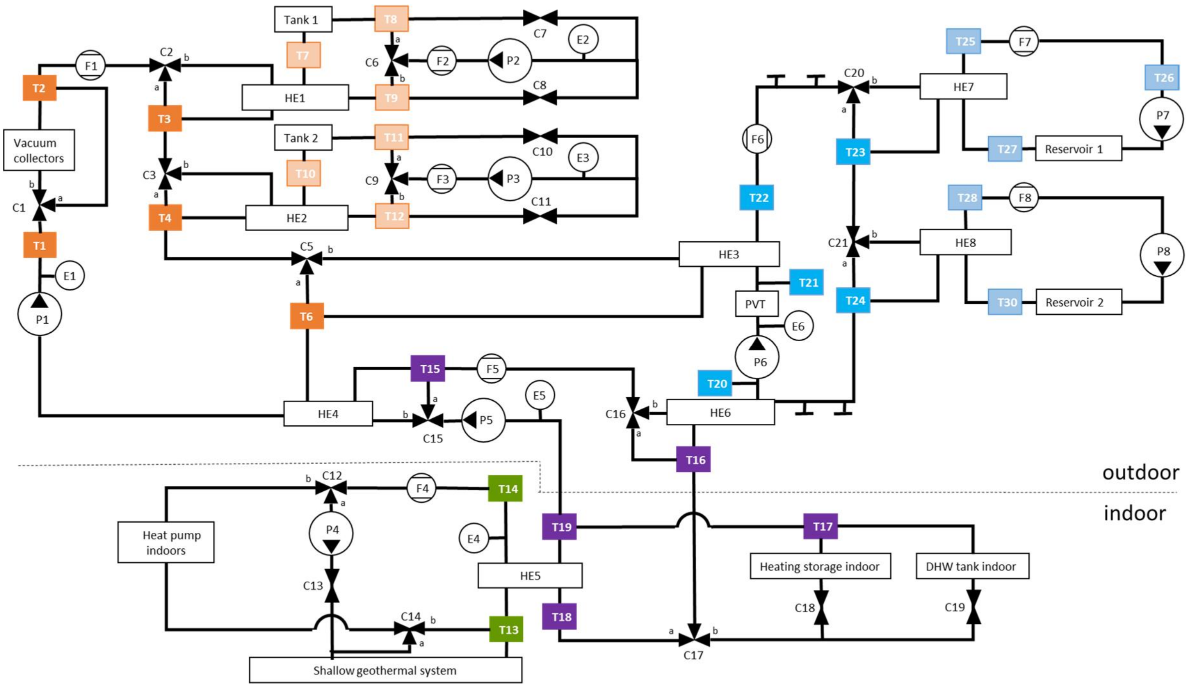

Figure 3 - Hydraulic diagram of the thermal system.

The thermal system, shown in Figure 3, consists of four loops circulating heat transfer fluid through various devices. The loops are interconnected by heat exchangers. Essentially all devices and heat exchangers are equipped with bypass valves. In the model, the loops are assumed lossless: heat transfer occurs only with active devices and heat exchangers along the loop. The short-term heat storages are represented by two indoor hot water tanks both having capacity of 200 litres. As mentioned above, the heat (space heating, domestic hot water) and electricity (appliances, lighting) demands of the building were pre-simulated. The heat demands are modelled as withdrawal of hot water from the corresponding short-term heat storage tanks.

In MPC, the heat storage tanks, the shallow geothermal system and "Reservoir 1" (a swimming pool) are all modelled as simple heat storages; they have a single, uniform temperature, and when active they exchange heat with their loop according to Newton's law of cooling. This affects the storage temperature according to heat capacity. The storages may also have other heat exchanges, e.g., losses to the environment. The "Reservoir 2" is actually a brook, which we model as a heat bath (fixed temperature).

The indoor storage tanks have given loads (space heating and domestic hot water), which in MPC model can be extracted from the tank or be produced by the heat pump. The heat pump actually heats the top parts of the tanks, which produces significant stratification that is difficult to model. Having the heat pump heat only the output appears more realistic than having it heat the whole tank. It is assumed that the heat pump has a fixed COP, freely variable power and its output can be directed to the two indoor tanks at will. At least five thermal nodes describe most of the heat storages in the detailed model. The detailed model describes switching of the heat pump between heating the two different tanks.

Solar thermal and PV/T collectors are modelled alike. Incident radiation intensity I perpendicular to the collector is assumed known (weather input). Each collector has an effective area A such that absorbed solar power equals IA. The share of this power converted to electricity equals $\epsilon_0 + \epsilon_1 T$, where T is the temperature of the solar collector and ϵ_i are known parameters (zero for a pure thermal collector). The rest of the absorbed power becomes heat, which transfers to the fluid loop (if active) and ambient air according to Newton's law of cooling. Heat capacity of the collectors is assumed so small that their temperatures are always at equilibrium.

The battery is modelled as a simple storage: a fixed proportion of charging power is assumed lost; the rest is stored and can be discharged later. Self-discharge and battery wear are not modelled. In addition to storage capacity, there are limits to charging and discharging current.

In the MPC model, the pumps of the heat transfer loops consume a fixed power when active. Individual active devices of the heat system can also consume power. Power consumption from changing controls (e.g., operating bypass valves) is ignored. Uncontrolled pre-simulated domestic electric load is assumed known. Power can be produced by PV/T system, discharged from battery, or bought from the grid at a known (but time-varying) price. The model would also support selling power to the grid, but due to zero feed-in price at the site, this is only reasonable to do in exceptional cases, for example, when storages are full or potentially produced heat is predicted to have no later use. The tariff levels in euro cents/kWh were as follows: 7.685 during the day, 5.988 during the night (21:00 PM - 6:00 AM) and weekends. The rule-based control strategy does not consider the electricity price levels at all - it only attempts to minimize the power drawn from external grid based on state of charge of the battery and imbalance between electricity generation and loads. The battery is only charged when the output of PV/T system exceeds the total electrical loads. The excess electricity, if cannot be entirely used to charge the battery, is exported to the grid. The battery discharges when the loads exceed on-site electricity production until state of charge drops to a minimum of 30 percent. With rule-based control, the battery stores only renewable electricity produced on-site. The rule-based control strategy prioritizes the heat sources according to levels of energy costs and importance of the loads. This means that available output of solar collectors would have higher priority over heat pump and that charging the short-term storage tank of domestic hot water has a higher priority over other heat storages until it reaches a certain high-enough set point temperature. In practice, the heat flows are directed mostly in the following way. The heat output of vacuum solar collectors is transferred to short-term domestic hot water or space heating tanks, and when not possible - to seasonal heat storage. When the temperature levels of water in the seasonal storages allow, and when vacuum collectors are not available, the heat is transferred from seasonal storage to the short-term storages. Finally, the ground-source heat pump ensures the minimum temperatures in both short-term storages.

5. Results and discussion

Table 2 summarises the costs of the simulated system operation under the two control strategies. Under MPC, the figures in parentheses are the total direct costs of purchased electricity whereas those outside parentheses are corrected for the difference in stored electricity and heat at the end of corresponding test week as described in Section 3. The differences in stored energy between MPC and rule-based control are also shown.

Table 2 - Operation energy costs of the system controlled by the two control systems during test weeks and differences in energy content of storages at the end of test weeks.

Test week	Total cost, €		Difference in stored electricity, kWh	Difference in stored heat, kWh
	Rule-based	MPC		
The coldest	6.44	4.39 (4.69)	7.49	-34.7
The warmest	0.01	0.70 (0.31)	0.61	-108.7
Median temperature	0.01	1.24 (0.65)	2.74	-184.4

It can be seen from Table 2 that at the end of all of the three test weeks, use of model-predictive control resulted in a higher energy content in the battery compared to the case when the system was operated using the rule-based control. In the case of stored heat the result is opposite. The energy content of the battery was directly observable and the price used for valuation of stored electricity was the night electricity tariff. To calculate differences in stored heat we used the difference of total enthalpy of water stored in the tanks as well as heat capacity of activated ground and its average temperature. The prices used for valuation of stored heat were set as fractions of the price of stored electricity. The information about the differences in final states of storages and used prices of stored heat is presented in Table 3.

Table 3 - The differences in content of energy storages, applied prices for valuation of the energy content and resulting corrections to total costs.

Test week	Energy storage	Difference in stored energy, kWh	Value of energy as fraction of price of stored electricity (0.05988 €/kWh)	Correction, €
The coldest	Battery	7.5	1.0	0.45
	Swimming pool	-56.3	0.1	-0.34
	Seasonal tanks	17.5	0.2	0.21
	DHW tank	-3.2	0.1	-0.02
	Space heating tank	-0.6	0.1	0.00
	Geothermal	0.4	0.1	0.00
	Total	**-34.7**	-	**0.30**
The warmest	Battery	0.6	1.0	0.04
	Swimming pool	-146.7	0.1	-0.88
	Seasonal tanks	40.0	0.2	0.48
	DHW tank	-4.5	0.1	-0.03
	Space heating tank	2.0	0.0	0.00
	Geothermal	-0.1	0.1	0.00
	Total	**-108.7**	-	**-0.39**
Median temperature	Battery	2.7	1.0	0.16
	Swimming pool	-239.2	0.1	-1.43
	Seasonal tanks	61.7	0.2	0.74
	DHW tank	-9.5	0.1	-0.06
	Space heating tank	0.0	0.0	0.00
	Geothermal	-0.2	0.1	0.00
	Total	**-184.4**	-	**-0.59**

The value of energy content in the shallow geothermal storage shown in Table 3 was calculated based on the differences in its final average temperatures and thermal capacity of the active ground. The total heat capacity of ground expressed in kWh per Kelvin was 190.7. At the end of the coldest week the ground was on average 2 degrees warmer, and at the end of the warmest and the median temperature week respectively 0.46 and 1.19 degrees colder with model-predictive control compared to rule-based.

The results presented in Table 2 suggest that the best performance of model-predictive control system compared to the rule-based one, both with and without corrections for the final states in heat storages is achieved in the coldest week. During the warmer weeks there is significant on-site electricity generation by the PV/T system and the system is able to store the excess electricity in sufficient amounts to almost entirely cover electrical loads, including operation of heat pump to prepare domestic hot water. This is exactly what happens with rule-based control and can be seen by negative net exchange with electrical grid in Table 4 as well as Figure 5 and Figure 6.

Table 4 - Interaction of the system with electrical grid when controlled by the two control systems during test weeks.

Test week	Consumption (paid), kWh		Net exchange, kWh	
	Rule-based	MPC	Rule-based	MPC
The coldest	95.3	75.5	95.2	75.5
The warmest	0.1	4.8	-127.8	-110.1
Median temperature	0.2	10.3	-116.5	-119.1

The following three figures show consumption of electricity from electrical grid and the values of daily indices of on-site energy fraction and matching for electricity. The indices were calculated from the data having one-minute time resolution and for this reason the values of indices may differ from the expected from hourly presentation of electricity consumption from grid.

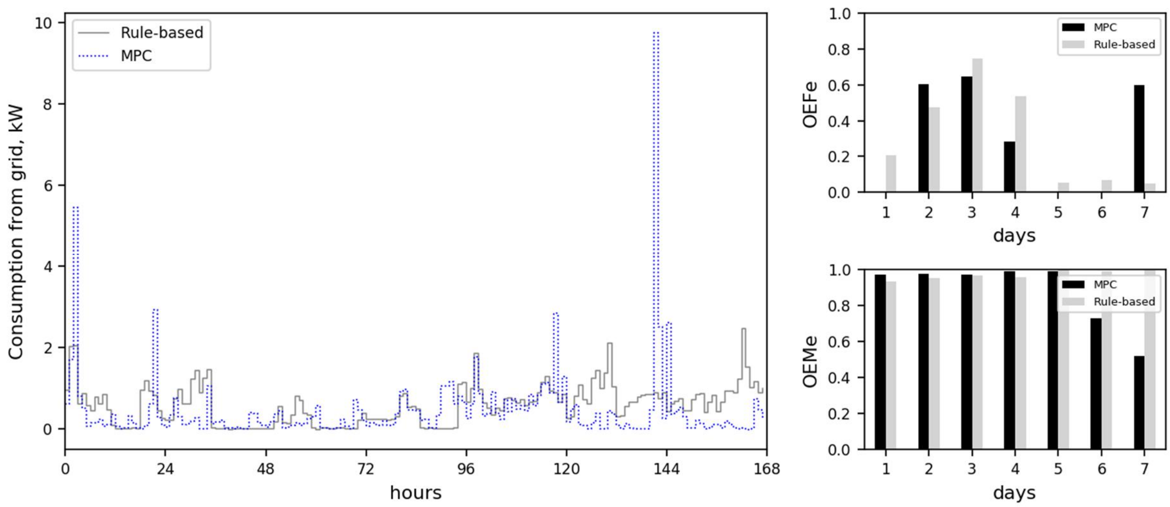

Figure 4 - Electricity consumption from grid and daily on-site energy indices during the coldest week

During the coldest week, the model-predictive control is charging the battery during the night and as a result consumes less electricity from grid during the day when the electricity price is higher. This affects the values of OEFe index on days 5, 6 and 7.

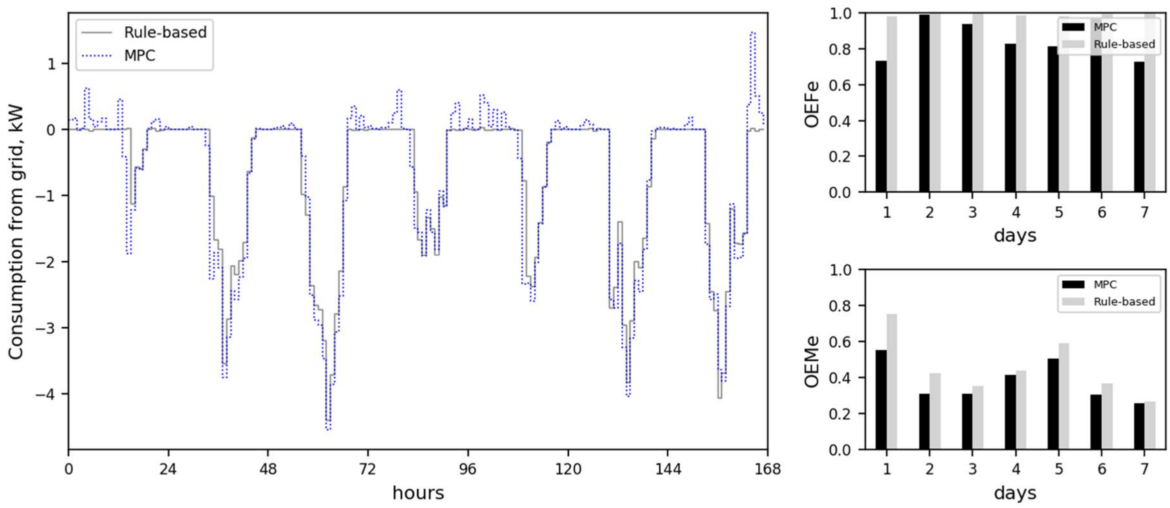

Figure 5 - Electricity consumption from grid and daily on-site energy indices during the median temperature week

During both warmer weeks, due to excess on-site electricity generation the values of OEFe are relatively high for both systems and the values of OEMe are relatively low. Low values of on-site energy matching index is explained by the stress on the external grid caused by feeding the surplus electricity which can't be entirely stored in the battery.

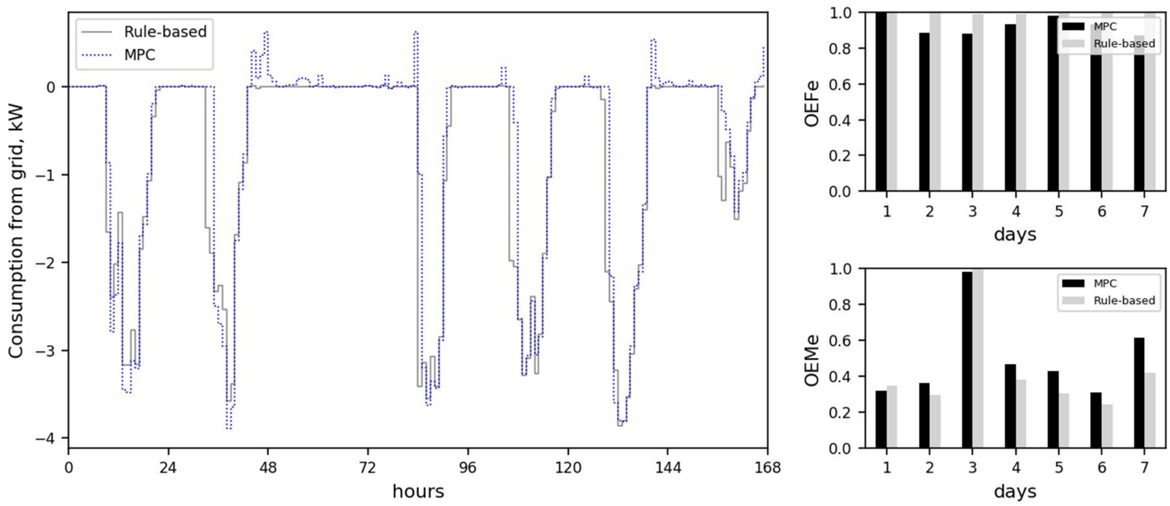

Figure 6 - Electricity consumption from grid and daily on-site energy indices during the warmest week

During the warm weeks, the model-predictive control still causes the system to consume electricity from grid during some hours. This may be due to improperly selected final prices, model mismatches as well as poor optimization solutions due to the short time available for optimization.

The prices used to estimate the value of stored energy were not constant during optimization. The used values were tied to the electricity price at the end of prediction horizon, and therefore it is not entirely clear what values should be used when correcting the total costs. From practical point of view, the most value of stored heat would most likely be attributed to domestic hot water and space heating tanks from which the heat could be used immediately, as well as seasonal storages based on hot water. At the same time, the most influence on the amount of correction is caused by the swimming pool, which main role is being a heat sink.

It should also be noticed that the observed surplus of electricity on the site is intended for charging an electrical vehicle. Charging and discharging the vehicle would most certainly improve the results of model-predictive control system. However, at this time we did not have sufficient data about the vehicle, which is thus completely absent from the models.

6. Conclusion

Model-predictive control operates the system reasonably well in the coldest periods, which are the most critical from the point of view of thermal systems studied in this work. Its performance in warmer times was less impressive, falling short of the rule-based strategy. MPC has the advantage of being able to buy cheap electricity at night and store it in the battery for later use. This advantage disappears in the sunnier seasons: there is little need to buy power as PV/T tends to cover the demand. Alternative optimisation techniques that would produce better solutions faster than mixed integer programming should be explored. Non-linear optimisation would also allow better modelling of some features of the heat system. The optimisation problem is inherently non-convex though, so only approximate solutions can be expected in limited time.

Determining appropriate prices for valuing the energy content of the different storages at the end of the planning horizon is challenging. They steer the long-term behaviour of MPC and should measure the usefulness of energy to cover the thermal demands while meeting their temperature requirements. This varies by season: to start heating up the seasonal tanks for winter, one should raise their final time price, whereas it can be lowered in the spring, when less use for stored heat is expected. One could also set target levels for the storages. However, it is not clear how to determine them either. A possible approach would be to compute them from an optimisation problem spanning a full year. That would require a much coarser model to be solvable.

7. Acknowledgements

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