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Comparison of four rule-based demand response control algorithms in an electrically and heat pump-heated residential building

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Highlights

Comparison of four rule-based DR control algorithms is studied.

These DRs are applied for heat generation system with two-storage tank system.

Heat generation systems are a GSHP or storing electric heating system.

The maximum savings in annual heating energy and cost are 10% and 15%.

Abstract

This study aims to investigate the effect of demand response (DR) actions on energy consumption and energy cost with two alternative heat generation systems in a detached house in a cold climate. The heat generation systems are a ground source heat pump coupled with a two-storage tank system (GSHP heating system) and a water-based electric heating system coupled with a similar storage tank system (storing electric heating system). Four rule-based DR control algorithms were applied and studied for two alternative heat generation systems. Two rule-based DR control algorithms from previous study were applied and investigated for these heat generation systems based on real-time hourly electricity price and future hourly electricity prices based on the blocking-maximum subarray method. Two new rule-based DR control algorithms based on future hourly electricity prices were developed and investigated for these heat generation systems based on the sliding-maximum subarray method and moving average method. This research was implemented with the validated dynamic building simulation tool IDA ICE. The obtained results show that the maximum annual savings in the heating energy and cost take place using the rule-based DR control algorithm based on the sliding-maximum subarray method. As well, these savings are about 10 % and 15 %, respectively, for the GSHP heating system; and about 1 % and 8 %, respectively, for the storing electric heating system.

Keywords: Demand response, rule-based control algorithm, heating energy, two-storage tank system.

1. Introduction

Buildings are one of the largest energy consumers and emitters of CO₂, and they consume over 40 % of the overall energy consumed in the world. Demand response (DR) can participate in load management programs to support the electrical power of the grid to mitigate peak demand and prevent exposure of its infrastructure to critical strains [1-5]. Without DR, the grid operators must rely on and use expensive and polluting auxiliary power plants during peak periods of electricity usage; it may also stop supplying certain areas if the demanded power cannot be provided. At the building level, DR control algorithms assist in shifting a part of the electricity demand of heating, ventilation and air conditioning (HVAC) from periods of high demand and price to lower periods [6-11]. These shifts can reduce the building's energy costs while also improving the grid-wide load factor of the electric power system.

Because of the obvious effects of indoor temperature on the electricity demand in heating and cooling systems, variable indoor temperature set points can diminish electricity demand [12] and [13]. One important feature in DR control strategies in building point-of-view is to maintain thermal comfort [14-18]. Thus, several scientists have studied the thermal comfort of occupants in buildings based on, for instance, socio-economic, cultural studies and consideration of future climate scenarios [14] and [19-21] by using different approaches such as predicted mean vote (PMV) [14] and [15].

As energy can be stored in buildings, increasing the thermal mass of a building decreases heating energy demand [22]. This also increases the energy efficiency of buildings and it reduces their energy costs [23]. It has been found that DR has played an important role in peak load reduction [24-28].

Performance of DR actions on buildings depends on a control algorithm. Arteconi et al. [29] evaluated the benefits of DR actions on electricity consumption and operational costs, both from the final user's and the overall system's perspective. They showed that increasing the number of participating consumers increases the flexibility of the system and, therefore, reduces the overall operational costs. Moreover, they resulted that total cost saving ranges at most between about 400 € and 200 € per participant per year. Greensfelder et al. [30] conducted optimization of building thermal mass using a predictive optimal controller to define supervisory strategies in terms of building global cooling temperature set points. A

global minimization algorithm determined optimal set point trajectories for each day divided into four distinct time periods. Cost savings were found to range from 0 to 14% depending on the building, climate, and characteristics of the rate signal. D. Corbin et al. [31] described a model integrated Matlab and EnergyPlus with a modified particle swarm optimizer to predict optimal building control strategies. First, they adjust the model to minimize hourly cooling set points and found that 5% cost savings during the study period. Second, they adjusted it to minimize daily energy consumption minimizing daily energy cost and found that up to 54% energy saving. Alimohammadisagvand et al. [15] studied three different rule-based DR control algorithms to minimize the electricity cost. They found that 10% cost saving by using predictive rule-based DR control algorithm. Also, Alimohammadisagvand et al. [32] developed these rule-based DR control algorithms for heated residential houses equipped with heat pump coupled with one storage tank for domestic hot water (DHW) consumption and space heating demand. They resulted that maximum savings of annual electricity consumption and cost are 12% and 10% respectively.

According to the literature review, only one storage tank has been used until now to cover domestic hot water consumption and space heating demand with and without DR in a residential building. The novelties of this study are to use a two-storage tank system as the part of the heating system of the residential building, and to develop two new predictive rule-based DR control algorithms. As well, applying these rule-based DR control algorithms in the two-storage tank system in which such a simulation-based study has not been taken into account before. This study uses a ground source heat pump coupled with a two-storage tank (GSHP heating system) and electric heaters installed in a two-storage tank (storing electric heating system) to cover domestic hot water consumption and space heating demand separately. Moreover, a momentary and three predictive rule-based DR control algorithms have been integrated into the model to monitor and control tanks' and space heating temperatures and reduce the peak load while maintaining the thermal comfort of the occupants at acceptable levels.

2. Building description

2.1 Studied building

The building type shown in Figure 1 is a Finnish two-story detached house studied in [15]. The floor area of the building is 180 m², and it has six rooms and a kitchen, with the room height of 2.6 m.

Figure 1. Two-story building (180 m²) with the area of each zone and window.

The building type studied is passive with massive structure. The massive passive building envelope specifications are presented in Table 1. All the walls of buildings are light weight concrete, but the roof and the intermediate and base floor are of massive concrete. The thermal insulation level and air tightness of the house follows the Finnish guidelines for Finnish passive houses [33].

Table 1. Building envelope specifications.

Elements of construction	Material composition (thickness of the layer) - external structures from inside to outside	Overall thickness (mm)
External wall	Light weight concrete block (130mm), polyurethane (340mm), light weight concrete block (90mm)	560
Internal wall	Light weight concrete block (100mm)	100
Roof	Filler (5mm), concrete (100mm), mineral wool (490mm), water proof sheet (10mm)	605
Base floor	Wood (14mm), light weight concrete (15mm), concrete (100mm), EPS thermal insulation (480mm)	609
Intermediate floor	Wood (15mm), light weight concrete (15mm), concrete (100mm), filler (5mm)	135

Table 2 shows the level of the buildings' thermal insulation with their U-value, window properties and air tightness.

Table 2. U-values, glazing properties and air tightness of the building.

U-values (W/m ² ,K)					Window properties		Air tightness
External wall	Roof	Base floor	Doors	Windows	g ¹	ST ²	q ₅₀ (m ³ /h,m ²)
0.08	0.07	0.08	0.5	0.8	0.5	0.4	0.7

¹ Total solar heat transmittance (g)

² Direct solar transmittance (ST)

2.2 Heating system

The thermal storage tank system of the studied building consists of two separate storage tanks belonging to space heating demand by space heating tank and DHW consumption by DHW tank. In this regard, DHW is preheated by a space heating tank. The generated heating energy is produced by a GSHP heating system (shown in Figure 2a) or by a storing electric heating system (shown in Figure 2b).

The heat distribution system of the building is a water-based floor heating system. The tap water provided by a DHW tank is 55 °C [34]. The supply water temperature for hydronic radiator heat distribution system is controlled according to the outdoor temperature, and dimensioning temperatures of the supply and return water are 40/30 °C at a design outdoor temperature -26 °C. The water temperature of a space heating tank is heated up to a defined set point temperature by GSHP or an electric heater. Further, room temperature is controlled by a PI-controller. The domestic cold water (DCW) is connected to the bottom of the space heating tank and it is preheated by flowing water through coil of the space heating tank before incoming inside of the DHW tank. As the DHW tank is preheated in a space heating tank, the heat demand level of a DHW tank to reach the aimed set point temperature is lower. Thus, the operation time of GSHP to heat DHW tank decreases meaning that the average of COP increases. Then, the DHW is heated up to the defined set point temperature by GSHP connected to a heat exchanger in a DHW tank or electric heater. The storage tanks used in this study are real commercial products [35] with 0.5 m³ size installed in the bathroom and have polyurethane insulation with 100 mm thickness.

Figure 2. Configurations of the heat generation system for a two-storage tank, including a DHW tank (DHWT) and space heating tank (SHT) model: a) GSHP heating system model, b) electric heating storage system model.

2.2.1 GSHP heating system

Heat pump used in this study is real commercial product [36]. The COP and heating power of the selected GSHP are, respectively, 4.9 and 8.9 kW at the standardized test point (0/35 °C) defined in EN 14511-2 [37]. This GSHP can increase water temperature up to 65 °C. It also has variable condensation temperature, switches between tanks and does not work simultaneously for both tanks. Heating of the DHW tank is prioritized, which means that firstly, DHW tank's temperature is monitored and its set point temperature is applied, then the space heating tank is heated if it is needed. The GSHP heats the water temperature of the space heating tank without heat exchanger and DHW tank with heat exchanger. It means that there is no temperature difference between the water temperature of the space heating tank and the supply water from the GSHP, and around 2 °C temperature difference between water temperature of DHW tank and GSHP.

2.2.2 Storing electric heating system

The power of an electric heater in the storing electric heating system model is 9 kW installed at the top of each storage tank. The electric heaters run based on a defined set point temperature for each tank. The electric heater heats the water temperature of a space heating tank and DHW tank directly.

2.3 Ventilation system

The building has a mechanical supply and exhaust ventilation system with heat recovery, which is the most common ventilation system in new Finnish detached houses. The supply air temperature efficiency of heat recovery is 80 %. The ventilation system is a constant air volume system and the ventilation rate of the building is 0.5 1/h. DR is not used to control ventilation air flow rates or reheating the supply air.

2.4 Behaviour of occupants

Internal heat gains are considered an important component in heating load production in buildings [38]. Typical consumption profiles of appliances and lighting of Finnish detached houses were used [39] and [40] to find out the internal heat gains from lighting and equipment. These values for the studied buildings are 8.5 and 22.2 kWh/(m²,a) [15]. The number of occupants, activities and clothing levels affects thermal comfort. Different activity and clothing levels of four occupants were studied earlier to define acceptable indoor temperature set points in [15]. The number of occupants, activity level and clothing level in this study are 4, 1.2 met and 0.96 clo, respectively.

Since the DHW consumption forms the major portion of the heat demand of the studied building, the DHW consumption is simulated with annual consumption level defined by Finnish building code [41] and an hourly consumption profile, which is based on the monthly [42] and daily profiles defined in the EN 15316 standard [43].

3. Methodology

3.1 Structure of the simulation study

Figure 3 shows the computational arrangement of this study. It has two main parts, including a control algorithm and the IDA ICE building simulation tool.

Figure 3. The computational arrangement of the investigation.

The control algorithm part receives inputs from the hourly electricity price (HEP), the weather data, the acceptable indoor temperature set points, and the temperature set points of the DHW and space heating tanks. The IDA ICE dynamic simulation tool receives inputs from the control algorithm, the weather data and the detailed building information. Finally, the IDA ICE produces the intended results, including heating electricity consumption and cost.

3.2 Acceptable indoor temperature set points

This paper used the acceptable indoor air temperature set points for heating defined in [15] by the Fanger approach with the purpose of predicting the thermal comfort of occupants in buildings. The various categories of thermal comfort defined in the EN 15251 standard [44] were used to define the minimum and maximum temperature set points based on the lower and higher PMV during the heating season for different activity levels, clothing levels and indoor air velocities [45]. In this study, the acceptable indoor temperature set points were found with regard to the number of occupants, activity level, clothing level and indoor air velocity presented in chapter 2.4.

3.3 IDA ICE simulation tool

The simulation part of this paper was implemented by IDA Indoor Climate and Energy (IDA ICE) [46]. The IDA ICE 4.7 whole building simulation software is a detailed and dynamic multi-zone simulation application with variable time step for simulation of, for example, energy use, indoor air quality and thermal comfort in buildings. It was validated against the

EN 15265-2007 standard [47] and the maximum inaccuracy levels for heating and cooling demand were 8 % and 11 %. Also, it has been validated in several studies [32] and [48-51] which shows strong justification for using the IDA ICE in this paper.

The hot water storage tanks were modeled with IDA ICE by the one-dimensional stratified storage tank model. The mixing process inside the hot water storage tank was defined by the mixing factor stated heat exchange between layers. The height of the storage tank is divided into different layers, and in this study the number of layers used for both tanks was 10. The mixing factor forms the storage tank's thermal stratification, which depends, for example, on storage tank configuration. Thus, the mixing factor must be cautiously determined to reach the simulated thermal stratification close to the measured data. The authors used validated mixing factor for this analysis presented in [32].

3.4 Weather data

This paper used the Finnish test reference year (TRY2012) as a weather data for dynamic simulations. The weather data consists of detailed hourly data of temperature, relative humidity, wind velocity, solar radiation describing the current climatic conditions of Southern Finland. They were accumulated and computed by recording a 30-year period (1980–2009) at the weather station of Helsinki-Vantaa airport [52]. The annual average temperature for the Helsinki-Vantaa region is +5.4 °C, placing the region within Finnish climatic zone 1 [41]. The average number of degree days at the indoor temperature of 17.0 °C is 3952 Kd.

4. Rule-based demand response control algorithms

The end user can effectively reduce the energy costs of the building by applying a DR mechanism based on HEP, hourly electricity price. Electricity price varies from hour to hour and may vary significantly hourly in Finland and the Nord Pool electricity market [53] announces energy price for every hour. This mechanism can be implemented by using different temperature set points for space heating, DHW tank and space heating tank while maintaining the thermal comfort of the occupants at the acceptable level.

This study investigate two rule-based DR control algorithms which were presented in [15] and [32], and developed two new rule-based DR control algorithms based on the trend of future HEPs. The previous versions of presented rule-based DR control algorithms were able to control the temperature set point of space heating [15] and a single storage tank that covers both space heating demand and DHW consumption [32]. These two rule-based DR

control algorithms and two new ones were developed and studied to the control temperature level of space heating, DHW tank and space heating tank in this study.

4.1 Momentary rule-based DR control algorithm (Momentary control algorithm)

The momentary control algorithm uses the current minimum indoor temperature of the building, maximum temperature of the DHW and space heating tanks and HEP as input signals. The algorithm controls the operation of the heat generation system and regulates the temperature set point for space heating [15], DHW and space heating tanks, according to the input signals. If HEP is equal or less than the limiting price (LP), the heat generation system is turned on, the normal temperature set point of 21 °C used for detached houses in accordance with the Finnish building code [54] and [41], is used for space heating and the maximum temperature set points are used for DHW and space heating tanks. If HEP is higher than the limiting price, the heat generation system is turned off if the indoor and both storage tanks' temperatures are at the acceptable level. While the heat generation system is turned off, energy stored in the DHW and space heating tanks are used for DHW consumption and space heating. Otherwise, the heat generation system is turned on and the minimum temperature set point is used for space heating and the normal temperature set points are used for the DHW and space heating tanks. Figure 4 shows the flowchart of the control mechanism.

Figure 4. The flowchart of the momentary control algorithm.

LP is the limiting price, $T_{\min}$ is the minimum indoor temperature of the building, T_{set} is the indoor temperature set point, $T_{\text{set,normal}}$ is the normal temperature set point, $T_{\text{set,min}}$ is the acceptable minimum indoor temperature set point defined in [15], $T_{\text{set,DHWT}}$ is the temperature set point of the DHW tank [32], $T_{\text{set,SHT}}$ is the temperature set point of the space heating tank, $T_{\text{set,DHWT,normal}}$ is the normal temperature set point used for DHW tank, $T_{\text{set,SHT,normal}}$ is the normal temperature set point used for the space heating tank, $T_{\text{set,DHWT,max}}$ is the maximum temperature set point of the DHW tank, $T_{\text{set,SHT,max}}$ is the maximum temperature set point of the space heating tank, $T_{\text{max,DHWT}}$ is the maximum temperature of the DHW tank, and $T_{\text{max,SHT}}$ is the maximum temperature of the space heating tank.

4.2 Predictive rule-based DR control algorithms

The principle of the predictive rule-based control algorithms is to monitor the current indoor and storage tanks' temperatures, and define the indoor temperature set point, DHW tank and space heating tank temperature set points according to the trend of future HEPs. These temperature set points are determined by control signals (CS), -1, 0 and +1, generated by different methods, including a blocking-maximum subarray problem, a sliding-maximum subarray problem and moving average.

The $CS=+1$ means that the trend of future HEPs is rising, thus the heat generation system is turned on, set point of space heating is controlled depending on the maximum indoor temperature and average outdoor temperature of the previous 24 hours, and the maximum temperature set points are used for DHW and space heating tanks. If HEP has a falling trend ($CS=-1$), the heat generation system is turned off if the indoor, DHW and space heating tanks' temperatures are at the acceptable level. Otherwise the heat generation system is turned on and the minimum temperature is used for space heating and the normal temperature set points are used for DHW and space heating tanks. In other conditions, the heat generation system is turned on and the normal temperature set points are used for space heating, DHW and space heating tanks. The flowchart of the predictive control mechanism is as presented in Figure 5.

Figure 5. The flowchart of predictive rule-based DR control algorithms.

HEPs can be accordingly sorted to realize their raising, leveling out or falling trend; hence, corresponding CSs can be assigned to the limited number of future HEPs, n , as length of the hours horizon (NordPool [53] announced 24 hours ahead of HEPs). The CS is defined based on different concepts as described in the following chapters, 4.2.1-4.2.3.

4.2.1 The predictive rule-based DR control algorithm based on blocking-maximum subarray problem (Blocking control algorithm)

This blocking control algorithm developed for these heat generation systems has two main parts to check the current HEP and the trend of future HEPs [27]. Thus, its variables are the limiting price and the length of the time horizon, n hours, to be considered by a blocking-maximum subarray problem to figure out the HEPs' trend.

If HEP is higher than the limiting price ($CS=-1$), the heat generation system is turned off if the indoor, DHW and space heating tanks' temperatures are at the acceptable level, otherwise it is turned on. Also, the temperature set point of space heating, DHW and space heating tanks are minimum and normal values.

Then, if HEP is lower than the limiting price, the trend of future HEPs is checked. To check this, a blocking-maximum subarray problem is applied to calculate the CS [15] and [32]. The blocking-maximum subarray problem calculates a contiguous subarray which has the largest sum within a one-dimensional array of numbers containing at least one positive number. The CS for the next n hours (length of the time horizon) is calculated only once at the beginning of every period and the length of each period is n hours (e.g., 1 to $n+1$, $n+1$ to $2n+1$, $2n+1$ to $3n+1$ and continues in accordance with this rule), shown in Figure 6.

4.2.2 The predictive rule-based DR control algorithm based on sliding-maximum subarray problem (Sliding control algorithm)

The first novel predictive rule-based DR control algorithm is sliding control algorithm. It is close to the blocking control algorithm type and has two parts, including checking the current HEP and trend of future HEPs.

The first step to check the current HEP is similar to the blocking control algorithm. But, the concept of checking future HEPs trend is based on a sliding-maximum subarray problem.

The CS for the next n hours (length of the time horizon) is calculated in the beginning of every hour, not like blocking-maximum subarray problem which calculates the CS only once at the beginning of every period of length of the time horizon. This means that the CS is updated every hour (1 to $n+1$, 2 to $n+2$, 3 to $n+3$ and continues in accordance with this rule), shown in Figure 6.

Figure 6. Calculated periods for blocking and sliding-maximum subarray problems (in this example $n=3h$).

4.2.3 The predictive rule-based DR control algorithm based on a moving average (Moving average control algorithm)

The second novel predictive rule-based DR control algorithm is moving average control algorithm. It calculates the CS based on the moving average method. The CS is calculated in accordance with the momentary HEP, the average of future HEPs from hour p to hour q ($HEP_{avr}^{+p,+q}$) and down or up constant marginal value during the calculation period.

The $CS=-1$ if the HEP is higher than the average 24 future HEPs meaning that the HEPs is falling. The $CS=+1$ if the HEP is lower than the summation of the average 24 future HEPs ($HEP_{avr}^{+1,+24}$) and the down marginal value, or the average 6 to 12 future HEPs ($HEP_{avr}^{+6,+12}$) is higher than summation of the average 6 to 30 future HEPs ($HEP_{avr}^{+6,+30}$) and the up marginal value. Based on the moving average control algorithm, this means that HEPs is raising. Otherwise, the CS is 0 (HEPs is leveling out). Based on this, the pseudocode for the control mechanism is as given in the equation:

$$\text{If } \left\{ \begin{array}{l} HEP < HEP_{avr}^{+1,+24} + \text{marginal value}_{\text{down}} \\ \text{or} \\ HEP_{avr}^{+6,+12} > HEP_{avr}^{+6,+30} + \text{marginal value}_{\text{up}} \end{array} \right\} \text{ then } CS=+1$$

elseif $HEP > HEP_{avr}^{+1,+24}$, then $CS=-1$

else $CS=0$

End if

5. Results and Discussion

The results present the heating energy consumption and cost for the GSHP and storing electric heating systems. Then, four rule-based DR control algorithms were applied to reduce the peak load of the heating energy demand while maintaining thermal comfort of the occupants at the acceptable levels.

5.1 Breakdown of electricity consumption of the reference case

Table 3 shows the breakdown of the total electricity consumption of the reference case building with the GSHP and storing electric heating systems. The normal temperature set point of space heating is 21 °C and normal water temperature of DHW tank is 55 °C [34] for both heating systems. The set point temperature of delivered supply water from GSHP is 57 °C and the set point temperature of electric heater is 55 °C of the DHW tank. The temperature set point of the space heating tank is 45 °C for both heating systems.

Table 3. Breakdown of total electricity consumption in the reference case building.

Heat generation system	Electricity consumption (kWh/(m ² ,a))					
	Space heating and DHW	AHU heating	HVAC aux.	Lighting	Equipment ^a	Total
GSHP heating system	17.2	1.5	5	8.5	22.2	54.4
storing electric heating system	69.9	1.5	5	8.5	22.2	107.1

^a It is assumed 86 % of the electricity consumption of equipment ends up as internal heat gain [55].

In heat generation system coupled with the two-storage tank system, the electricity consumption of space heating and DHW tanks on total one is 31.7 and 65.3 % for the GSHP and storing electric heating systems, respectively. The GSHP heating system decreases the electricity consumption of space heating and DHW demands of storing electric heating system by 75.4 %. The electricity consumption of lighting and equipment is also a significant amount of the total, and it is 56.4 and 28.7 % for the GSHP and storing electric heating systems, respectively.

Compared to the same building type equipped with the GSHP coupled with the one-storage tank system [32], using the two-storage tank system can save up to 22% electricity consumption for heating system. Thus, the two-storage tank system with and without DR control algorithm is a good alternative system to save more electricity than a one-storage tank system.

5.2 Performance of rule-based DR control algorithms

The presented control algorithms were implemented in the IDA ICE by the logic applications. Figure 7 shows as an example, the operation of the GSHP with and without the studied rule-based DR control algorithms during the selected example period. The rule-based DR control algorithms run the GSHP heating system according to their principles. Figure 7 shows that the rule-based DR control algorithms try to minimize the use of the expensive electricity. For instance, from 554 to 559 hour they heat up the storage tanks and space heating before the HEP starts to increase, and continue heating up after the HEP has decreased. The operation of the GSHP in the reference case without the rule-based DR control algorithm just follows the heat demand of the building and it operates more than the other cases during the more expensive period.

Figure 7. The hourly heating energy cost of the GSHP heating system with and without (reference case) rule-based DR control algorithms during the example period.

Afterward, the annual performance of each rule-based control algorithm is analysed in heating energy and cost point-of-view and presented in Table 4-Table 7. Their results are compared with the corresponding reference case (Table 3), in which the negative and positive values express the saved and unsaved values.

Table 4 shows the performance of the momentary control algorithm during a one-year simulation for the GSHP and storing electric heating systems. The limiting price is variable to observe maximum heating energy and cost savings. The results of both heat generation systems show that the maximum yearly heating energy and cost savings takes place by

LP=45 €/MWh. The heating energy can be saved by 0.1 % for the GSHP heating system and unsaved by 1.5 % for storing the electric heating system. In addition, the cost of heating energy is reduced by 6.5 % and 5.7 % for GSHP and storing electric heating systems, respectively.

Table 4. Results of the momentary control algorithm in different LPs (savings with negative values and unsavings with positive values).

Savings with GSHP heating system		
LP (€/MWh)	Energy (%)	Cost (%)
45	-0.1	-6.5
50	1.3	-4.2
60	2.3	-1.8
70	2.6	-0.7
80	2.9	0
90	3	0.4
100	2.9	0.4
Savings with storing electric heating system		
LP (€/MWh)	Energy (%)	Cost (%)
45	1.5	-5.7
50	2	-4
60	2.2	-2.1
70	2.3	-1.1
80	2.5	-0.4
90	2.5	-0.1
100	2.4	-0.1

As, the variables of the blocking and sliding control algorithms' principles are the limiting prices and the length of the time horizon to maximise the heating energy cost saving, Table 5 and Table 6 present the results of the blocking and sliding control algorithms, respectively, for the GSHP and storing electric heating systems. The maximum heating energy and cost savings for both heat generation systems take place at LP=40 €/MWh. For the GSHP heating system, the 24 hours of the time horizon saves more heating energy cost than other ones; however, the differences are small. Thus, the maximum heating energy savings of the blocking and sliding control algorithms are 11.2 and 9.5 %, respectively. Heating energy cost savings are 14.2 and 14.5 %, respectively. In the same way, for the storing electric heating system, the 24 hours of the time horizon saves more heating energy and cost. The maximum savings of heating energy for the blocking and sliding control algorithms are 1.7 and 0.6 %, respectively. In addition, heating energy cost savings are 6.6 and 7.7 %, respectively.

respectively. It can be noted that the effect of the limiting price is more significant than the length of the time horizon in the performance of the blocking and sliding principles.

Table 5. Results of the blocking control algorithm in different LPs and the length of the time horizon (savings with negative values and unsavings with positive values).

Savings with GSHP heating system												
Energy (%)							Cost (%)					
LP (€/MWh)	Length of the time horizon						Length of the time horizon					
	4h	8h	12h	16h	20h	24h	4h	8h	12h	16h	20h	24h
No	-6.5	-8.8	-9.7	-9.8	-9.8	-9.8	-9.0	-10.5	-11.8	-11.2	-11.0	-11.2
40	-9.1	-10.6	-11.1	-11.3	-11.4	-11.2	-13.0	-13.9	-14.3	-14.2	-14.2	-14.1
50	-7.3	-9.5	-10.1	-10.3	-10.3	-10.2	-11.5	-12.9	-13.5	-13.2	-13.1	-13.3
55	-7.1	-9.2	-10.0	-10.1	-10.2	-10.2	-11.0	-12.4	-13.2	-12.8	-12.7	-13.1
60	-6.9	-9.1	-10.0	-10.1	-10.0	-10.0	-10.6	-12.1	-12.9	-12.5	-12.4	-12.7
70	-6.7	-8.9	-9.8	-10.0	-9.9	-9.9	-10.2	-11.6	-12.5	-12.1	-12.0	-12.3
80	-6.7	-8.9	-9.7	-9.8	-9.9	-9.9	-10.0	-11.4	-12.4	-11.9	-11.9	-12.1
Savings with storing electric heating system												
LP (€/MWh)	Length of the time horizon						Length of the time horizon					
	4h	8h	12h	16h	20h	24h	4h	8h	12h	16h	20h	24h
No	2.3	1.1	0.7	0.4	0.3	0.2	-1.1	-1.7	-2.7	-2.2	-2.1	-2.3
40	-0.5	-1.2	-1.4	-1.7	-1.7	-1.7	-6.2	-6.4	-6.6	-6.5	-6.6	-6.7
50	1.4	0.4	0.0	-0.3	-0.4	-0.3	-4.3	-4.8	-5.1	-5.1	-5.1	-5.3
55	1.7	0.6	0.2	-0.1	-0.2	-0.3	-3.6	-4.2	-4.6	-4.5	-4.4	-4.9
60	1.9	0.8	0.3	0.0	0.0	0.0	-3.2	-3.7	-4.4	-4.1	-4.0	-4.4
70	2.1	0.9	0.5	0.2	0.1	0.1	-2.6	-3.2	-3.8	-3.5	-3.5	-3.9
80	2.1	1.0	0.6	0.3	0.1	0.1	-2.4	-2.9	-3.5	-3.1	-3.2	-3.5

Table 6. Results of the sliding in different LPs and the length of the time horizon (savings with negative values and unsavings with positive values).

Savings with GSHP heating system												
Energy (%)							Cost (%)					
LP (€/MWh)	Length of the time horizon						Length of the time horizon					
	4h	8h	12h	16h	20h	24h	4h	8h	12h	16h	20h	24h
No	2.7	0.7	-2.8	-4.7	-5.5	-6.7	-1.0	-2.9	-6.1	-8.2	-8.7	-9.8
40	-3.9	-5.1	-7.2	-8.2	-8.8	-9.5	-10.5	-11.5	-13.0	-13.7	-14.1	-14.5
50	0.3	-1.4	-4.2	-5.9	-6.5	-7.6	-6.1	-7.5	-10.0	-11.3	-11.8	-12.6
55	1.1	-0.6	-3.8	-5.5	-6.2	-7.3	-4.8	-6.4	-9.0	-10.6	-11.0	-12.0
60	1.7	-0.2	-3.4	-5.3	-6.0	-7.0	-3.8	-5.5	-8.3	-10.1	-10.5	-11.4
70	2.1	0.3	-3.0	-5.0	-5.6	-6.9	-2.7	-4.4	-7.3	-9.2	-9.7	-10.8
80	2.4	0.4	-2.9	-4.8	-5.4	-6.8	-2.3	-4.1	-7.1	-8.9	-9.3	-10.4
Savings with storing electric heating system												
LP (€/MWh)	Length of the time horizon						Length of the time horizon					
	4h	8h	12h	16h	20h	24h	4h	8h	12h	16h	20h	24h
No	7.8	6.3	4.2	3.2	2.7	1.9	3.9	2.3	0.1	-1.3	-1.7	-2.4
40	2.8	1.9	0.7	0.2	-0.1	-0.6	-5.3	-6.1	-7.0	-7.2	-7.5	-7.7
50	5.9	4.6	3.1	2.2	1.9	1.2	-1.5	-2.6	-4.1	-4.9	-5.2	-5.7
55	6.6	5.2	3.4	2.5	2.1	1.4	-0.2	-1.5	-3.2	-4.1	-4.4	-5.1
60	6.9	5.5	3.7	2.7	2.2	1.6	0.8	-0.6	-2.4	-3.6	-3.9	-4.4
70	7.2	5.9	3.9	2.9	2.5	1.8	2.0	0.6	-1.3	-2.6	-2.9	-3.6
80	7.5	6.0	4.0	3.1	2.7	1.9	2.4	0.9	-1.1	-2.2	-2.4	-3.2

The moving average control algorithm's principle depends on the average of 24 future hours and marginal values. Based on these variables, the heating energy and cost savings are maximised if the marginal value is ± 55 €/MWh for both systems (shown in Table 7). The heating energy savings are 11.4 and 1.8 %, respectively, for the GSHP and storing electric heating systems. Also, the heating energy cost savings are 13.8 and 6.7 %, respectively.

Table 7. Results of the moving average control algorithm in different marginal values (savings with negative values and unsavings with positive values).

Savings with GSHP heating system		
Marginal values (€/MWh)	Energy (%)	Cost (%)
±5	-1	-6.3
±7	-3.7	-8.9
±10	-6.7	-11.5
±15	-9.3	-13
±20	-10	-13.1
±25	-10.5	-13.3
±30	-10.9	-13.5
±40	-11.3	-13.6
±45	-11.3	-13.6
±50	-11.4	-13.7
±55	-11.4	-13.8
Savings with storing an electric heating system		
Marginal values (€/MWh)	Energy (%)	Cost (%)
±5	5.6	-1.3
±7	3.9	-3.3
±10	1.6	-5.5
±15	-0.3	-6.4
±20	-0.7	-6.2
±25	-1.1	-6.3
±30	-1.3	-6.3
±40	-1.7	-6.4
±45	-1.7	-6.4
±50	-1.8	-6.5
±55	-1.8	-6.7

The optimum limiting price value for the momentary, blocking and sliding control algorithms, and optimum marginal value for moving average control algorithm are similar for both heat generation systems. As a result, Table 8 summarises the optimal parameters of the four studied rule-based DR control algorithms and the achieved savings.

Table 8. Summarising optimal parameters of studied rule-based DR control algorithms and achieved savings (savings with negative values and unsavings with positive values).

Control algorithm	LP (€/MWh)	Length of the time horizon (h)	Marginal values (€/MWh)	Savings of heating energy (%)		Savings of heating energy cost (%)	
				GSHP heating system	Storing electric heating system	GSHP heating system	Storing electric heating system
Momentary	45	-	-	-0.1	1.5	-6.5	-5.7
Blocking	40	24	-	-11.2	-1.7	-14.1	-6.6
Sliding	40	24	-	-9.5	-0.6	-14.5	-7.7
Moving average	-	-	±55	-11.4	-1.8	-13.8	-6.7

The results showed that the rule-based DR control algorithms can be economically beneficial. The amount of heating energy and cost savings depend on the control algorithm principle. Even if the cost savings in percentage with the storing electric heating system are smaller than with the GSHP heating system, the financial savings are significantly higher with the storing electric heating system. The maximum achieved annual cost savings by using the rule-based DR control algorithms with the storing electric heating are 0.62, 0.54, 0.51 and 0.45 €/m²,a for the sliding, blocking, moving average and momentary control algorithms while the corresponding savings are 0.32, 0.31, 0.30 and 0.14 €/m²,a with the GSHP heating system.

5.3 Influence of the hourly electricity price

The performance of the rule-based DR control algorithm depends on different factors in which the HEP is one of them (introduced in Chapter 4). Figure 8a, shown performance of the GSHP heating system, and Figure 8b, shown performance of the storing electric heating system, present how the DR control algorithms act in a different way based on the HEP periods, therefore their heating energy costs are different in different periods. The main reason for this is that the storage tanks are heated with different temperature set points and their heating periods are different. It can be mentioned that in most of the periods, the predictive rule-based DR control algorithms consume less heating energy, they also have lower heating energy cost compared with the momentary control algorithm. Between predictive rule-based DR control algorithms, the sliding is more economically beneficial because it allows the water temperatures of the DHW and space heating tanks to drop more than other control algorithms. Therefore, the annual assessment of the heating energy consumption and cost savings point-of-view, the sliding control algorithm has the best

performance, then blocking, moving average and momentary control algorithms, respectively. The heating energy consumption and cost's trend for different rule-based DR control algorithms in different HEP periods for both the GSHP and storing electric heating systems are similar. The results, Figure 8, of storing the electric heating system is almost 4.5 times higher, which can be attributed to the COP of the GSHP.

Figure 8. One-year heating energy costs of four rule-based DR control algorithms in their optimal conditions and reference case for two-storage tank system in different hourly electricity price periods.

Since the HEP is less than 40 €/MWh in the cases shown in the Figure 8, more electricity is imported by presented rule-based DR control algorithm cases compared to the reference

case. For the reason that the limiting price for the optimised momentary control algorithm is 45 €/MWh, it is 40 €/MWh for the optimised blocking and sliding control algorithms, and marginal value for the optimised moving average control algorithm is 55 €/MWh. For the rest of HEPs (higher than 40 €/MWh), the heat generation system turns off if the indoor and storage tank temperatures are at the acceptable levels; thus the reference case consumes more electricity and generates more heating energy cost compared to all rule-based DR control algorithms.

5.4 Variation of the temperature set points

Different rule-based DR control algorithms operate with different logics, also the set point temperatures of both water storage tanks and space heating are varying in different ways. Therefore, according to the best performance of each rule-based DR control algorithm from a cost saving point-of-view, Table 9 presents the number of hours of the set point temperatures realized during the year with the studied rule-based control algorithms. The momentary control algorithm has two alternative set point temperatures for space heating (19.5 and 21 °C), DHW tank (57 and 67 °C) and space heating tank (30 and 50°C). But, the blocking, sliding and moving average control algorithms have three alternative set point temperatures for space heating (19.5, 21 and 24.9 °C), and two alternative set point temperatures for DHW tank (57 and 67 °C) and space heating tank (30 and 50 °C). As the heat generation systems adjust set point temperatures hourly, the number of set point temperatures for space heating or storage tanks is 8784.

It shows that the sliding control algorithm uses more hours at the maximum set point temperatures for space heating and storage tanks than other predictive rule-based DR control algorithms, but it is more economically beneficial. It must be noted that the differences between predictive rule-based DR control algorithms in a cost saving point-of-view are insignificant; however, their number of hours of set point temperatures are very different.

Table 9. The number of hours of set point temperatures for the space heating, DHW tank (DHWT) and space heating tank (SHT).

Control algorithm	Set point temperature of space heating (°C)			Set point temperature				
				SHT (°C)			DHWT (°C)	
	19.5	21	24.9	30	45	50	57	67
Reference	-	8784	-	-	7652	-	1132	-
Momentary	1768	7016	-	1741	-	5581	19	1443
Blocking	3058	5646	80	7011	-	4	1428	341
Sliding	3251	5245	288	6888	-	419	649	828
Moving average	4158	4591	35	7085	-	19	1661	19

The heating energy can be stored in the building and storage tanks. Figure 9 shows the one-year duration curve of the average indoor temperature for different rule-based DR control algorithms during 5500 hours, and for the rest of the year (3284 hours); the average indoor temperature difference between different rule-based DR control algorithms is very insignificant. Additionally, it shows indoor temperature variation derived by different indoor temperature set points. As the reference case uses a fixed indoor temperature set point for heating (21 °C), the average indoor temperature is higher most of the year. Also, momentary control algorithm uses more normal set point temperature, thus it keeps indoor temperature warmer than predictive rule-based DR control algorithms. The sliding control algorithm uses higher number of hours in maximum set point temperatures for the space heating compared with other predictive rule-based DR control algorithms, then its average indoor temperature is higher. In contrast, the average indoor temperature influenced by blocking and moving average control algorithms is lower.

As the average indoor temperature differences between rule-based DR control algorithms are small, it can be noted that the stored heating energy in the building is almost similar for the presented rule-based DR control algorithms (shown in Figure 9) because the building's structures are massive and the temperature drift is very slow.

Figure 9. The 5500 hours duration curve of the indoor average temperature for different rule-based DR control algorithms' and reference cases.

The stored heating energy by storage tanks is used based on an hourly schedule for DHW consumption and space heating demand. The one-year duration curve of storage tanks' maximum temperatures is shown in Figure 10. In comparison with the reference case, the maximum temperature of DHW and space heating tanks are variable between 55 and 65 °C for the rule-based DR control algorithm cases. In the momentary control algorithm, for a long period both storage tanks are in the maximum temperatures, which explain lower heating energy cost savings compared with predictive rule-based DR control algorithms. In predictive rule-based DR control algorithms, as much as the number of hours to raise storage tanks' temperatures to the maximum ones is higher, the storage tanks are warmer and able to store heating energy for a longer time; thus its energy cost saving is higher.

Figure 10. One-year duration curve of the maximum temperatures of the DHW tank (DHWT) and space heating tank (SHT) for different rule-based DR control algorithms.

The proposed rule-based DR control algorithms can be used for DR control of heating of different building types (e.g., apartment, office and commercial buildings) equipped with hydronic space heating and a two-tank thermal energy storage system.

6. Conclusions

This study investigates the effect of four rule-based demand response control algorithms on heating energy consumption and cost without sacrificing the occupant's thermal comfort in a detached house in Finland. The two-storage tank system consists of one tank covering space heating demand and one tank belonging to DHW consumption. This study uses two alternative heat generation systems, including a ground source heat pump coupled with two-storage tank system (GSHP heating system) and water-based electric heating coupled with the similar storage tank system (storing electric heating).

According to this study, two rule-based demand response control algorithms developed and two new ones introduced are able to reduce the heating energy and decrease the heating energy cost compared to the reference case, building without a demand response control. One rule-based demand response control algorithm is based on monitoring the current hourly electricity price (HEP) and the rest of the three are based on finding out the trend of future HEPs defined by different methods, including blocking-maximum subarray, sliding-maximum subarray and moving average.

The electricity consumption of space heating and DHW with the GSHP heating system is almost four times less than storing an electric one. The all rule-based demand response control algorithms were optimised to maximise saving in a heating energy cost point-of-view for both heating systems. For the GSHP heating system compared to its reference case, the heating energy cost savings are 14.5, 14.1, 13.8 and 6.5 %, respectively with sliding-maximum subarray, blocking-maximum subarray, moving average and momentary control algorithm. Moreover, for the storing electric heating system compared to its reference case, the heating energy cost savings are 7.7, 6.7, 6.6 and 5.7 %, respectively with sliding-maximum subarray, moving average, blocking-maximum subarray, and momentary control algorithm.

The performance of the rule-based demand response control algorithms has a small effect on the average indoor temperature of the building, because the building type is the massive passive one and temperature drifts are slow.

Presented rule-based demand response control algorithms can be applied to the demand response control of heating of any building type equipped with space heating and two-hydronic thermal energy storage tank system.

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