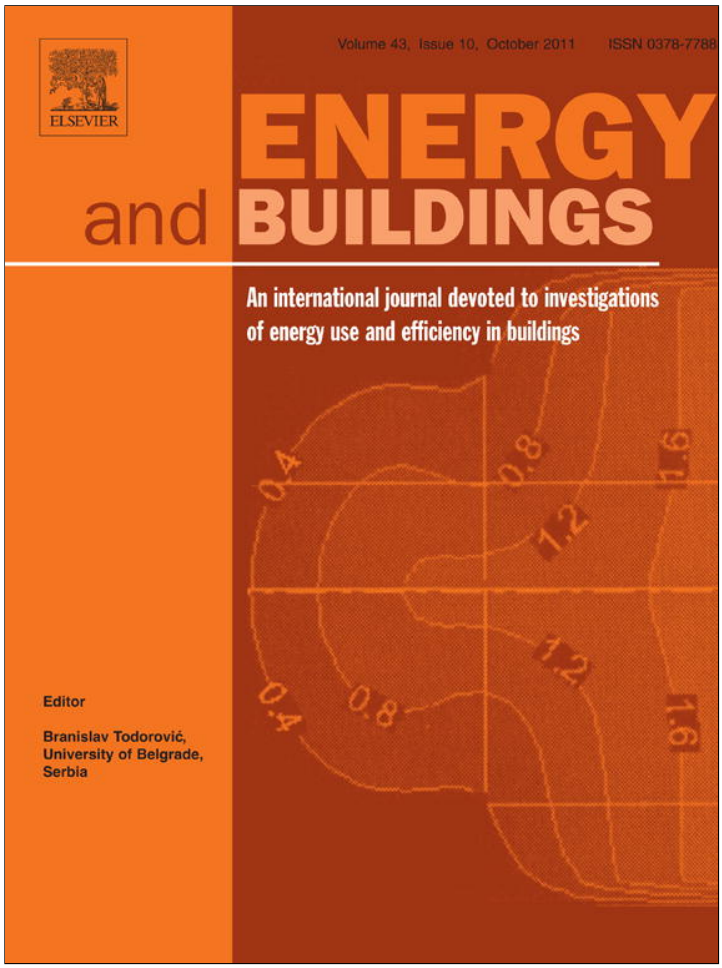
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An optimal control algorithm for borehole thermal energy storage systems

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ABSTRACT

The aim of this paper is to present an optimal control algorithm to manage borehole thermal energy storage systems (BTES). Such a system gets exhausted, if it is employed intensively, i.e. outlet fluid is outside acceptable temperature ranges, and can no longer provide the desired heat or cold. To avoid this problem a control algorithm is proposed, which simultaneously optimizes the operation costs. This algorithm is based on a dynamic programming technique and results in an array which provides the optimal heat flux for a given field temperature, date and demand. The controller is illustrated on a simulation of an existing building. Several weather scenarios have been examined and the system remained robust under all situations.

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1. Introduction

In most buildings more than 40% of the energy consumed is used for heating and cooling purposes. Providing technology to lower these costs is definitely one of the most efficient ways to reduce carbon dioxide emissions. One way to accomplish this goal is to heat and cool office buildings with an underground thermal energy storage system. Briefly, such systems consist of a large underground volume, which can be loaded with a huge amount of heat or cold and can hold this for several months. If such a system is loaded with excess heat during summer and with cold during winter, it is capable of acclimatizing a building year round. In essence it shifts the cold and heat between the seasons. The problem addressed in this paper concerns controlling such a system: how can be avoided that all heat is used midway winter? Conventional control algorithms deliver the demanded energy within ranges as long as the underground temperature is between 0 and 12 °C; otherwise it suddenly switches off.

Before this question can be answered the set-up will now be explained. An underground storage field typically consists of about one hundred vertical holes, drilled on the nodes of a square grid. Each hole is about 120 m deep and is filled with a water circuit. This construction looks like a big underground container, filled with ground. The pipes allow to exchange heat with the underground. The ground temperature varies between 0 °C and 12 °C. For cooling purposes, such temperatures can be applied directly, especially for top or floor cooling. Nevertheless, no building can be heated with such low temperatures. For that reason a heat pump is employed, which can extract heat from the field and warm it up to approximately 40 °C at low energy costs and high energy efficiency.

Why is an efficient controller for such an underground field important? Any ordinary system works well until it meets one of its boundaries. In this case, if the ground temperature crosses 12 °C, it is too warm to cool a building directly and consequently, the natural cooling function fails. Similarly, supplying heat becomes more expensive if temperature drops beneath zero degrees. Usually, a hardware solution is proposed to circumvent the problem. This can be done in two ways: (i) a classical acclimatization installation is established parallel to the underground system and/or (ii) the field and heat pump are designed too large in order to avoid reaching these bounds.

(i) In the first case the classical installation is dimensioned sufficiently large, so that it can cover all heat and cooling loads needed by the building. This is done to guarantee that the building is acclimatized at all times, whatever the state of the underground field may be.
(ii) The second measure (implementing a larger field) is not only more expensive to build, but may also increases the operation costs: at the end of the summer, the field might not be heated to its optimal high temperature. So heating during winter will be more costly. For the summer situation the opposite is true: ideally, the start temperature could be low, so that the building can be cooled effectively, but a too large field will still be quite warm, resulting in higher cooling costs. In conclusion, by increasing the size of the field, the temperature variation will be lower. So, the most efficient temperature ranges will not be

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reached, while the most profitable aim should be to encounter these temperature borders without ever trespassing them.

In conclusion, both solutions result in a robust system, which can always acclimatize the office building, but which is not economically well designed.

The common disadvantage of both solutions is that the price and thus pay back period is increased severely, resulting in less interest in this technology. So, forced by economical logic, the next generation of underground storage devices should be cheaper, but with similar performances. The simplest way to lower costs, is by drilling less holes, i.e. by reducing the capacity of the field. Unavoidable, if identical operation conditions are applied, the temperature bounds become more pronounced. A typical storage field is designed so that a given amount of heat and cold can be delivered during each season. However, for a smaller field, these guarantees can only be promised if no temperature bounds are ever trespassed. So, a first property of the controller is to keep the field within a given temperature range. Two other complications have to be taken into account:

(i) due to weather changes, it is not possible to predict the heat and cold demand of the building on a daily or weakly basis. Only on a seasonal scale, a reasonable estimation of the needs can be provided. For that reason, the second property of the controller is that it has to be able to deal with stochastic variations on the demand side.
(ii) a preferential third quality should be that the controller has to adjust the building's temperature at the lowest cost possible. This can be done by optimizing the choice between the classical heating and cooling installation and the heat pump coupled to the storage field.

According to the knowledge of the authors, no optimal control algorithm for long term energy storage, coupled to a heating, ventilation and cooling system (HVAC) has been described in the literature, although Spitler stresses the importance of such a control algorithm in [1]. He is co-author of papers describing models for ground-source heat pump systems [2,3], but no model based control algorithms have been descibed in these papers. Rink has written several papers about controlling heat pumps extended with a buffer and with variable energy prices [4,5], but none of these papers discusses long term energy storage or the coupling of an underground heat storage system to an HVAC system. In [6,7] (sub)optimal control algorithms for short term heat-pump and heat storage systems are described. In the latter, variable energy prices are taken into account, too. Recently, a control algorithm for hybrid thermal energy storage combined with a short term weather forecast was proposed in [8]. This control algorithm optimizes the short term policy of the system.

Two possible algorithms seem suited for this purpose: nonlinear model predictive control [9] and dynamic programming [10]. We have chosen for the latter, because it has the advantages that (i) it can cope with weather uncertainty and (ii) all computations can be performed off-line, i.e. in advance, which greatly facilitates the actual installation of the controller: almost no computer power is needed onsite and less starting problems in case of a power breakdown. Nonlinear model predictive control would have the advantage that it can quite easily switch to different operation modes, when for example the heating installation would stop working and that it can deal with high dimensional state space models.

Such a controller will thus allow to install both a smaller underground field and a smaller classical installation and consequently reduce the investment cost. Still, it can guarantee to supply all needed heat and cold.

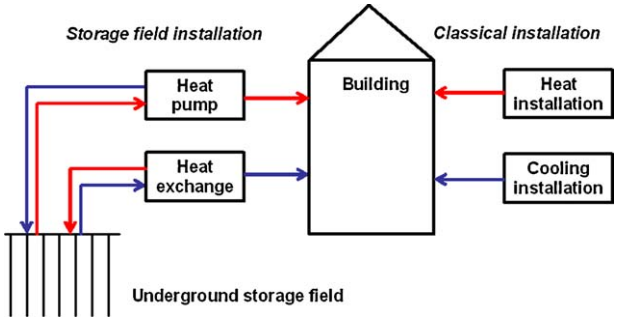


Fig. 1. Scheme of the storage field and classical installation.

Surprisingly, under certain conditions such controllers will sometimes extract heat or cold from the field, even if this is not demanded by the building. As will become clear, such an operation strategy can be the economically most efficient way of acclimatizing.

This paper is structured as follows: first, the acclimatization scheme is given. Next, the dynamics of the underground storage system are discussed. This is necessary to predict the outcome of any management action on the field. Next, the constraints are rigorously formulated. Besides the temperature constraints, also the energy fluxes from the field are bounded and some guarantees towards the client about the delivered heat and cold are given. Next the dynamic programming approach is described and finally some simulation examples are given.

2. Acclimatization scheme

The system used for this study is based on a scheme which has been installed in Flanders, Belgium, and is in operation since 2007.This scheme is shown in Fig. 1. It consists of two blocks: a classical HVAC installation, consisting of a gas fired boiler and an electricity consuming chiller, and the storage field installation, consisting of a field, coupled to a heat exchanger and a heat pump. Table 1 summarizes the heating and cooling prices. If heat has to be produced by the classical installation, this costs 47.1 €/MWh (40 €/MWh gas based on IEA energy prices for big consumers, www.IEA.org, and on an efficiency of typically 85%). Concerning the heat pump, we assumed for simplicity that the heat is supplied at 35 °C to the building for any outside temperature. The electricity price is 100 €/MWh, resulting in a heating price of 26.7 €/MWh. The classical compression cooling installation has a seasonal performance factor of three and the same electricity price. It can cool the building at 33.3 €/MWh. If the building is cooled from the field, no costs are made, i.e. costs of the circulation pumps are ignored. In this type of installation, the heat pump is not actively used to cool the building.

The red arrows in Fig. 1 symbolize heat transfer and the blue cold transfer. During the winter, mostly heat is extracted from the field. (For interpretation of the references to color in this sentence, the reader is referred to the web version of the article.) This cools the field and thus prepares it for the summer, when mostly cooling will be demanded. During the summer the opposite scenario takes place.

Table 1
Heating and cooling prices (excl. taxes) for the scenarios considered in this paper.

	Classical installation	Storage field
Heating	$p^{\text{heating}}_{\text{classical}} = 47.1$ €/MWh	$p^{\text{heating}}_{\text{field}} = 26.7$ €/MWh
Cooling	$p^{\text{cooling}}_{\text{classical}} = 33.3$ €/MWh	$p^{\text{cooling}}_{\text{field}} = 0$ €/MWh

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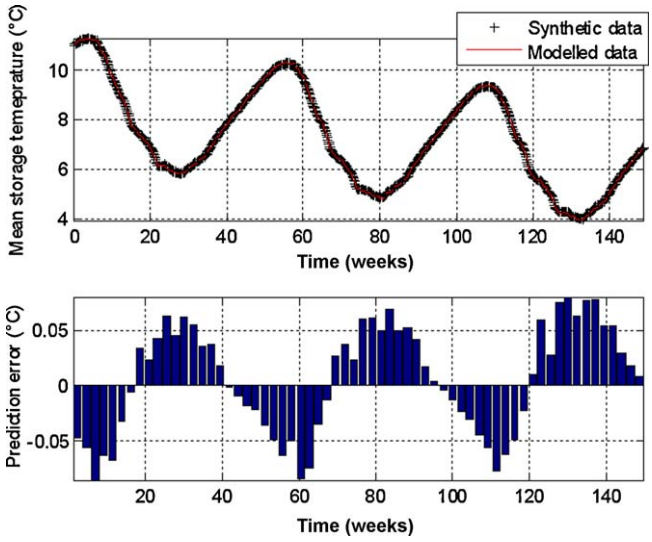


Fig. 2. The synthetic data and the model values are shown in the first plot. In the second plot, the prediction error is shown.

3. Dynamics

One of the most important milestones on which this control algorithm depends, is the model for the underground. This model enables the prediction of underground temperature changes due to a given operation strategy over relatively short periods (one week in this case). We decided to use a relatively simple model to describe the dynamics of the underground storage system, although more complex models have been presented in literature, e.g. [11]. A first order response model is used to describe the underground heat storage system

$$mc\dot{x} = f(x,u) = \lambda(T_\infty - x) - u \tag{1}$$

with x the temperature of the field (K), λ the thermal conductivity (W/K), T_∞ the undisturbed boundary temperature (274.15 K or 11 °C), i.e. the temperature of the ground far from the field, m the mass (kg), c the heat capacity (J/kg/K) and u the amount of heat extracted per hour (W). This equation has two unknowns (mc and λ). The first is a measure for the amount of heat that can be stored. This capacity should be sufficiently large, so that enough heat can be loaded. The second is a measure for conductivity. It should be sufficiently low, so that large time lags can be achieved. This combination of large capacity and low conductivity allows the system to shift large amounts of excess heat from summer to winter and vice versa for cold. To estimate both parameters, we started from synthetic data generated by a simulation of the underground system in the computer program TRNSYS. As a model to simulate the response of the real underground the duct ground heat storage model (DST) is used [12].

The parameters mc and λ are optimized so that the simple model (Eq. (1)) predicts the water temperature computed by the DST module as close as possible.

The results are visualized in Fig. 2. The sinusoidal structure in the error is due to simplification of the model and can be further reduced by increasing the model complexity, e.g. by introducing second order effects. However, since the root-mean-square value of the prediction error is only 0.0485 °C with maximum deviation of 0.0857 °C, it may be concluded that this simple model is sufficiently good in predicting the temperature calculated with the complex DST model, to be used in the controller.

4. Constraints

In almost any technology, people start with building very robust systems, far away from any physical constraint. Forced by economical motives, these systems have then to be made cheaper. An unavoidable disadvantage is that certain limitations of the system, so-called constraints, become prominent. The best way to cope with such constraints is to take them explicitly into account in the control algorithms. In this paragraph, the constraints are discussed.

A first constraint concerns the pumps used to circulate the water through the underground storage system. These pumps are limited to 78 m^3/h, corresponding to a maximum heat flux of 343 kW (temperature difference is 4 K, the circulation fluid is a mixture of water and antifreeze, with a heat capacity of 3.95 kJ/(kg K)). If larger pumps would be installed pressure drops will become important and consequently a lot of energy would be wasted. So, this constraint can be summarized as

$$\begin{aligned} h_1 &= u - 343\,\text{kW} \le 0 \\ h_2 &= -u - 343\,\text{kW} \le 0 \end{aligned} \tag{2}$$

In these equations u stands for the heat flux out of the field. If u is positive heat is extracted, otherwise cold is extracted.

The second set of constraints bounds the temperature of the field. The underground temperature should remain above 0°. At the other extreme edge, it becomes almost impossible to cool a building if the temperature of the field has increased above 12 °C. So,

$$\begin{aligned} h_3 &= -x \le 0 \\ h_4 &= x - 12\,^\circ\text{C} \le 0 \end{aligned} \tag{3}$$

with x the temperature.

Towards the acclimatization engineers, it is most convenient to guarantee a certain amount of heat and/or cold during the seasons. This enables them to select the correct size of the additional classical installation. Here, any function for guaranteed heat or cold supply may be chosen

$$\begin{aligned} &\text{Heat supply} : h_5 = -u + f(\text{time}) \le 0 \\ &\text{Cold supply} : h_6 = u - g(\text{time}) \le 0, \end{aligned} \tag{4}$$

With f(time) and g(time) arbitrary functions of time. To focus our mind rather simple functions have been used. During winter, which we define as the period from October 1st to April 1st, this system should be able to deliver continuously 200 kW heat, if desired. During the summer, the same amount of cold has to be supplied, if desired.

$$\begin{aligned} &\text{winter} : h_5 = -u + \min(q, 200\,\text{kW}) \le 0 \\ &\text{summer} : h_6 = u - \max(q, -200\,\text{kW}) \le 0 \end{aligned} \tag{5}$$

In these equations q stands for the heat/cold demanded of the building. If this demand is lower than 200 kW, only the demand q, has to be delivered. However, if more is needed, the field is only obliged to supply 200 kW. The rest can come from the classical installation, from the field or from both. The choice is directed towards minimum costs. Finally note that the two last equations may be replaced by other constraints, defining the user demands. Other constraints will alter the actual control policy, but can be found using the same approach.

5. Dynamic programming algorithm

It is hard to predict weather conditions a few months in advance. This makes it difficult to build a control algorithm taking weather effects explicitly into account. Dynamic programming is one of the few optimal control algorithms which can cope with this type of problems. In this algorithm time is discretized in steps of one week, the demand and delivered heat or cold are divided into 11 intervals

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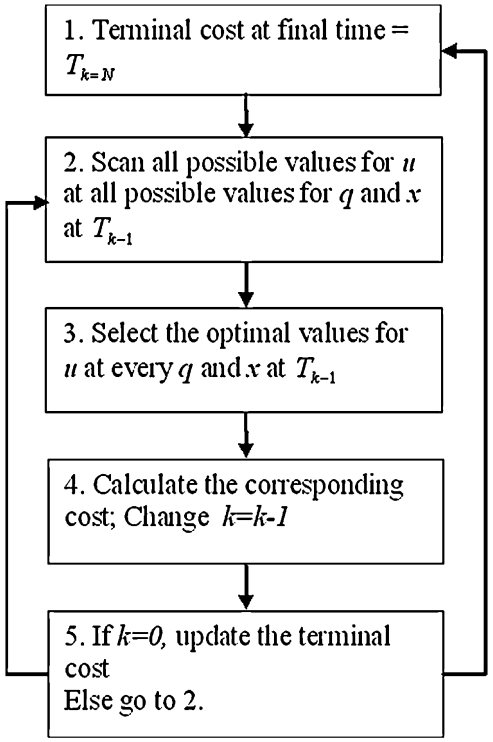


Fig. 3. Scheme of dynamic programming algorithm with value iteration.

between −343 and 343 kW and the temperature is divided in 105 intervals between 0 and 12 °C. In Fig. 3 a scheme of the dynamic programming algorithm is shown. Every step of this scheme will be explained.

5.1. Terminal cost

Because the algorithm starts at the end of the control cycle and calculates the control actions backwards, we start with defining an initial guess for terminal cost function. In our case the terminal cost function is the cost associated to every temperature on April 1st, when the winter stops. We argue that in the upcoming summer the field is used to supply cold. For that reason, it would be beneficial if the ground is as cold as possible. The initial terminal cost function $J_{\text{initial}}(x_N, q)$, is simply chosen to be proportional to the final temperatures x_N and is independent of the heat and cold demand q,

$$J_{\text{initial}}(x_N) \propto x_N \tag{6}$$

If this guess for the terminal cost function would not be optimal, it will be updated several times until it converged to the optimal value (vide infra). This (initial) terminal cost is shown at the right in Fig. 4.

5.2. Scan all possible heat extraction values

For every underground temperature and demand at the previous time step, all possible values for supplied heat are scanned:

- for every value, the constraints are checked. If a constraint is violated, the particular solution is no longer taken into account.
- a cost function is associated to all remaining values of the supplied heat u_k

$$J_k^+(u_k, x_k, q_k) = L(u_k, q_k) + J_{k+1}(f(x_k, u_k)) \tag{7}$$

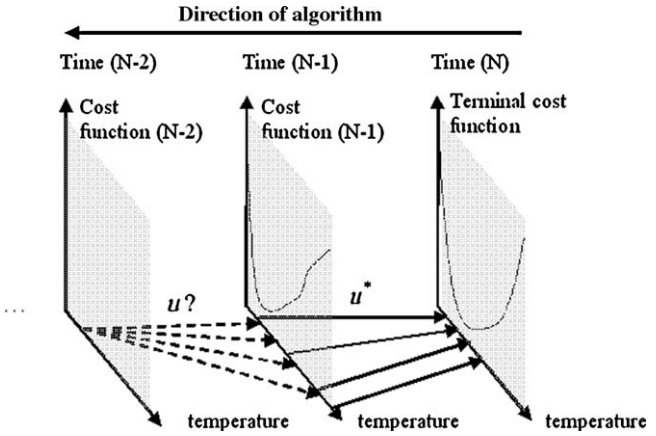


Fig. 4. Dynamic programming algorithm.

This operation policy will change the underground temperature, so the cost of the next week, evaluated at the final temperature $x_{k+1} = f(x_k, u_k)$, is used. This final temperature is found by integrating Eq. (1). The terminal cost is averaged over all demands by a distribution of the expected values. In practice this means that no weight is given to a situation where heat is demanded in mid-summer if this is very unlikely.

The stage cost $L(u_k, q_k)$, tells us the cost if the system is operated under a given control condition during the next week. The stage cost is given in Table 2. Note that opposite to e.g. [10], the stage cost is not averaged out over all demands, because we assume that the present demand is known.

If heat is demanded ($q_k > 0$) and the field is supplying heat ($u_k > 0$), the cost consists of two terms: that part which is not supplied by the field has to be produced by the classical installation. For this term, we take the gas price and efficiency into account (see Table 1). The second term contains the electrical costs of the heat pump with a coefficient of performance $COP_K = 0.25T_c/(T_c - x)$, with $T_c = 35$ °C. If heat is demanded and no heat is supplied ($q_k > 0$, $u_k < 0$), all heat has to come from the classical installation. If cold is demanded and no cold is provided ($q_k < 0$, $u_k > 0$), the cooling installation has to supply it at a relatively high cost. Finally, if cooling is demanded and supplied ($q_k < 0$, $u_k < 0$), only that part not supplied by the field has to be supplied by the classical installation. Note that if more heating or cooling is supplied than needed, this excess is lost free of charge. During summer, it is probably quite easy to heat the field, but under certain conditions during winter, the outside temperature might be too high to cool the field free of charge. However, this will largely depend on the situation and will be ignored during the remaining of this paper.

5.3. Select the optimal values for the control parameter

The optimal control parameters are those values which minimize the cost

$$u_k^*(x_k, q_k) = \arg\min_{u_k} J_k^+(u_k, x_k, q_k) \tag{8}$$

with $u_k^*(x_k, q_k)$ the control policy. Its value tells us the optimal amount of heat or cold that shall be extracted from the field in a certain week k for a given mean temperature x_k and a demanded amount of heat/cold q_k.

5.4. Calculate the corresponding cost

The cost associated with every control parameter can be used as terminal cost function for the previous week. Recursively, the

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Table 2
Stage cost. All symbols are explained in the text, with $\Delta T = 168$ h.

$L(u_k, q_k)$	$u_k > 0$	$u_k < 0$
$q_k > 0$	$(p^{\text{heating}}_{\text{classical}} \max(q_k - u_k, 0) + p^{\text{heating}}_{\text{field}} u_k)\Delta T$	$p^{\text{heating}}_{\text{classical}} q_k \Delta T$
$q_k < 0$	$p^{\text{cooling}}_{\text{classical}} \lvert q_k \rvert \Delta T$	$p^{\text{cooling}}_{\text{classical}} \max(\lvert q_k \rvert - \lvert u_k \rvert, 0)\Delta T$

optimal control parameters for each week can be identified. So the cost function for the current week is

$$J_k(x_k) = \underset{q_k}{E}\{\min_{u_k} J^+_k(x_k, u_k, q_k)\} \tag{9}$$

5.5. Value iteration

Next, the dynamic programming algorithm is run over several years backwards. Each time the cost function of April 1st is calculated, this function is used as an improved estimation of the terminal cost. After a couple of iterations it converges. In addition, it can be proved that it converges to the true terminal cost function [10]. In this study, we iterated over 5 years.

6. Results

6.1. Evolution of the cost function

In Fig. 5 the evolution of the cost as function of time and temperature is shown. To interpret this, start at the blue line on the left top. This line is the expected cost needed to acclimatize the office building until April next year. If the field is warmer than 4 °C no cost is shown, because for such high temperatures, the field cannot guarantee that it can deliver 200 kW cold all summer long. The next month the temperature range has shifted to higher temperatures. The reason for this is that if the temperature would be too close to zero, the field cannot guarantee to deliver 200 kW heat in the approaching winter. By the end of summer the temperature has risen above 10 °C, ready to supply heat during the winter. During the winter season the opposite is true: the field is cooling down. Note that during the summer season the cost function is rather flat, which means that a difference in temperature will hardly effect the cost, while in winter the temperature is much more critical.

When cold is extracted from the field, it is delivered free of charge to the office building, while if heat is extracted, it has to be upgraded, which is costly. This causes that most expenses are made in winter.

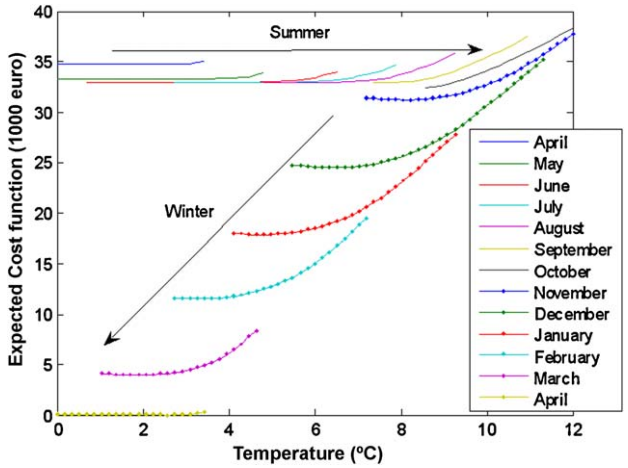


Fig. 5. Evolution of the cost function.

6.2. The control parameters in a typical week

For a particular week in February, the control policy is shown in Fig. 6. At this moment of the year, the aim is to cool the field in order to provide cooling during summer. At the same time, the field has to provide the demanded heating with a maximum of 200 kW. In this Fig. 6, seven regions can be identified:

(i) if the temperature is above 5.3 °C, the field would not be able to provide 200 kW cooling during the complete summer season. So constraint h_6 is violated. In practice, one could extract 343 kW to cool the field.
(ii) If the temperature is below 1.3 °C, the field cannot guarantee to provide 200 kW for the remaining winter season. So in this region constraint h_5 is violated. In practice one could extract as 343 kW cold to heat the field as soon as possible.
(iii) If 300 kW heating is demanded, the provided amount depends on the field temperature. Between 1.3 and 1.9 °C only the guaranteed 200 kW is supplied, above 1.9 °C, the demanded 300 kW is provided. If the field's temperature is between 5.1 and 5.3 °C, the 300 kW can still be supplied, but it is more beneficial to extract 343 kW and drain the 43 kW excess heat. If no action is taken, it will become impossible to guarantee a cooling of 200 kW cooling during the next summer.
(iv) If less than 200 kW is demanded, at least this amount is provided, so no constraints are violated. However, if the temperature of the field rises above 5.0 °C, it is beneficial to extract more heat than the demanded by the building. This excess has to be drained.
(v) If cold is demanded in this period of the year, no minimum deliveries are promised, so the controller is free to optimize the field's temperature. Between 0.5 and 1.5 °C, the field is actually too cold and additional heat is supplied to the field. This drives the field towards more optimal temperatures.
(vi) Between 1.5 and 3.6 °C the temperature is optimal and the demanded cold is supplied.

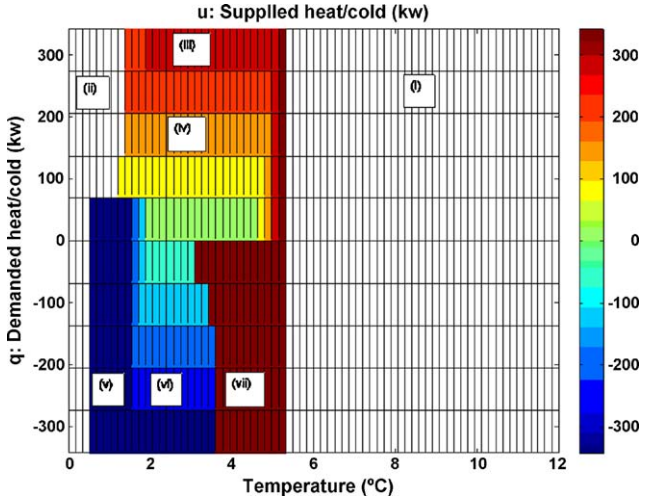


Fig. 6. Control law for a week in February: white: constraints are violated; blue: cold extracted; yellow, red: heat is extracted. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

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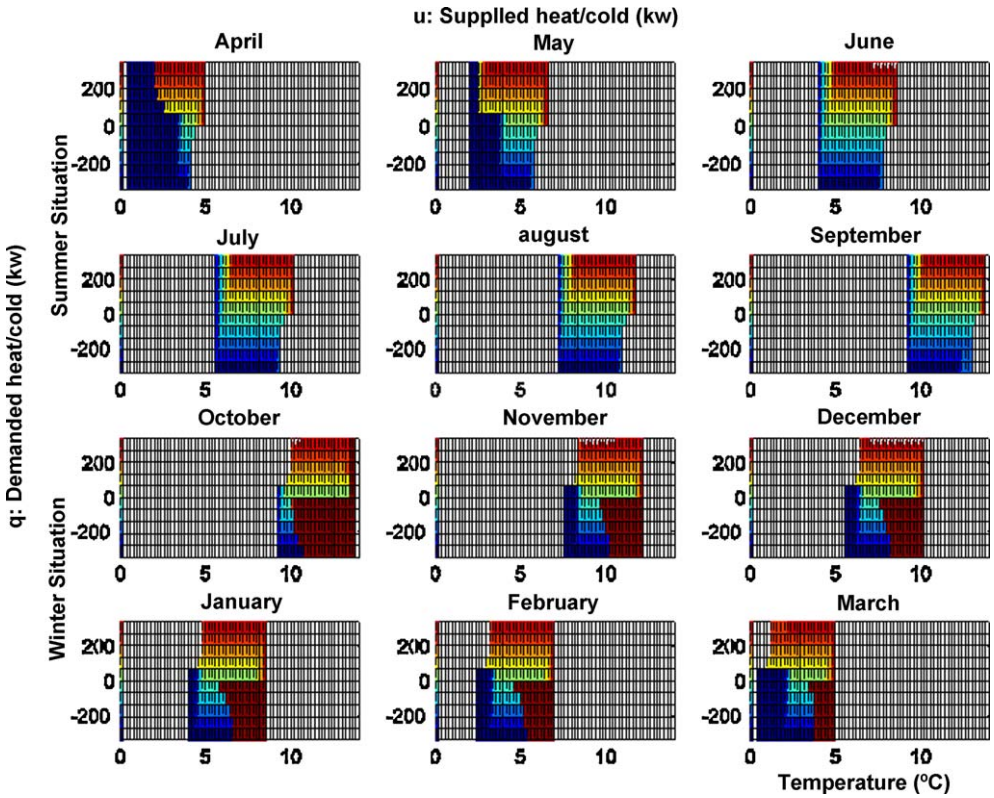


Fig. 7. Evolution of the control policy, u.

(vii) If the temperature exceeds this 3.6 °C, it is most beneficial if heat is extracted and drained, while the classical installation is providing the demanded cold. The reason for this action is that the field is actually too hot and if no action is taken, it will become impossible to provide 200 kW cooling during the coming summer.

6.3. Evolution of the control parameters

In Fig. 7 the control policy is shown for a typical week in every month of the year. Here can be seen that during the summer period the system is mostly forced to heat up by extracting cold if the temperature is too low. This is most pronounced in April, where one can see the large vertical blue bands in Fig. 7. Only when the field is too warm, heat is extracted, but this is rather rare. Towards the end of summer, the field is relatively warm and mostly the demanded heat is supplied. In winter, the opposite scenario takes place: the field is forced to cool down by extracting heat.

The succession of this control policy guarantees that the temperature remains in its desired range all year long. Depending on the demand, the optimal amount of energy extracted from or supplied to the field can vary slightly. At any time during summer at least 200 kW cold is supplied if demanded and during winter 200 kW heat can be delivered. Under these operating conditions, it is impossible to freeze the field or to heat it above 12 °C. Above all, the heating and cooling is partitioned between the classical installation and underground storage field, so that the total cost is minimized.

6.4. Case study

In this paragraph, we used the TRNSYS simulation environment combined with the DST module [12] to simulate a real underground heat storage field. To dimension the heating and cooling installation similar simulations have been used. The estimated heat and cold demand from these studies have been used. This DST module employs a sophisticated model for the underground, which is more realistic then the model used in this paper. This enables us to estimate the impact of model errors on the controller.

In Table 3 the results of seven scenarios are summarized. Note that the optimal control algorithm still optimizes towards minimal operation costs. If the cold or heat demand is normal, the estimated heating and cooling values for this building are used. However, since weather is unpredictable, several other scenarios have been simulated. If the winter/summer is mild, only 66% (1/1.5) of the reference demand is asked, while in a cold winter or hot summer 150% is asked. Under all combinations, the BTES is cheaper than the classical installation.

Comparing the classical controller with the optimal controller has to be done with caution, because the classical controller does not take the minimum delivery constraints (h_5 and h_6) into account. The costs of both control policies are summarized in Table 3:

(i) In the scenario of a mild winter followed by a mild summer, the classical installation is much cheaper. In this scenario, the optimal control policy has been more prudent, because it want to be able to provide 200 kW heat during winter or cold during summer. Looking back, this prudence was unnecessary and more expensive. So we may conclude that in this scenario the classical controller won by betting right.
(ii) In the scenarios mild and normal, normal and hot and cold and hot, this betting turned out badly and the 200 kW heat or cold could not be provided.
(iii) In the scenarios normal and mild, normal and normal both control policies results in comparable costs.
(iv) If a cold winter is followed by a normal summer, the optimal control policy is slightly cheaper.

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Table 3
Heating and cooling costs for a number of weather conditions and installations.

Weather conditions			Cost (k€)	
Winter	Summer	Installation without BTES	BTES + Classical installation	
			Optimal controller	Classical controller
Mild	Mild	47	47	31
Mild	Normal	54	42	Failure
Normal	Mild	63	49	51
Normal	Normal	70	51	49
Cold	Normal	95	71	77
Normal	Hot	80	54	Failure
Cold	Hot	105	84	Failure

To conclude, we are comparing two different control strategies: one restricted by additional constraints and the other not. Under several scenarios, the classical control scenario fails. Such failures will become more frequent if more economical installations will be installed.

Note that these costs are higher than predicted in Fig. 5, because the demands are sometimes higher than can be provided by the underground field. The difference is automatically supplied by the classical installation and causes this extra cost.

For the normal scenario, the temperatures and heat fluxes are shown in Fig. 8. Neither for this scenario, nor for any other, any constraint has been violated. The temperature series converges quite fast to an optimal cycle. This cycle corresponds to the lowest cost possible and is identical each year. This symmetry is caused by the identical demand cycle each year. The outlet temperature varies more severely than the mean temperature. The upper limit is about 15 °C. This is the maximum which can still be used to cool a building. However, a minimum of −4 °C might be too low to avoid freezing of the underground. In future generations of the controller, the outlet temperature should be taken into account as well. Regarding the heat fluxes, several regions can be seen:

(i) When the operation starts, a transient effect can be noticed: the field is too warm for October and is cooled by extracting more heat, even if cold was demanded.
(ii) During winter, the field is providing heat. Sometimes more than 343 kW is demanded and in those cases, the field supplies its maximum, i.e. 343 kW.
(iii) At the end of each winter more heat is extracted than demanded. This is done to cool the field for summer.

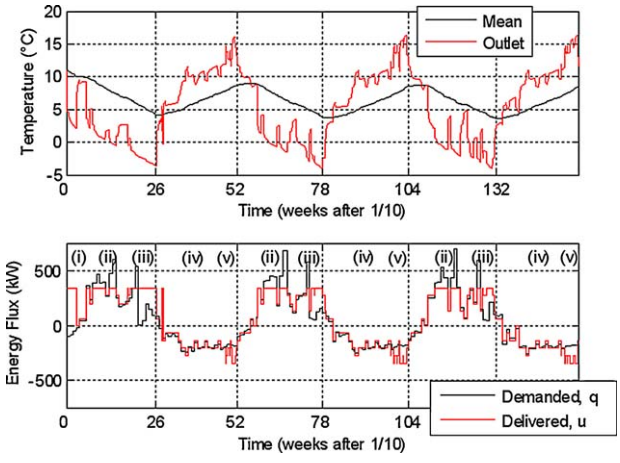


Fig. 8. Upper panel: mean and outlet storage temperatures; and lower panel: demanded and delivered heat fluxes.

(iv) During summer, the field can usually provide all cold needed by the building.
(v) At the end of summer, more cold than needed is extracted. This is done to warm the field for the upcoming winter.

7. Implementation

If such a controller were installed in a real BTES system, it needs a measure for the average temperature of the field. This could be measured by inserting a temperature sensor in the ground at several distances from the boreholes. The average value of the sensors would probably be a good measure for this parameter. An alternative could consist of utilizing the fluid temperature after a shut down for one or two days. Often office buildings are not used during the weekend and after such a period the fluid temperature is quite close to the mean field temperature.

An advantage of the dynamic programming approach is that the final outcome is a large array, which can easily be added to existing control algorithms.

8. Conclusion

A first step towards optimal operation of a underground heat storage system in the presence of weather uncertainty is presented. A dynamic programming controller is able to operate the system within a given set of constraints. The constraints considered in this study relate to the field's temperature, the amplitude of the heat flux and guaranteed heat and cold supplies. This controller is based on a simple first order model for the mean temperature of the field and is illustrated on a simulation example. The latter exemplifies that no constraints are violated and that the costs are always beneath those of the classical installation. Under certain operation conditions, the uncontrolled BTES installation operates at a lower cost. However, no heat or cold deliveries are guaranteed in this setup. A simplification that might affect the outcome of the controller is that excess heat/cold can be drained free of charge. Nonetheless, this controller is able to guarantee a continuous heat and/or cold supply.

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