The 15th International Symposium on District Heating and Cooling
September 4-7, 2016, Seoul, Republic of Korea (South Korea).

A METHOD FOR TAKING INTO ACCOUNT SEASONAL STORAGE IN A DISTRICT ENERGY SYSTEM OPTIMISATION PROBLEM

J. Robineau[1], J. Page[1,2] and F. Maréchal[1]

1. EPFL Valais-Wallis, Rue de l'Industrie 17, Sion, CH-1951, Switzerland

2. HES-SO Valais-Wallis, Route du Rawyl 47, Sion, CH-1950, Switzerland

Keywords: Seasonal storage, Micro-district heating network, Multi-objective optimisation

ABSTRACT

In this work, a method for taking into account seasonal storage in an energy optimisation problem is developed. A master-slave optimisation procedure is applied, in which the master optimisation is an evolutionary algorithm, while the slave optimisation is a Mixed Integer Linear Programming (MILP) problem. The results of this optimisation can provide insight on the choice of technologies during the study of potential new district heating networks, and especially evaluate if a seasonal storage is worthwhile.

The method developed is applied to a case study. The goal is to optimise the design of a micro-district heating system consisting of 3 buildings and a neighbouring source of industrial waste heat. The technologies considered are heat pumps, solar thermal collectors, a hot water storage tank, geothermal borehole seasonal storage, a gas boiler and industrial waste heat.

The results show that, with the given assumptions, the use of combined seasonal and daily thermal storage can significantly reduce operating costs (by 65 %), fossil fuel consumption and CO_2 emissions, with a payback time of 4.5 years compared to a reference solution with no storage.

INTRODUCTION

The European building sector accounts for 40% of total energy use and 36% of CO_2 emissions [1]. A major part of this energy is used to heat buildings. Renewable sources of heat, such as geothermal and solar, can be harnessed using district heating networks, thus allowing a decrease in CO_2 emission. Moreover, district heating can take advantage of waste heat recovery of energy intensive industries which would otherwise throw it away into the environment.

One of the drawbacks of many renewable or recovery energy sources is that they are intermittent, and are often not synchronised with demand. However, the use of thermal storage systems can greatly increase their share. As the fluctuations can be both daily and seasonal (example of solar), specific storage systems for each of these time scales can be combined. Nevertheless energy storage comes at a cost, typically decreasing with size. The appropriate choice in terms of size and combination of storage types should therefore be the results of a cost optimisation.

Optimisation methods can be applied to support the choice of design and operating strategy of an energy system, including district heating systems. In this work, a master-slave optimisation method was applied to a micro district heating network case study, in order to identify a set of optimal design options for the system. A methodology was developed to integrate seasonal storage in the optimisation, and it was combined with an existing daily thermal storage model.

After a brief literature review of previous work on integration of storage in energy optimisation, the article presents the methodology developed by the authors with a focus on the method to integrate seasonal storage. Then, the case study and main assumptions are presented. Finally, the results of the optimisation are shown and discussed.

STATE OF THE ART

A review of seasonal thermal storage technologies is given in [2]. One of these technologies consists in using the soil as a storage medium. In this concept, vertical boreholes are drilled in the ground to insert tubes in which a heat transport fluid circulates in a closed loop in order to inject (resp. extract) heat in (resp. from) the ground material. One of the advantages of such a system is its lower price compared to other seasonal storage systems, as was observed in [3]. However, these costs do not include the heat pumps which are required to bring the temperature to a useable level.

A review of simulation models used to model seasonal storage is given in [2] that, however, does not consider optimisation. There are numerous examples in the literature of energy supply optimisation models which consider thermal storage. However, they have often been designed for short term thermal storage (e.g. daily) rather than long term storage (seasonal), although some of the principles can be applied to both short and long term storage. An optimisation model including daily thermal storage was implemented in [4], which is also the model that was used for daily storage in this paper. The daily thermal storage is divided into a number of virtual storage tanks with ordered temperature levels. At a given time, a mass of fluid can be transferred from one temperature level to another, exchanging heat with the rest of the system as it does. The formulation of the model can be used for both optimisation of design and operation. A thermal storage model was also developed in [5], but the 2nd principle of thermodynamics was not considered (the system was divided into high and low temperature). As for long term storage, such a model was implemented for example in [6], but the model is non-linear due to the CHP operation being modelled using 3rd degree polynomials.

Combination of long term and short term storage is rare in the literature. Nevertheless, this was done by Rager in his thesis [7]. In his model, there is a daily storage in a multi-time problem, similar to the one developed by Fazlollahi et al. in [4]. The multi-time problem is embedded in a multi-period problem (i.e. each period is composed of several "times"), and a similar model is implemented at the level of the periods, corresponding to the seasonal storage.

METHODOLOGY

The methodology that was used in the present study consists in the following main steps:

1. Typical days are generated from the available data
2. A specific Mixed Integer Linear Programming (MILP) model is created for each typical day
3. A two stage master/slave multi-objective optimisation is carried out

Generation of typical days

Typical days are used as a means to reduce the complexity of the MILP problem by limiting the number of periods, and hence the number of variables. The generation of typical days was done by applying the k-means centroid clustering algorithm developed by Fazlollahi et al. in [8]. The k-means algorithm minimises the Euclidian distance between each observation (i.e. a real day) and the centre of the cluster (i.e. the typical day) to which it belongs, the distance being calculated over all measurements (i.e. 24 hourly values in a day) of selected attributes (i.e. heating demand, solar irradiance).

The number of clusters was chosen based on the assessment of 3 statistical measures. Additionally, for each attribute, five quality indicators detailed in [8] were calculated in order to compare the typical days obtained with the original data. Once the typical days have been generated, an extreme day is added in order to take into account the highest demand during the year for the sizing of the equipment. Moreover, all of the 365 days of the year are associated to a typical day, and the number of occurrences of each typical day is calculated.

A nearby industry provides a source of waste heat during certain periods of the year. Due to the nature of the industry, the availability of the source is both intermittent and unpredictable (it can be activated at varying time intervals and for varying durations). To integrate the use of this industrial waste heat, the thermal power and temperature levels have to be defined for each period (i.e. each hour of each typical day). To achieve this, a procedure was developed taking into account the stochastic nature of the industrial waste heat source. The following steps were carried out:

1. The industry's daily activation profile was created using 3 years of operating data. A boolean variable was associated to each real day if the source was available (i.e. with a heat output >0).
2. As each real day $i \in \{1, \ldots, 365 \times 3\}$ over the 3 years of operating data has a corresponding typical day $d \in TD = \{1, \ldots, N_d\}$, the probability p_d of activation of the industry was calculated using:

$$p_d = \frac{\mathrm{card}(A_i = 1 \mid d_i = d)}{\mathrm{card}(d_i = d)} \quad \forall d \tag{1}$$

   where A_i is the boolean variable corresponding to the activation of the industry during day i and $d_i \in TD$ the typical day which is used to represent that day.
3. Two typical days are derived from each original typical day. In one of the derived typical days, the industry is activated, and in the other it is not. All other data (heating demands, etc.) are identical to the original typical day.
4. The number of occurrences of each derived typical day is calculated using the probability of activation obtained in the previous step and the number of occurrences of the original typical day.
5. The average waste heat load available is calculated for each typical day that the industry is activated. This is done by calculating, for each hour, the average over the 3 years of data represented by the typical day.
6. A similar procedure is applied to calculate the average temperatures of the industrial waste heat source for each typical day, except that the average is only calculated on non-zero values.

It is to be noted that the typical days generated using this method are not sequential, meaning that a given typical day can represent real days scattered across the year.

Mixed Integer Linear Programming model

Each typical day was represented by a specific MILP model. The MILP problem consists in minimising the operating cost of a set of energy conversion technologies which produce heat, either to fulfil the demand of given buildings, or to store it in daily or seasonal thermal storage units so that it can be used at a later period. The heat cascade constraint is applied to make sure the thermodynamic principles are respected. The problem is multi-period and consists of 24 periods corresponding to the hours of the day. The objective function is expressed as:

$$\min_{y,f}\left[\sum_{p=1}^{N_p}\sum_{u=1}^{N_u}(OC1_u \times y_{u,p} + OC2_u \times f_{u,p}) \times \Delta p\right] \quad (2)$$

where $f_{u,p}$ (resp. $y_{u,p}$) is the continuous (resp. binary) decision variable accounting for the usage level (resp. activation) of unit $u \in U$ during period $p \in \{1,\ldots,24\}$. The set of units U is composed of all the energy conversion technologies, building demands to satisfy, energy sources and storage technologies. $OC1_u$ and $OC2_u$ are the fixed and variable operating costs, respectively, associated to unit u. No investment cost is considered in the MILP model.

It is subject to the following constraints:

- The usage of unit u during period p is governed by:

$$F_u^{\min} \times y_{u,p} \le f_{u,p} \le F_u^{\max} \times y_{u,p} \quad \forall u, p \quad (3)$$

  where $F_u^{\min}$ and $F_u^{\max}$ are the minimum and maximum capacity of unit u respectively. Their values can be fixed by the master optimisation. The usage level of building demands is fixed and equal to 1.

- For each temperature interval $k \in K = \{1,\ldots,N_k\}$, the heat cascade constraint is defined as follows:

$$\sum_{u=1}^{N_u}\left[f_{u,p} \times \left(\sum_{u_h=1}^{N_{u_h}}\dot{Q}_{u_h,k,p} - \sum_{u_c=1}^{N_{u_c}}\dot{Q}_{u_c,k,p}\right)\right] + \dot{R}_{k+1,p} - \dot{R}_{k,p} = 0 \quad \forall k, p \quad (4)$$

$$\dot{R}_{k,p} \ge 0 \quad \forall k, p, \quad \dot{R}_{1,p} = 0, \quad \dot{R}_{1,p} = 0 \quad \forall p \quad (5)$$

  where $\dot{Q}_{u_h,k,p}$ (resp. $\dot{Q}_{u_c,k,p}$) represents the reference heat requirement of the hot stream u_h (resp. cold stream u_c) associated to unit u, in temperature interval k and period p. $\dot{R}_{k,p}$ is a continuous variable for the residual heat from the temperature interval k, which cascades down to the lower temperature interval $k-1$.

There are two types of thermal storage units included in the model: daily storage and seasonal storage. For the daily storage, the model from Fazlollahi et al. in [4] was used. The storage is discretised into 3 temperature levels: 25, 50 and 75°C. The heat can be charged into the storage either at low temperature, corresponding to a cold stream going from 25 to 50 °C (discharge via a hot stream: 50 to 25°C), or high temperature, corresponding to a cold stream going from 50 to 75 °C (discharge via a hot stream: 75 to 50°C). The generic set of equations describing the daily storage can be found in [4]. The total daily storage volume (high temperature + low temperature) is fixed in the MILP problem, but can be a decision variable of the master optimisation.

Multi-objective optimisation

A master-slave optimisation procedure was applied and is illustrated in Figure 1.

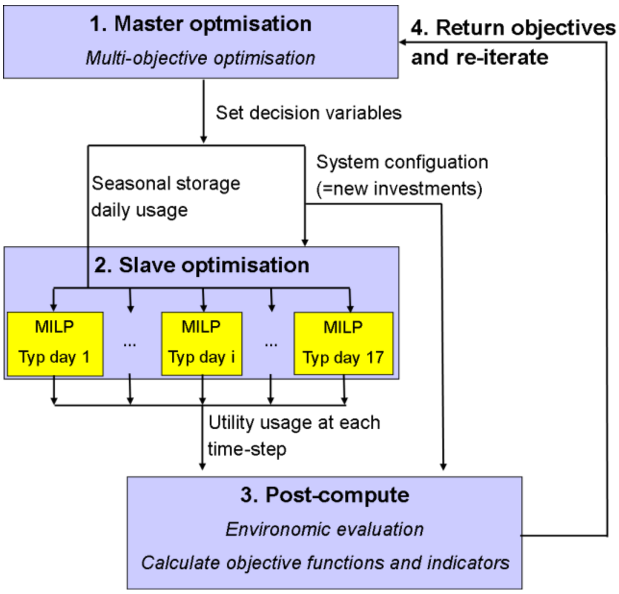

Figure 1. Master slave optimisation procedure

The following steps are carried out at each iteration, for a given number of iterations:

1. The multi-objective master optimisation generates a set of continuous and binary decision variables. These decision variables control both i) the existence, sizing and overall operation of the seasonal storage, and ii) the selection and sizing of the daily storage units and energy conversion technologies. The algorithm used here is the evolutionary algorithm developed by Leyland in his PhD thesis [9].
2. The decision variables of the master optimisation are passed on to the slave optimisation, which is in fact a set of independent MILP optimisation sub-problems (one for each typical day).

3. The results of all the slave optimisations as well as the decision variables of the master optimisation are passed on to a post compute function which calculates the objective functions of the master optimisation, as well as any other indicator.
4. The objectives are returned, evaluated and ranked by the master optimisation, which can then generate a new set of decision variables and re-iterate the whole process.

Seasonal storage model

In the MILP sub-problem, the seasonal storage is represented as two units: one unit associated to a cold stream representing the charging (the cold stream is taking heat from the system), one unit associated to a hot stream representing the discharging of the storage (the hot stream is providing heat to the system).

The temperatures of the hot and cold streams are rough assumptions based on the study carried out in [10] and are defined as follows:

- In charging mode: the temperature of the fluid injected into the seasonal storage was set to 40°C. This means that any source of heat at a higher temperature can be charged into the seasonal storage. The output temperature (which also has to be fixed to define the cold stream) was set to 20 °C. This requires the soil to be at a lower temperature.
- In discharging mode: the temperature of the fluid extracted from the storage was set to 25°C, which means that a heat pump would need to be installed to increase the temperature to a level compatible with the demand. Similarly, this requires the soil to be at a higher temperature. This is only valid under the assumption that enough heat has been stored in the soil. The input temperature was set to 5°C (i.e. evaporator of a heat pump).

The total amount of heat Q_{ss}^{in} (resp. Q_{ss}^{out}) that can be charged (resp. discharged) into (resp. from) the seasonal storage over a day is fixed for a given typical day. This leads to the following equations:

$$\sum_{p=1}^{24} f_{ss,p}^{in} \times \dot{Q}_{ss,p}^{in} = Q_{ss}^{in} \tag{6}$$

$$\sum_{p=1}^{24} f_{ss,p}^{out} \times \dot{Q}_{ss,p}^{out} = Q_{ss}^{out} \tag{7}$$

where $\dot{Q}_{ss,p}^{in}$ (resp. $\dot{Q}_{ss,p}^{out}$) is the reference heat requirement of the seasonal storage charging (resp. discharging) unit at period p, and $f_{ss,p}^{in}$ (resp. $f_{ss,p}^{out}$) is the usage level decision variable of the same unit.

The decision variables of the master optimisation dealing with the seasonal storage are:

- The existence of the seasonal storage Y_{ss} (binary variable)
- The total amount of heat $Q_{ss,d}$ (continuous variable) that can be charged or discharged each typical day d except one which is left out in order to balance the storage over the year. $Q_{ss,d}$ takes a positive value if it is charged, and a negative value if it is discharged.

Those decision variables are used to define the seasonal storage constraints of the MILP sub-problems through the following equations:

$$Q_{ss}^{in} = \begin{cases} Y_{ss} \times Q_{ss,d} & \text{if } Q_{ss,d} \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad \forall d \tag{8}$$

$$Q_{ss}^{out} = \begin{cases} 0 & \text{if } Q_{ss,d} \geq 0 \\ -Y_{ss} \times Q_{ss,d} & \text{otherwise} \end{cases} \quad \forall d \tag{9}$$

This means that for a given day, the seasonal storage can either be in charging or discharging mode (not both on the same day).

In order to close the energy balance of the seasonal storage over the year, the energy charged into the storage for one of the typical days $d' \in TD$ is calculated (instead of being a free decision variable) using:

$$Q_{ss,d'} = \frac{1}{n_{d'}} \times \left(\sum_{\substack{d \in TD \\ d \neq d'}} Q_{ss,d} \times n_d \right) \tag{10}$$

where n_d is the number of occurrences of typical day d during the year.

The choice of the "balancing" typical day corresponds to the one with the highest number of occurrences. A higher number of occurrences $n_{d'}$ makes $Q_{ss,d'}$ less sensitive to variations in the decision variables $Q_{ss,d}$ and therefore reduces the risk of having unrealistic values.

The size of the borehole storage l_b (i.e. total length) is calculated in such a way that the maximum daily charge or discharge can be exactly fulfilled if it is operated at the maximum power throughout the whole day (linear thermal power of 40 W/m was taken from [10]):

$$l_b[\text{m}] = \frac{\max_{d \in TD} \left| Q_{ss,d} \right|}{40[\frac{\text{W}}{\text{m}}] \times 24[\text{h}]} \tag{11}$$

The maximum charging/discharging rate is also fixed in the MILP sub-problem based on these values:

$$f_{ss,p}^{in/out} \times \dot{Q}_{ss,p}^{in/out} \leq 40 \times l_b \quad \forall p \tag{12}$$

To choose the range of decision variables $Q_{ss,d}$, the assumption was made that if the daily demand of all the buildings was lower than the average daily demand during the year, then the seasonal storage should only be able to discharge heat ($Q_{ss,d} \leq 0$). On the contrary, it should only be able to charge ($Q_{ss,d} \geq 0$). Moreover, the maximum energy that can be charged into or discharged out of the seasonal storage on any given day corresponds roughly to the maximum daily solar heat produced.

CASE STUDY

The methodology described above was applied to a case study. The goal was to optimise the heat supply system of a micro-district consisting of 3 office buildings, where only space heating was considered. Out of the 3 buildings, 2 already exist (TB and EB) and they both have an existing independent heat supply infrastructure (the two buildings are currently not connected via a district heating network). Building TB is equipped with a gas boiler of 1000 kW, while EB has 285 m² of solar thermal collectors and two ground source heat pumps of 52 kW_{el} each. The third building (FB) is currently being planning and its heat supply system has yet to be decided.

The idea is to connect the three buildings via a micro-district heating network (µ-DHN) in order to share the infrastructure and maximise the use of fossil-free energy sources. The µ-DHN is also connected to a nearby industry providing an intermittent source of waste heat. The µ-DHN/building interface is bi-directional, meaning that buildings can either provide or take heat. The other technologies that were considered as investment options in the optimisation were: geothermal borehole (seasonal storage), a hot water tank (daily storage) and a high temperature heat pump.

RESULTS

The attributes used for the generation of the typical days were the simulated hourly heating demand profiles of the two existing buildings TB and EB and the hourly solar irradiance profile for a reference year. For the heating demand of building FB, a scaling factor of 256/190 was applied to the demand profile of EB. The extreme day was chosen based on the peak demand of TB.

Applying the methodology described above, 9 typical days (including the extreme day), each consisting of 24 hourly values, were generated to represent the yearly profiles.

As described in the methodology, those typical days were then duplicated to take into account the availability of the industrial waste heat source. This then led to 17 typical days, for which the data on availability, heat load and temperatures of the waste heat were also known. The extreme day was not duplicated as there was only one (the waste heat source was activated during that day).

The multi-objective optimisation procedure described above was applied to the case study, whereby the two objective functions were:

- Investment cost: only the investment cost of new equipment was considered, including the investment cost of the µ-DHN which was chosen by default.
- Operating cost: only fuel and electricity costs were considered (e.g. no maintenance).

The decision variables of the master optimisation were the existence of the technologies considered as investment options, the size of the technologies and the daily usage of the seasonal storage for each typical day except one. The size of the latter (number and depth of boreholes) results from the decision variables chosen for the daily usage. The range of values that the decision variables could take is given in Table 1.

Table 1. List and range of values of master decision variables

Decision variable	**Range**
Seas. storage (on/off)	{0;1}
Seas. storage (daily usage in kWh)	[-1000;0] or [0;1000] (depending on typ. day)
Daily storage (on/off)	{0;1}
Daily storage (size in m^3)	[10;353]
HP (on/off)	{0;1}
HP (size in kW_{el})	[30;300]

In the slave optimisation, where the operation of the system is optimised for each typical day, heat can only be supplied from a higher temperature heat source (hot stream) to a lower temperature heat sink (cold stream). This constraint is respected thanks to the heat cascade described in equation (4). The temperature levels of all the hot and cold streams are given in Table 2. The input and output temperatures of the cold streams representing the buildings' heating demand are a function of the outdoor temperature, as are the heating requirements. The heat pumps have a constant hot stream and cold stream temperature for the condenser and evaporator respectively. The condenser temperature can be optimised in order to adapt to the building requirements while maximising the coefficient of performance. This is achieved by representing the heat pump as several units, each associated to a different condenser hot stream, and adding a constraint that prevents more than one of these units to be activated at a given period (in order to prevent duplication of the heat pump). Excess heat which is not stored in one of the storage units is dissipated in a "free" cooling tower.

Table 2. Input/output temperatures of all hot and cold streams in the case study

Name	**T_{in} / T_{out} (°C)**
TB demand	Function of outdoor temp. (max: 60 / 80)
EB/FB demand	Function of outdoor temp. (max: 35 / 45)
Gas boiler	210 / 190
Solar thermal	85 / 50
Low-temp. HP	Evap: 6 Cond: 30 - 55
High temp. HP	Evap: 10 - 20 Cond: 40 - 80
Industrial waste heat	60 / 25
Ground water source	10 / 13
Low-temp. daily storage	25 / 50 (charging mode)
High-temp. daily storage	50 / 75 (charging mode)
Seasonal storage	Charging mode: 20 / 40 Discharging mode : 25 / 5

The results of the multi-objective optimisation are represented on Figure 2. On this graph, each point represents a solution of the multi-objective optimisation (corresponding to a given set of master decision variables). The value of one objective (operating cost) is plotted against the other (investment cost) for each solution. The results shown here took around 2 days to obtain using Matlab 2014b running on a computer with the following characteristics: Intel Core i7-4600U CPU @ 2.1 GHz, 8 Gb RAM, Windows 7 64 bits.

The colours used in Figure 2 show the superstructure of each solution, that is to say the technology choices regardless of their size (i.e. the combination of binary decision variables). For a given superstructure, different solutions are obtained due to the variation of the continuous decision variables. As the reference solution corresponds to the case where no new equipment is chosen (all binary decision variables set to 0), the system configuration cannot vary, leading to a unique solution. The investment cost of the reference solution corresponds to the µ-DHN, which is always present.

The first observation which can be made is that the demand of the future building FB can entirely be fulfilled with the existing heat supply systems providing that a heating network is installed to connect the buildings together and with the industry. This solution corresponds to the lowest investment, but also has the highest operating cost among Pareto solutions.

On the other end of the spectrum, the solution giving the lowest operating cost uses all the investment options available. Compared to the reference, it requires an additional investment of 142 k€, but allows 32 k€ of savings per year, leading to a theoretical payback time of 4 years and 6 months with the economic assumptions that were taken.

The solutions of the Pareto front can be broken down into different "clusters", which are mostly differentiated by their superstructure. Table 3 zooms on 6 Pareto optimal solutions which are shown on Figure 2, and which are each representative of a cluster of solutions.

Table 3. Investment choices for selected Pareto solutions

	Seas. stor.[1] (m)	**Daily stor. (m^3)**	**HP (kW_{el})**
1	943	43	84
2	996	11	49
3	798	0	78
4	0	10	120
5	0	0	67
6	0	10	0

DISCUSSION

A closer analysis of the results show that the seasonal storage is only interesting when combined with a new high temperature heat pump (points in grey and purple in Figure 2). Indeed, the heat available from the seasonal storage is too low to be used anywhere, and the existing heat pumps are already used at full capacity to supply heat to the low temperature buildings. As a result, it would be a good idea to force the selection of the heat pump to be chosen if the seasonal storage is chosen. This would result in reduced search space and therefore faster convergence towards optimality.

[1] For sizing of the seasonal storage, the total borehole length in metres is considered here. This total length then needs to be divided into a number of boreholes which each have a limited depth.

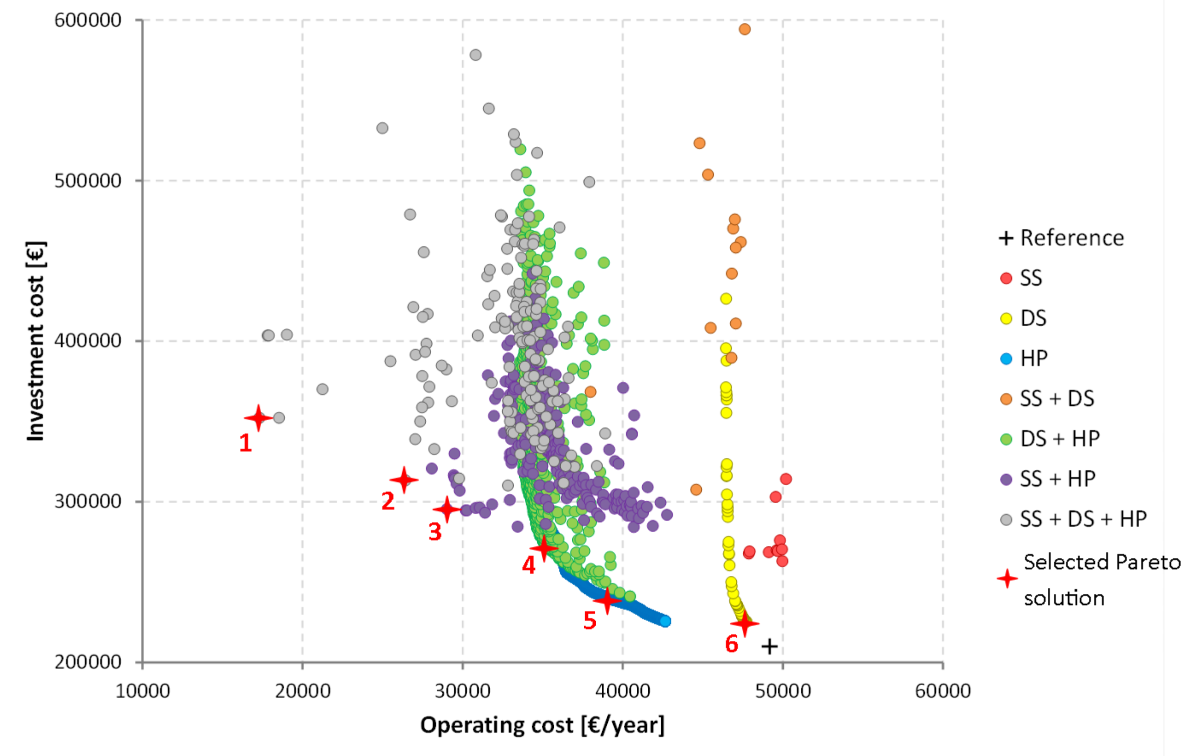

Figure 2. Superstructure of the 5012 solutions of the multi-objective optimisation (SS: seasonal storage; DS: daily storage; HP: heat pump)

Depending on the solution, 5 to 19 % of the heat demand transits in the seasonal storage, if it exists. This corresponds to between 62 and 226 % of the solar heat produced, meaning that most of the heat stored in the seasonal storage must come from the industrial waste heat. In fact, a lot of the heat stored in the seasonal storage is dissipated in the cooling tower. This happens because the daily amount of heat going into/out of the seasonal storage is fixed in the master, leading to constraints in the MILP problems which have to be fulfilled no matter what. To prevent this, restricted matches should be applied between the seasonal storage and the cooling tower. Also, the range of values for the decision variables of the seasonal storage should be chosen more wisely. Finally, a cost factor should be applied to the cooling tower to reduce its use.

A very different behaviour is observed between solutions with and without seasonal storage. The latter tend to converge nicely towards a well-defined Pareto front for each superstructure, which clearly marks the boundary between feasible and non-feasible solutions. On the other hand, solutions with seasonal storage are very scattered and no clear Pareto front can be identified. This can be explained by the fact that the size and operating strategy of the seasonal storage is defined by the combination of 16 decision variables in the master optimisation, leading to a complex interaction between those decision variables and the objective functions, whereas it is only defined by one decision variable for the other equipment. As a consequence, the best solutions obtained with seasonal storage are most likely not the optimal ones, and perhaps better solutions could be obtained should more iterations be carried out.

A major limitation in the current model should be pointed out here, and improved in the future. This concerns the temperature level of the storage. According to the temperature levels that were chosen for the hot and cold streams, the soil should be below 20°C in charging mode, and above 25°C in discharging mode. In reality, this corresponds to a case where the soil has been heated up prior to the cycle, as the average temperature of the soil is usually lower than that. Moreover, the temperature of the soil depends on the charge state, and the hot/cold stream temperature should be adapted accordingly. For example, at the beginning of summer, the temperature of the soil will be lower than at the end of summer, and it is easier to charge the storage at that period. However, the optimisation cannot know the charge state because the typical days are not sequential (each typical day corresponds to as many charge states as its number of occurrences). Obtaining a reasonable number of sequential typical days is very tricky because of the stochastic nature of the activation of the waste heat source. Finally, heat losses should also be accounted for, but this would also require the typical days to be sequential.

CONCLUSION

In this work, a methodology for integrating seasonal storage in a district energy system optimisation has been developed. A master-slave optimisation procedure was used, in which the master is a multi-objective evolutionary algorithm and the slave a set of independent MILP problems. The master decision variables are the investment choices, but also the daily amount of heat charged or discharged into/out of the seasonal storage.

The methodology was applied to a case study where the goal was to optimise the design of the heat supply system of a micro-district heating network consisting of 3 buildings and a neighbouring source of industrial waste heat. The technologies considered were heat pumps, solar thermal collectors, a hot water storage tank, geothermal borehole seasonal storage, a gas boiler and industrial waste heat.

The results showed that the use of combined seasonal and daily thermal storage can significantly reduce operating costs (by 65 %), with a payback time of 4.5 years compared to a reference solution with no storage. However, these results are most likely sub-optimal due to the large search space which was not fully explored and complex interaction between decision variables and objective values.

Although the case study presented in this work is simple, the methodology developed for the seasonal storage can be used in case studies including more technologies. The results can provide insight on the choice of technologies during the study of a new DHN.

OUTLOOK

Several perspectives of improvement to the seasonal storage model have been identified and need to be addressed:

- systematic coupling of seasonal storage and heat pump
- improving the range of values for the seasonal storage decision variables
- taking into account heat losses and variation of soil temperature

The last point requires having sequential typical days, which is challenging when there is a stochastic heat source independent of the time of year. An option could be to consider longer typical operating periods (e.g. typical weeks). Another option would be to produce a dynamical simulation of a handful of optimisation results, with either actual waste heat production data or Monte Carlo time series based on the actual data, as a validation of their feasibility.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the European Commission for providing financial support during the conduct of research under the FP7-PEOPLE-2013 Marie Curie Initial Training Network “CI-NERGY” project with Grant Agreement Number 606851.

This method was applied in the Austria research project called ‘RecoverHeat’ funded by the Austrian ‘Klima- und Energiefonds’ within the programme “Energy Mission Austria” and the 1st Call of “e!MISSION” 2012, FFG project number 838769.

We thank our research partners for their valuable collaboration in particular the team from the Austrian Institute of Technology (AIT), especially Tim Selke and Renate Teppner, as well as Edith Haslinger and Olivier Pol (ATP), without whose inputs an important part of this work would not have been possible.

REFERENCES

[1] J. O. Lewis, S. N. Hógáin, and A. Borghi, ‘Cities of Tomorrow – Action Today. URBACT II Capitalisation. Building energy efficiency in European cities’, May 2013.

[2] P. Pinel, C. A. Cruickshank, I. Beausoleil-Morrison, and A. Wills, ‘A review of available methods for seasonal storage of solar thermal energy in residential applications’, *Renew. Sustain. Energy Rev.*, vol. 15, no. 7, pp. 3341–3359, Sep. 2011.

[3] T. Schmidt, D. Mangold, and H. Hüller-Steinhagen, ‘Seasonal thermal energy storage in Germany’, presented at the ISES Solar World Congress, Göteborg, Sweden, 2003.

[4] S. Fazlollahi, G. Becker, and F. Maréchal, ‘Multi-objectives, multi-period optimization of district energy systems: II—Daily thermal storage’, *Comput. Chem. Eng.*, vol. 71, pp. 648–662, Dec. 2014.

[5] D. Steen, M. Stadler, G. Cardoso, M. Groissböck, N. DeForest, and C. Marnay, ‘Modeling of thermal storage systems in MILP distributed energy resource models’, *Appl. Energy*, vol. 137, pp. 782–792, Jan. 2015.

[6] T.-M. Tveit, T. Savola, A. Gebremedhin, and C.-J. Fogelholm, ‘Multi-period MINLP model for optimising operation and structural changes to CHP plants in district heating networks with long-term thermal storage’, *Energy Convers. Manag.*, vol. 50, no. 3, pp. 639–647, Mar. 2009.

[7] J. M. F. Rager, ‘Urban Energy System Design from the Heat Perspective using mathematical Programming including thermal Storage’, EPFL, Lausanne.

[8] S. Fazlollahi, S. L. Bungener, P. Mandel, G. Becker, and F. Maréchal, ‘Multi-objectives, multi-period optimization of district energy systems: I. Selection of typical operating periods’, *Comput. Chem. Eng.*, vol. 65, pp. 54–66, Jun. 2014.

[9] G. B. Leyland, ‘Multi-objective optimisation applied to industrial energy problems’, EPFL, Lausanne, 2002.

[10] E. Haslinger, M. Fuchsluger, and R. Niederbrucker, ‘RecoverHeat Deliverable D2.1: Subjects report Geothermal use of the subsurface at the site XXX’, Austrian Institute of Technology, 838769, May 2014.