Improving the Integer Linear Programming Model for an Ecovat Buffer by Adding a Global Planning

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***Abstract*—The Ecovat is a seasonal thermal storage solution consisting of large underground water tank divided into a number of segments that can be individually charged/discharged. The goal of the Ecovat is to supply heat demand to a neighbourhood throughout the entire year. In this work we extend an integer linear programming model describing the charging/discharging of such an Ecovat buffer by adding a global (yearly) planning step to the model. We compare the results from the model using this extension to previously obtained results and show significant improvements. We also show that the model is very robust against prediction errors.**

I. Introduction

In an effort to reduce green house gas emissions as well as the dependency on (the finite supply of) fossil fuels we see an increasing trend towards renewable alternatives. A disadvantage of these renewables is that their generation peaks often do not coincide with peaks in demand, both on a daily basis and on a seasonal scale. A way to alleviate this problem is the introduction of (thermal) storage (e.g. [1], [2]) into the system. A lot of research has been done on such thermal storage (for an overview of thermal storage technologies see e.g. [3]), as well as on seasonal thermal storage in particular (e.g. [4]).

The Ecovat [5] system is a seasonal thermal storage solution. It consists of a large underground water tank consisting of a number of vertical segments that can be individually charged/discharged using heat exchangers integrated into the buffer walls. The buffer is accompanied by a number of heat pumps, photovoltaic thermal (PVT) panels and a resistance heater, which can be used as energy sources. For a more detailed description of the system we refer to [6].

In previous work [6] we developed an integer linear programming (ILP) model to optimize the charging/discharging of an Ecovat buffer. However, as noted in that work one of the shortcomings of the model is the inability to plan ahead for future opportunities or needs. This shortcoming was especially visible for the case where a demand temperature of 60 °C was needed. In that case the energy content of the buffer stayed very low for a large portion of the simulated year leading to higher costs for supplying the heat demand.

In this work we propose adding a global planning step for a complete year prior to solving the ILP model. In this global planning daily targets for the energy content of the buffer are generated based on the predicted energy prices and heat demand for the optimization period. The ILP model of [6] is then altered slightly to make sure that the energy content of the buffer stays close to these generated targets.

II. Model

The goal of the Ecovat buffer is to supply the heat demand, both for space heating and tap water, of a neighbourhood while minimizing costs. This means the buffer will be charged with energy at times when it is locally available, e.g. from PVT panels, or when the energy price is low.

The problem we aim to solve is to generate a target for the energy content of the Ecovat buffer at the end of every day over the time horizon, which ensures that enough energy is available throughout the year. We use 15 minute intervals, which means that a target is set every 96 intervals. To ensure some flexibility in the ILP model we require the energy content to stay between a predetermined minimum and maximum capacity, C_{min} and C_{max} respectively. Furthermore we require the energy content of the buffer at the end of the time horizon to be at least equal to the energy content at the start to ensure a smooth operation of the system after the time horizon as well.

We define the set of time intervals as $\mathcal{I} = \{1, .., N_{int}\}$ and the set of segments in the buffer as $\mathcal{S} = \{1, .., N_{seg}\}$. As a measure of the energy content in the buffer we define the amount of useful energy, U_i, as the amount of energy in all segments at temperatures higher than the demand temperature, T_d, at the end of interval i:

$$U_i = \sum_{s|T_{i,s}>T_d} E_s \ (T_{i,s} - T_d) \qquad \forall\ i \in \mathcal{I}\ , \tag{1}$$

where E_s is the amount of energy needed to raise the temperature of segment s by 1 °C and $T_{i,s}$ is the temperature of segment s at the end of interval i.

To generate the energy targets for every day in the time horizon we solve the following problem:

$$\min_{x_i} \sum_i p_i\ x_i\ e_i, \tag{2a}$$

$$\text{s.t.} \quad U_i = U_{i-1} + e_i\ x_i - d_i \qquad \forall\ i \in \mathcal{I}, \tag{2b}$$

$$C_{min} \leqslant U_i \leqslant C_{max} \qquad \forall\ i \in \mathcal{I}, \tag{2c}$$

$$U_{N_{int}} \geqslant U_0, \tag{2d}$$

$$0 \leqslant x_i \leqslant 1, \tag{2e}$$

where x_i is the decision variable that determines how much energy is stored during interval i, e_i is the maximum amount of energy that can be stored during interval i, p_i is the predicted energy price during interval i and d_i is the predicted heat demand during interval i. The values of x_i can then be used to calculate the corresponding daily energy targets.

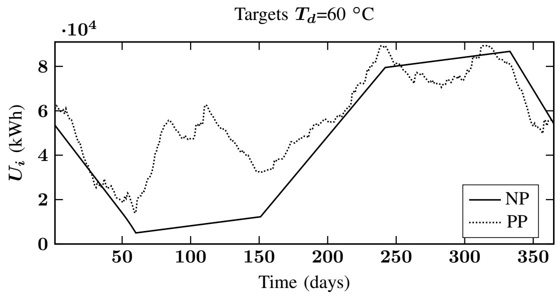

Fig. 1. Targets using perfect predictions or no predictions for a heat demand temperature of 60 °C.

As input for this problem we need predictions for the heat demand d and the energy prices p during the time horizon. An estimate for the expected daily heat demand can be obtained from historical data, however, reliable predictions for the energy prices are much harder to obtain. For this reason we compare results from a case where we assume perfect predictions (PP) for the energy prices with a case where we have no predictions (NP) to determine how robust our model is to prediction errors. In the NP case we simply distribute the intervals during which we store energy in the buffer equally over the entire horizon. Figure 1 shows the generated targets for the PP case (using real Dutch energy prices from 2014) as well as for the NP case for a demand temperature of 60 °C, starting at January 1. The targets for both cases differ significantly from each other. In the next section we further investigate the influence of these differences on the overall performance of the Ecovat.

The output of optimization problem (2) can be used as input for the ILP model described in [6]. For this an extra term is added to the objective function of the ILP model, which quadratically penalizes for being under target, U_i, at the end of each day and linearly rewards for being over the target.

III. Results

To investigate the impact of adding target values to the model in [6], we carried out a test using the same inputs for the ILP model as used in that paper. This means that heat demand profiles are used that are averages of historical data from 2005 to 2011 and energy prices from the year 2014.

We compare results using the ILP model with and without adding the global planning step described in this paper in Figure 2. A significant improvement when using the global planning is observed. The problem of the buffer being low on energy has been resolved as expected, while the objective value (total costs) is only slightly increased, from -27174 to -26992 (for the PP case). However, this increase in objective value is compensated by the much higher energy content of the buffer at the end of the time horizon when using a global planning.

Figure 2 also shows the evolution of the temperature distribution over the 5 segments in the Ecovat buffer in both the PP and NP cases. We can see that both cases look very similar even though the targets shown in Figure 1 are very different. The objective values are also very similar; -26992 in the PP case versus -26891 in the NP case. We carried out further tests using energy prices from 2011, 2013 and 2015

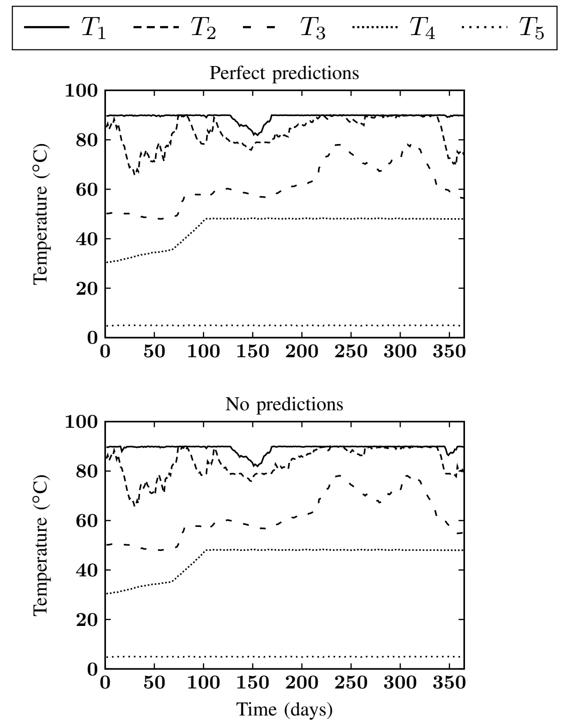

Fig. 2. Showing the evolution of the temperature distribution over the 5 segments ($T_1, .., T_5$) in the Ecovat buffer for both the PP and NP cases. The demand temperature in this case is 60 °C.

and found similar results. The largest difference in objective value between PP and NP cases found is 1.8%, showing that the presented model is very robust against prediction errors.

IV. Conclusion

In this work we have presented an extension to the ILP model for an Ecovat buffer. This extension consists of incorporating a global planning step into the model. We showed that this significantly improves the results when compared to the model without a global planning. Furthermore, we showed that the proposed extension is very robust against prediction errors in the energy prices by a comparison between a case using perfect predictions and a case where no predictions are used. This means the model does not require accurate, hard to obtain, predictions for energy prices to perform well.

Acknowledgment

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References

[1] I. Dincer and M. Rosen, *Thermal Energy Storage. Systems and Applications*, 2002.

[2] I. Dincer, "On thermal energy storage systems and applications in buildings," *Energy and Buildings*, vol. 34, p. 377, 2002.

[3] A. Arteconi, N. Hewitt, and F. Polonara, "State of the art of thermal storage for demand-side management," *Applied Energy*, vol. 93, p. 371, 2012.

[4] J. Xu, R. Wang, and Y. Li, "A review of available technologies for seasonal thermal energy storage," *Solar Energy*, vol. 103, p. 610, 2014.

[5] "Ecovat Renewable Energy Technologies BV." www.ecovat.eu, accessed on March 1, 2017.

[6] G. de Goeijen, G. Smit, and J. Hurink, "An integer linear programming model for an ecovat buffer," *Energies*, vol. 9, p. 592, 2016.