Optimized Cold Storage Energy Management
Miami and Los Angeles Case Study

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Abstract: Smart management of cold thermal energy storages could help future sustainable energy systems drawing large shares of electricity from renewable sources to balance fluctuating generation. This paper introduces a model-based predictive control strategy for cold thermal energy storages. A novel ice storage model for simulating and optimizing partial charge and discharge storage operation is developed and validated. The optimization problem is solved using a Forward Dynamic Programming approach. A case study analysis for a very hot and humid location (Miami) and a rather temperate climate (Los Angeles) and for each four building types (apartment building, hospital, office, and school) reveals that total cost savings of up to 20% compared to conventional control strategies are possible.

1 INTRODUCTION

Increased electricity generation from renewable energy sources requires storage solutions or enhanced flexibility of the demand side to handle fluctuating supply (U.S. Energy Information Administration, 2015). Smart management of cooling loads, accounting for 15% of primary energy use in United States buildings in 2010, may help improving economics and stability of future sustainable energy systems utilizing large shares of solar or wind energy (Johansson et al., 2012; Zhang and Lu, 2013). The climate change may even further increase both cooling energy demand and peak loads in the 21st century (Wang and Chen, 2014).

Power-to-cold solutions utilizing cold thermal energy storages (CTES) can decouple the electric load from the cooling demand and are economically very attractive due to small capital expenditures, especially compared to electrochemical storages (Claessen and Poutré, 2014). For improving operating expenses (OPEX), control of these systems is of major importance. Model-based predictive controls (MPC) aiming to minimize OPEX require accurate but runtime-efficient models.

A near-optimal control strategy for ice thermal energy storages (ITES) operation was introduced by Braun (2011). Henze et al. (1997) developed a predictive optimal controller for a cooling system with ITES using a Reverse Dynamic Programming (RDP) approach. Other researchers examined different algorithms for the optimization problem, such as a particle swarm algorithm (Lee et al., 2009), or tested the model-based predictive controller at a university cooling system including a chilled water storage (CWS) (Ma et al., 2012).

Previous research on cost-optimal control of cooling systems with thermal energy storage is lacking simulation with accurate storage models. Furthermore, there is still a need of development of optimal control algorithms based on annual case studies examinations. Thus, this paper contributes to the the development of

- a novel model for partial charge and discharge of ice thermal energy storages;
- an optimal control strategy based on Forward Dynamic Programming (FDP) incorporating final costs;
- a full year case study for four building types in two American cities: Miami and Los Angeles.

Therefore, the paper is separated into three sections. First, the experimental setup will be explained and the model will be described briefly. Then, the optimization problem and its solution approach will be outlined. Finally, the case study

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will quantify advantages from using an optimal control approach.

2 EXPERIMENTAL SETUP

The cooling system investigated for this paper consists of a two-stage compression chiller and appropriate condenser-side dry air-cooled heat exchanger (cooling fans). An ice thermal energy storage (ITES) manufactured by Fafco is used as cold thermal energy storage (CTES), as highlighted in the schematic in Figure 1. Building cooling loads are simulated by electric heaters that can dump heat into the ice storage or transfer heat to the evaporator side of the chiller.

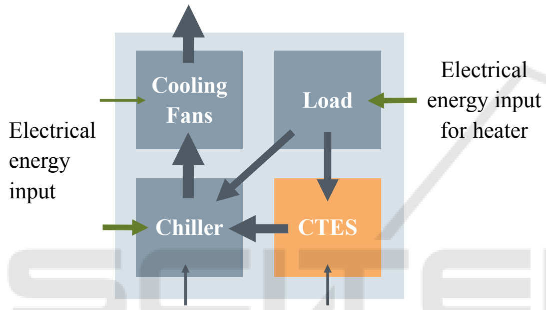

Figure 1: Schematic representation of the cold thermal energy storage (CTES) experimental setup, including electricity and heat flows.

To derive accurate models of the entire cooling system, several sets of experiments were run:

- 14 complete charge and discharge cycles;
- Four experiments with simultaneous operation of chiller and heaters;
- Six partial charge and discharge cycles.

Heat flow rates are computed from measured temperatures and mass flow rates. The ITES state of charge is determined in two different ways. By an estimation of the initial state of charge and integral balancing of the measured heat flow rates, SOC is determined. Due to the difference in density of water and ice, freezing of water and melting of ice result in a change of volume within the storage (at constant mass). This is detected with a float sensor and denoted as volumetric state of charge (SOC_V). Variations in density from sensible cooling or heating of water and ice are also measured by the float sensor. However, since these changes are small compared to the density change induced by the phase change, SOC_V hardly includes any effects from sensible cooling or heating.

The system under test is illustrated in Figure 2.

Figure 2: Compression chiller and ice storage system under test.

3 MODEL

The model developed for this research is based upon a previously published model of an ice storage supported cooling system (Thiem et al., 2015). The whole cooling system model consists of several submodels. Whereas chiller, cooling fans, and heater can be modelled with well-known relations from literature (Lee et al., 2012), modelling of the ITES is more challenging due to its large inertia and several nonlinear characteristics depending on its current state.

The previously published model of the ice storage is mainly based on two quantities, the heat exchanger effectiveness (ε)

$$\varepsilon = \frac{\left(T_{\mathrm{ITES,in}} - T_{\mathrm{ITES,out}}\right)}{\left(T_{\mathrm{ITES,in}} - T_{\mathrm{PCM}}\right)} = f^{(5)}(SOC_V, \dot{m}), \quad (1)$$

and the charge/discharge effectiveness (ξ)

$$\xi = \frac{\dot{Q}_{\mathrm{ITES,eff}}}{\dot{Q}_{\mathrm{ITES,HTF}} - \dot{Q}_{\mathrm{ITES,gain}}} = f^{(\mathrm{exp})}(SOC_V). \quad (2)$$

In these equations $T_{\mathrm{ITES,in}}$ and $T_{\mathrm{ITES,out}}$ denote the in- and outlet temperature, respectively; T_{PCM} the phase change temperature of the medium inside the storage (0 °C for water); $\dot{Q}_{\mathrm{ITES,HTF}}$ the heat flow rate transferred by the heat transfer fluid (HTF) pumped through the storage heat exchanger tubes, $\dot{Q}_{\mathrm{ITES,gain}}$ the heat gained from ambience; and $\dot{Q}_{\mathrm{ITES,eff}}$ the effective heat transfer rate related to a change in volumetric state of charge (SOC_V).

With these quantities, outlet temperature and next time step both real and volumetric state of charge can be computed. The efficiency of the chiller depends on its evaporation temperature, which itself depends on the current thermal resistance of the ice layers surrounding the pipes in the storage. Commonly ε and ξ are fitted as a function of the volumetric state of charge (SOC_V). SOC is less reliable due to the integration of uncertainties in measured heat flow rates.

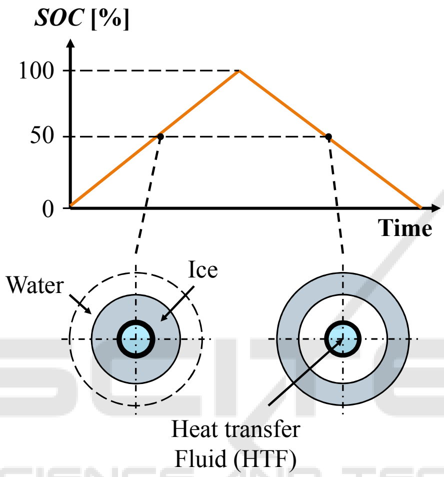

Figure 3: Misleading scalar quantity state of charge (SOC): Complete charge-discharge cycle.

As highlighted in Figure 3, for complete charge and discharge cycles, distinct layers of water and ice form around the HTF tubes, respectively. Two separate fits for ice storage charge and discharge can be determined. The previous modelling approach based on a fit of SOC_V is sufficient. However, for partial charge and discharge cycles, i.e. storage operation that does not charge or discharge the storage completely, the model needs to account for previous operation of the ice storage. Therefore, ε and ξ are determined as function of a newly introduced relative state of charge ($SOC_{V,\mathrm{rel}}$). $SOC_{V,\mathrm{rel}}$ comprises information on previous maximum partial charge and discharge to model layers of water and ice that build up around the tubes in reality. More details on this approach can be found in Born (2015).

The accuracy of this updated modelling approach is shown in Figure 4. In this figure, a parity plot of the volumetric state of charge shows that 90% of simulated data of all experimental sets (see Section 2) are within a 2.91% error margin.

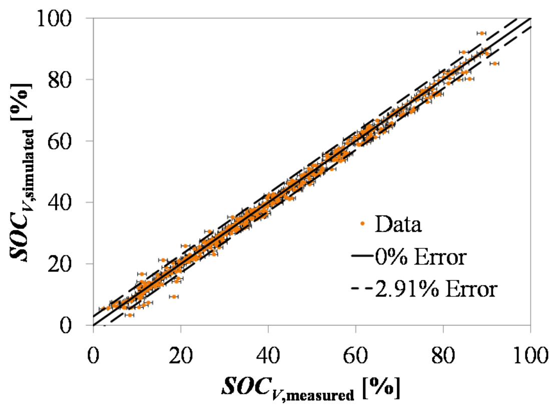

Figure 4: Volumetric state of charge (SOC_V) parity plot for the modified ε-model.

In addition to the introduced ITES model, a stratified chilled water storage (CWS) model is taken from literature (Wilden and Truman, 1985).

4 OPTIMIZATION PROBLEM

An optimal control problem is formulated based on the models that were briefly introduced in the previous section. The objective of the optimal control strategy is to minimize operating expenses (C) for a fixed-design cooling system. The objective function is given by

$$C = C_{\mathrm{el,e}} + C_{\mathrm{el,d}} + C_{\mathrm{su}} + C_{\mathrm{fin}}, \tag{3}$$

with the electricity energy charge ($C_{\mathrm{el,e}}$), electricity demand charge ($C_{\mathrm{el,d}}$), compressor start-up costs (C_{su}), and final costs for each period (C_{fin}):

$$C_{\mathrm{el,e}} = \int_{\Delta t_d} \sum_{i=1}^{N} P_{\mathrm{el},i}\, p_{\mathrm{el,e}} \mathrm{d}\tilde{t}, \tag{4}$$

$$C_{\mathrm{el,d}} = \max\left(\sum_{i=1}^{N} P_{\mathrm{el},i}\, , P_{\mathrm{el,max,0}}\right) p_{\mathrm{el,d}} \frac{\Delta t_d}{\Delta t_m}, \tag{5}$$

$$C_{\mathrm{su}} = \sum_{c=1}^{K} \sum_{j=1}^{M_c} p_{\mathrm{su},c}, \tag{6}$$

$$C_{\mathrm{fin}} = \frac{\bar{p}_{\mathrm{el,e}}}{EER} E_{\mathrm{CTES,cap}} \Delta SOC_d. \tag{7}$$

In Equations 4-7 $P_{\mathrm{el},i}$ denotes the electric power drawn by component i; N the number of components; $p_{\mathrm{el,e}}$ the electricity energy charge; $p_{\mathrm{el,d}}$ the electricity demand charge; $p_{\mathrm{su},c}$ start-up costs and M_c the number of start-ups for compressor c ; K the number of compressors; EER the energy efficiency ratio of the chiller; $E_{\text{CTES,cap}}$ the storage capacity; and ΔSOC_d the change of state of charge during period d. The time interval of the current period is tagged as Δt_d, Δt_m is the length of the month.

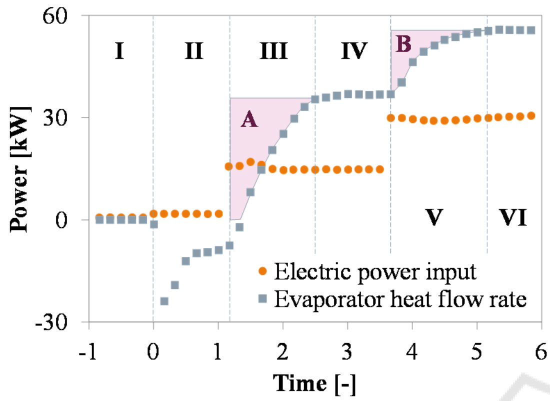

Figure 5: Approximation of compressor start-up costs.

Computation of start-up costs of the two compressors under test is shown in Figure 5. In this figure, electric power input and evaporator heat flow rate during a typical chiller start-up are plotted versus time. In Phase I, the chiller is turned off. In Phase II chilled water pumps are on, the heat flow rate shows an artefact from the previous hot water discharge. The first compressor starts in Phase III, heat transfer at the evaporator lacks the electric power drawn (Area A). In Phase IV the first compressor runs steady-state. The second compressor starts in Phase V, and once again evaporator heat transfer is delayed (Area B). In the final Phase VI the compression chiller is running steady-state. The highlighted Areas A and B are directly related to the start-up costs of the two compressors by computing the energy charge for the electric power wasted until steady-state cooling output is established. This is a very conservative approach that does not include any lifetime degradation effects during start-ups.

The introduction of final costs (C_{fin}) in the objective function is necessary to avoid complete discharge of the storage at the end of period d. For that reason low final states of charge are penalized and high final states of charge awarded.

The optimal chiller operating strategy (π) describes when and how to operate the chiller. It is determined by solving

$$\pi = \operatorname{argmin}\{C\}. \tag{8}$$

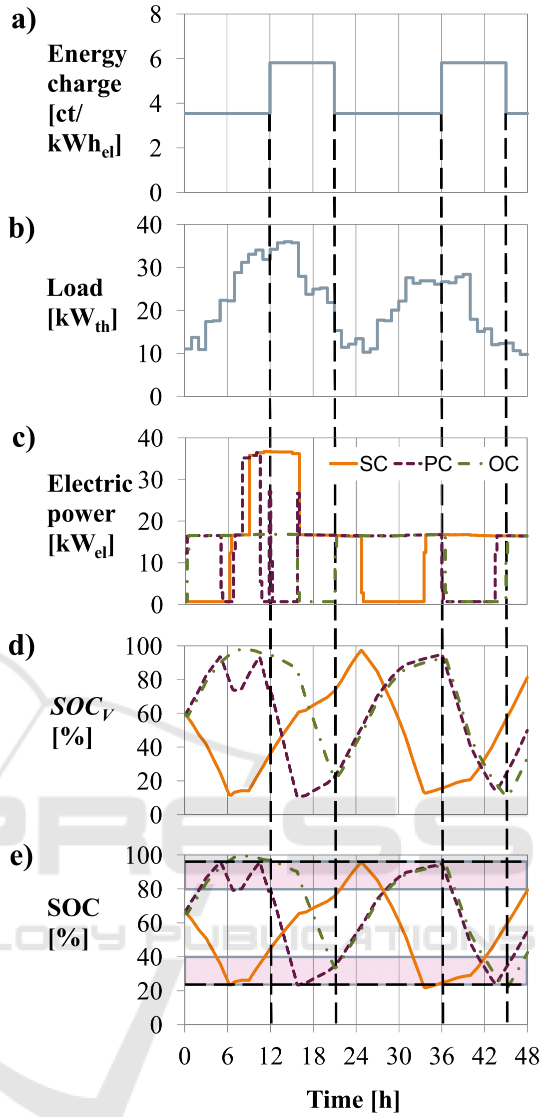

Figure 6: SOC-controlled (SC), Price-controlled (PC), and Optimal-controlled (OC) strategy for an example period of 48 hours: a) Electricity energy charge, b) Cooling load, c) Compression chiller electric power input, d) Volumetric state of charge (SOC_V), and e) State of charge (SOC).

The presented optimization problem is mixed-integer, non-linear (MINLP) with costs introduced on maximum load (demand charges), and costs inserted between time steps (start-up costs). A Dynamic Programming algorithm can reduce the problem complexity to solve it within a reasonable amount of time (Bellman, 2003). For this, the problem is discretised not only in time ($\Delta t =$ 15 min), but also in state-of-charge ($\Delta SOC = 0.5\%$). Because the ITES model requires information on the preceding operating strategy, a Reverse Dynamic Programming (RDP) approach is not feasible. Thus, a Forward Dynamic Programming (FDP) algorithm is implemented. With this algorithm, a 24 hour period is solved in approximately 50 seconds.

The optimal control (OC) strategy is compared to two conventional, reference strategies: SOC-controlled (SC), and price-controlled (PC) operation. The SOC-controlled strategy is simulated based on the following criteria:

- Turn chiller on, if $SOC < 25\%$;
- And turn chiller off, if $SOC > 95\%$.

The price-controlled strategy is determined in the following way:

- Turn chiller on, if $p_{\mathrm{el,e}} < \bar{p}_{\mathrm{el,e}}$;
- Turn chiller off, if $p_{\mathrm{el,e}} > \bar{p}_{\mathrm{el,e}}$;
- Turn chiller on, if $SOC < 25\%$ and keep on until $SOC > 40\%$;
- And turn chiller off, if $SOC > 95\%$, and keep off until $SOC < 80\%$.

To avoid over-depletion of the storage in SC and PC operation, the second compressor is started, if the chiller is on but not able to satisfy the cooling load (which would additionally require the discharge of the storage).

Results for all three strategies for an example period of 48 hours are compared in Figure 6. Electricity energy charges are shown in Figure 6 a). The on-peak period lasts from 12 p.m. to 9 p.m. Figure 6 b) outlines the cooling load, which is for these and ongoing results assumed to be deterministically known to the optimal controller. The electric power drawn by the chiller is illustrated in Figure 6 c). One may notice that both conventional strategies use the second compressor at some point in time. With two compressors in parallel, the chiller operates less efficient. Additionally, both conventional strategies are not able to forecast the cooling load or ambient temperatures, and adjust their strategies to these constraints. Furthermore, they are only able to consider storage constraints based on the simple rules listed above. Finally, Figure 6 d) and e) show the volumetric and real state of charge, respectively. For this example period, both SC and PC strategy leave the storage with a higher initial state of charge for the next period than the OC strategy, but at the cost of extensive chiller operation during on-peak periods.

5 CASE STUDY

A large scale case study is intended to quantify benefits that result from utilizing the OC strategy over conventional operating strategies.

For this case study, building cooling and electrical loads are simulated using EnergyPlus. Four DOE commercial reference buildings (high-rise apartment, hospital, large office, and secondary school) are compared (Deru et al., 2011). In the following, results are presented for the very hot and humid climate of Miami and the Mediterranean climate of Los Angeles. Time of use rates are very well established in the United States and thus help quantifying the results. The Florida Power & Light General Service Large Demand Time of Use (GSLDT-1) rate is used for Miami (Florida Power & Light (FPL), 2015). For Los Angeles the real time pricing rate TOU-8-RTP for general service, large demand with hourly varying prices is used (Southern California Edison, 2015).

Loads are proportionally scaled down to fit the experimental test system, and afterwards results are inverted back.

Specific invest costs for ice storages (i_{ITES}) and chilled water storages (i_{CWS}) were calculated with the following equations (Gebhardt et al., 2002):

$$\frac{i_{\mathrm{ITES}}}{\$/\mathrm{kWh}} = 66.8 \cdot \left(\frac{E_{\mathrm{ITES,cap}}}{\mathrm{kWh}}\right)^{-0.1051}, \tag{9}$$

$$\frac{i_{\mathrm{CWS}}}{\$/\mathrm{kWh}} = 380.8 \cdot \left(\frac{E_{\mathrm{CWS,cap}}}{\mathrm{kWh}}\right)^{-0.213}. \tag{10}$$

Annual Operation and Maintenance (O&M) costs for the compression chiller were assumed as 4% of the initial chiller invest (I_{CC}) (Gebhardt et al., 2002):

$$\frac{I_{\mathrm{CC}}}{\dot{Q}_{\mathrm{CC,cap}}}\frac{\mathrm{kWh}}{\$} = \left(5503 \cdot \left(\frac{\dot{Q}_{\mathrm{CC,cap}}}{\mathrm{kW}}\right)^{-0.6794} + 198\right). \tag{11}$$

Both ITES and CWS are only discharged, when storage outlet temperatures are able to satisfy air conditioning supply temperatures (≤ 8 °C). For each case study, both storages are sized to the same capacity.

The optimal control strategy is determined for 24 hour deterministic prediction and optimization horizons, sweeping forward from day to day.

Results for Miami are summarized in Figure 7, for Los Angeles in Figure 8. In these figures, total annual costs for the four different building types, two different storages (ITES and CWS), and different operating strategies are shown. Total annual costs are computed as the sum of capital expenditures (CAPEX, annuity for storage invest at an interest rate of 7% and depreciation time of 20 years), operation and maintenance (O&M), fixed customer energy charges (Fixed), other electricity energy charges due to other electrical loads but cooling (Energy (other)), energy charges related to cooling (Energy (cooling)), electricity demand charges (Demand), and compressor start-up costs (Start-up).

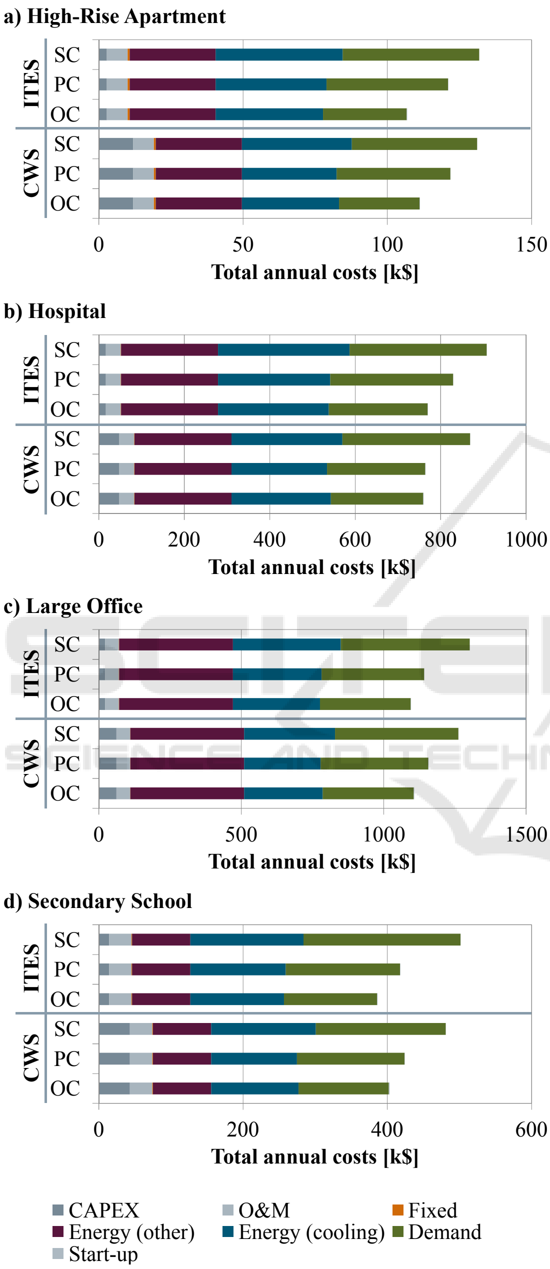

Figure 7: Results of annual simulation/optimization for buildings located in Miami: Ice thermal energy storage (ITES) and chilled water storage (CWS) supported cooling systems using a SOC-controlled (SC), price-controlled (PC) or optimal-controlled (OC) strategy.

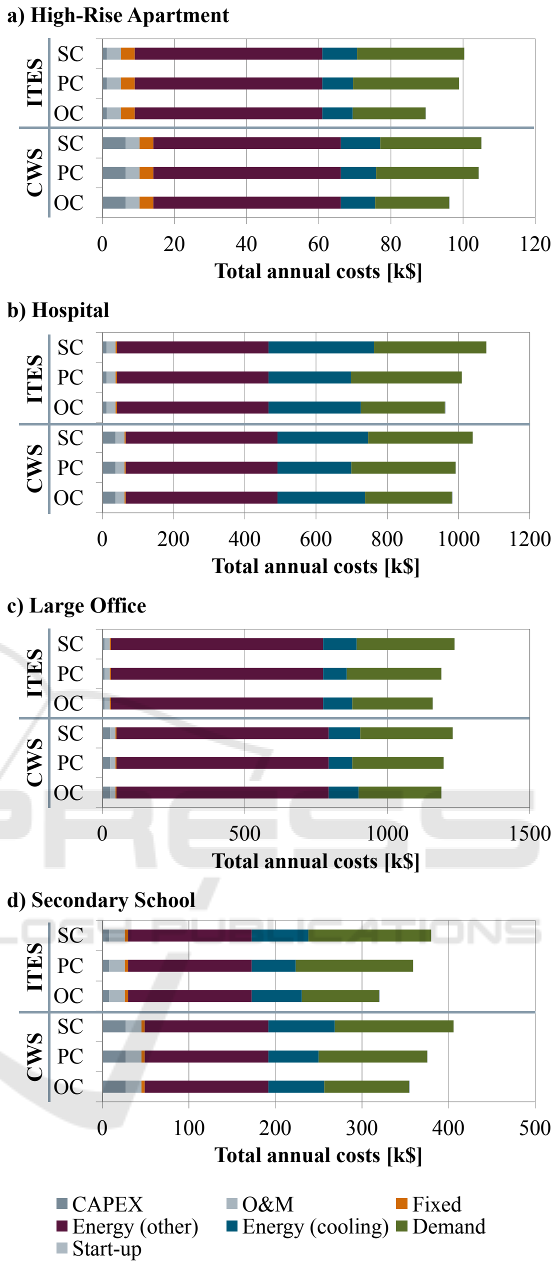

Figure 8: Results of annual simulation/optimization for buildings located in Los Angeles: Ice thermal energy storage (ITES) and chilled water storage (CWS) supported cooling systems using a SOC-controlled (SC), price-controlled (PC) or optimal-controlled (OC) strategy.

Based on the assumptions, the case study shows that using the OC strategy total cost savings of app. 2-10% compared to the PC strategy and of app. 5-20% compared to the SC strategy are possible. Exact savings depend on both location (climate, electricity rate), and particular object (building, electrical and cooling equipment in use).

Cost savings in the very hot and humid climate of Miami with large cooling loads are possible due to both reducing energy and demand charges. Savings in the more temperate climate of Los Angeles with less persistent cooling loads are mainly because of reductions in demand charges (peak shaving).

For the building types and their according storage sizes investigated during this research, ice storages tend to be less capital intense than chilled water storages, and thus are economically more attractive. However, one may realize that energy charges are smaller for CWS than for ITES. Lower evaporation temperatures required for charging ice storages decrease efficiency of the chiller and therefore electric power drawn by the chiller tends to be higher.

For this research project, efficiency of the compression chiller determined during the experiments was not altered for scaling to higher loads and larger chiller sizes. For large scale compression chillers, more efficient compressors may be used. However, this will only change absolute costs, but does not change the statements made about the relative advantages of the OC strategy.

6 CONCLUSIONS

This paper briefly introduced a novel model for partial charge and discharge of ice storages incorporating the preceding storage operating strategy. The model was validated in a set of experiments.

The model was implemented in a model-based predictive controller, which uses a Forward Dynamic Programming algorithm for solving the optimization problem.

A large scale case study for four different building types in two locations (Miami and Los Angeles) revealed that utilizing the optimal control strategy annual cost savings of up to 20% compared to conventional control strategies are possible. Ice storages tend to be economically more attractive due lower invest costs, but compression chillers need to operate at lower evaporation temperatures, which requires more primary energy input.

The introduced model-based controller may be utilized in future sustainable energy systems incorporating large shares of renewable energy sources. For this, dynamic electricity prices could be used to force cooling systems with cold thermal energy storage to run in a strategy beneficial to the power grid.

Future research will focus on hardware implementation and validation of the optimal control approach.

ACKNOWLEDGEMENTS

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