Effect of Liquid Fraction Sensing Accuracy on the Performance of a Smart Energy Management System for Residential Heat-Pump Heating with Latent Thermal Energy Storage and in situ Photovoltaic Generation

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ABSTRACT

Latent thermal energy storages (LTESs) in combination with heat pumps and smart control strategies can maximize the utilization of renewable energy sources for heating and cooling. However, smart energy management with model predictive control (MPC) requires monitoring the total energy stored in the LTES, which is determined by the liquid fraction of the phase change material (PCM). Measuring the liquid fraction is challenging and the diverse liquid-fraction sensing approaches pose a trade-off between accuracy and ease of implementation. The present study aims to quantify the effect of the liquid fraction sensing accuracy on the performance of MPC strategies for heating systems with LTES. For this purpose, a residential heating application with an energy management system is analyzed. The heating system consists of a heat pump, an LTES and a photovoltaic array. The heat pump can be driven by the photovoltaic array and the electric grid. The energy management system uses MPC based on Mixed-Integer Linear Programming. Representative seasonal profiles for the heating load and weather conditions are used as forecasts for the MPC. The performance of the energy management system is assessed in terms of total heating cost for different error values in the estimation of the liquid fraction of the PCM in the LTES. The heating cost is found to proportionally increase with the absolute error in liquid fraction due to reduced utilization of the LTES capacity.

1. INTRODUCTION

Decarbonization of heating and cooling is imperative for climate change mitigation (IRENA 2023). For this purpose, the utilization of heat pumps driven by electricity from renewable energy sources can reduce the carbon foot print of heating and cooling (Poppi et al. 2018). However, the mismatch between the availability of renewable energy sources, such as photovoltaic electricity, and heating and cooling demands limits the effective utilization of renewable energy. Latent thermal energy storages (LTESs) are a low-cost alternative that can alleviate this mismatch between availability and demand (IRENA 2020). In addition, maximum renewable energy utilization can be achieved with the implementation of a smart energy management system based on model predictive control (Beck et al. 2017; Fischer et al. 2014; Vivian and Mazzi 2019).

In a LTES, a phase change material (PCM) is periodically melted and solidified to store and release thermal energy (Zalba et al. 2003). Hence, the total thermal energy in the storage is proportional to the liquid fraction of the PCM. To maximize renewable energy utilization, a predictive control strategy optimally budgets the energy inside the LTES based on predictions for the heating/cooling demand and the renewable energy availability (Afram and Janabi-Sharifi 2014). Hence, monitoring of the liquid fraction is key for the implementation of predictive control strategies.

Sensing the liquid fraction in a real-world LTES is challenging and most measuring approaches pose a trade-off between accuracy and ease of implementation (Zsembinszki et al. 2020). For example, the most straightforward approach to determine the temporal variation of the thermal energy inside an LTES considers the thermal energy change for the heat transfer fluid that flows through the storage. This heat-balance approach requires accurately measuring the flow rate and the temperature change in the heat transfer fluid. Then, the total thermal energy inside the LTES needs to be updated based on the measurements, which leads to an integration of measurement errors.

A model predictive control (MPC) strategy allows to optimize the operation of a system by considering dynamic models of the process and forecasts for input parameters. The optimal operation state of the system at each timeslot is determined by considering a finite horizon. The optimal operation state is continuously updated for each timeslot. In a smart energy management system, the predictive control strategy aims to optimally budget the energy flows from different components to optimize an objective function, which is usually the economic cost (Vivian and Mazzi 2019). Hence, for MPC is of vital importance to know in real time the state of charge of the energy storage components and the forecasted energy availability and demand.
The present study aims to better understand the effect of limited measuring accuracy of the liquid fraction on the performance of an MPC strategy for a residential heating application. The dynamics of a residential heating system consisting of a heat pump, an LTES and a photovoltaic array are analyzed via numerical simulation during the entire heating season. The photovoltaic electricity utilization is evaluated considering two control strategies for the operation of the heat pump. Namely, a rule-based control strategy and an MPC strategy. Mixed-Integer Linear Programming (MILP) is used to determine the optimal operating schedule for the heat pump. A fixed error in the initial value of the liquid fraction is introduced to assess the impact of the liquid fraction sensing accuracy on total heating cost.

2. METHODS

2.1 Problem description

The heating system is schematically illustrated in Figure 1. The system is composed of a house, a heat pump, a latent thermal energy storage (LTES), and a photovoltaic array. The energy stored in the LTES is used to supply the heating demand of the house. The LTES in turn is charged by an air-to-water heat pump. The heat pump is powered by the photovoltaic array and/or the electric grid. Any excess electricity that is produced by the photovoltaic array is injected into the electric grid.

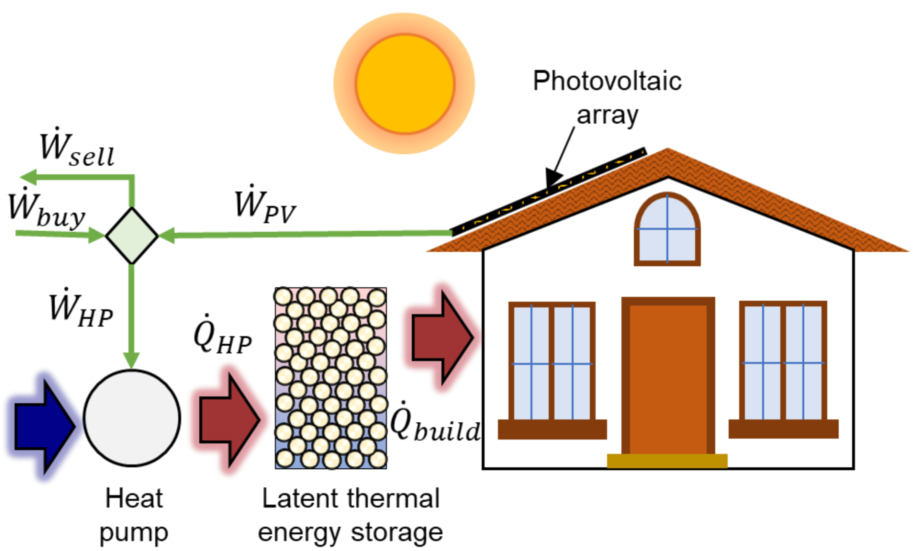

Figure 1: Schematic illustration of heat-pump residential heating system with a latent thermal energy storage and an in situ photovoltaic array.

For the analysis, the heating load is determined for a detached, well-insulated, modern house located in Venice, Italy. The house consists of a single-story square building with a floor area of 144 m^2 and 3 m height. Double glazed windows cover 20% of the external wall area. The foundation is slab on grade and the roof is composed of a concrete slab and a layer of insulation. The overall thermal transmittance (U-value) of the building components is listed in Table 1. The total capacitance of the building is 1036.8 kJ/K. The heating load is calculated for the heating season (October 22 to April 7) using TRNSYS (Klein, S.A. et al 2017) with the Meteonorm Weather data.
For the calculation, occupancy gains are assumed to be negligible, and a schedule is used for the internal temperature set point. During awake hours, from 6 am to 11 pm the set point is 22°C, while during nighttime the set point is 18°C. The heating demand for the entire season is estimated to be 42.5 kWh/m^2.

The nominal heating capacity of the air-to-water heat pump is 5 kW, and the average temperature of the heated water is assumed to be constant and equal to 40°C. The COP is fitted as a linear function of the ambient temperature considering the input data for the TRNSYS Type 941_v2a, as expressed in equation (1). The power consumption of the heat pump is calculated as indicated by equation (2).

$$COP = 0.096\,T_{amb} + 2.465 \tag{1}$$

$$\dot{W}_{HP} = \frac{\dot{Q}_{HP}}{COP} \tag{2}$$

Table 1: Overall thermal transmittance (U-value) of building components in W/m^{2}K.

External wall	Ground	Roof	Windows
0.339	0.313	0.128	1.1

The LTES has a volume of 250 L and is assumed to be filled with organic PCM, which has a melting temperature of 35°C, a liquid density of 770 kg/m^3, and a heat of fusion of 240 kJ/kg. Hence, the latent storage capacity is 12.8 kWh. The LTES is assumed to be isothermal and to have a variable charging and discharging power that perfectly adapts to instant power availability and demand. Also, the storage of sensible thermal energy is neglected; the storage is considered to be depleted when the liquid fraction reaches zero and saturated when the liquid fraction reaches one. The energy balance for the LTES is expressed by equation (3).

$$\rho V \lambda \frac{d\gamma}{dt} = \dot{Q}_{HP} - \dot{Q}_{build} \tag{3}$$

The peak power output of the photovoltaic array is 5 kW, and the real transient power output is estimated considering the meteorological data for the TRNSYS Type103. The self-consumption of photovoltaic power is found as the minimum value between the generated photovoltaic power and the power consumption of the heat pump (equation (4))

$$\dot{W}_{PV,self} = \min\left(\dot{W}_{PV}, \dot{W}_{HP}\right) \tag{4}$$

Hence, the power consumption from the grid and the power sold to the grid can be found as in equations (5) and (6).

$$\dot{W}_{buy} = \dot{W}_{HP} - \dot{W}_{PV,self} \tag{5}$$

$$\dot{W}_{sell} = \dot{W}_{PV} - \dot{W}_{PV,self} \tag{6}$$

The price of the electricity consumed from the grid (0.20 €/kWh) is significantly higher than the price of the electricity sold to the grid (0.05 €/kWh). Hence, the objective of the control strategy is to minimize the total heating cost as expressed in equation (7).

$$c_{tot} = \sum_{t} \left(\beta_{buy}\left(\dot{W}_{HP} - \dot{W}_{PV,self}\right) - \beta_{sell}\left(\dot{W}_{PV} - \dot{W}_{PV,self}\right)\right)\Delta t \tag{7}$$

2.2 Control strategy

The control system must determine when to turn on and off the heat pump in order to:

- Guarantee that the building heating load is always met.
- Keep the liquid fraction inside the LTES between 0 and 1.
- Minimize the total heating cost.

To assess the performance of different controls strategies, a numerical dynamic model of the system is implemented. For the dynamic model the energy balance equation for the LTES is discretized as expressed in equation (8).

$$\frac{\rho V \lambda}{\Delta t}(\gamma_t - \gamma_{t-\Delta t}) = x_{HP}\dot{Q}_{HP,nom} - \dot{Q}_{build} \tag{8}$$

Where, x_{HP} is the control signal for the heat pump. Whenever the heat pump is running, it is assumed that the delivered heat rate is equal to the nominal capacity.

A simple rule-based control strategy can be proposed according to the rules listed in Table 2. In this strategy, during periods without solar energy availability, the heat pump stays off as long as the LTES is not depleted. If the LTES is depleted, the heat pump is turned on to supply the building heating demand, but the LTES is not charged. During periods with solar energy availability, the heat pump is turned on if the output of the photovoltaic array is at least greater than a fraction, α, of the heat pump power consumption. In this study, the threshold fraction to turn on the heat pump is set equal to 0.5. If the LTES is saturated, the heat pump is turned off.

Table 2: Rule-based control strategy.

Rule	**Condition**	**Heat pump state, x_{HP}**
1	$\gamma_t \geq 1$	0
2	$\gamma_t \leq 0$	1
3	$0 < \gamma_t < 1$ and $\dot{W}_{PV,t} < \alpha \dot{W}_{HP,t}$	0
4	$0 < \gamma_t < 1$ and $\dot{W}_{PV,t} \geq \alpha \dot{W}_{HP,t}$	1

The performance of the rule-based control strategy is compared against the performance of an MPC strategy that aims to minimize the total heating cost. Hence, the objective function for the MPC strategy is the total heating cost as expressed in equation (7). The decision variables for the optimization are the control signal for the heat pump, x_{HP}, the liquid fraction of the LTES, γ, the heat pump power consumption, $\dot{W}_{HP}$ and the photovoltaic power self-consumption $\dot{W}_{PV,self}$. The building heating demand, $\dot{Q}_{build}$, the heat pump COP, and the generated photovoltaic power $\dot{W}_{PV}$, are assumed to be known as forecasts. The optimization is constrained by the energy balance for the LTES, equation (8), the power consumed by the heat pump, equation (2), and the definition of the self-self-consumed photovoltaic power, equation (4). The definition of the self-consumed photovoltaic power can be re-written as two inequalities, as follows.

$$\begin{aligned} \dot{W}_{PV,self} &\leq \dot{W}_{HP} \\ \dot{W}_{PV,self} &\leq \dot{W}_{PV} \end{aligned} \tag{9}$$

In addition, the optimization is constrained by the limiting values for the liquid fraction ($0 \geq \gamma \geq 1$). The heat-pump power consumption and the photovoltaic self-consumption are constrained to be positive quantities with an upper limit equal to the heat-pump nominal capacity. The optimal heat-pump scheduling is solved via Mixed-Integer Linear Programming using MATLAB. The optimization horizon is 24 h with time steps of 1 h. The optimal scheduling is recalculated every hour and estimated for the entire heating season.

2.3 Effect of liquid fraction sensing accuracy

The MPC strategy considers the current liquid fraction in the LTES and the forecasted values for the heating demand, the photovoltaic power output, and the ambient temperature, to determine an optimal heat-pump schedule that minimizes the total heating costs. However, for real-world LTES accurate monitoring of the liquid fraction is challenging. Hence, the effect of liquid fraction sensing accuracy on the performance of the MPC strategy is analyzed. For this purpose, the initial value of the liquid fraction that is used as an input for the constrained optimization is modified to account for a fixed error value, as indicated in (10). However, the dynamics of the system evolves with the actual value for the liquid fraction. Negative and positive error values between -0.5 and 0.5 are assessed.

$$\gamma_{0,opt} = \gamma_0 + \Delta\gamma_{error} \tag{10}$$

3. RESULTS AND DISCUSSION

3.1. Comparison of control strategies

Figure 2 illustrates the dynamic behavior of the heating system under rule-based and MPC strategies during three consecutive days of the heating season. Generally, the heating load has a large value early in the morning when the awake set point of 22°C is activated. As the day progresses, the heating load reduces due to heat gain from the windows and starts increasing again in the afternoon until the nighttime setpoint of 18°C is activated. For both control strategies, the heat pump operates solely during the awake period from 6:00 am to 11:00 pm. However, for the MPC strategy there is a larger overlap between the heat pump operating period and the solar energy availability period. Hence, the total heating cost with the MPC strategy (216.7 €) is lower than for the rule-based control strategy (246.2 €). The cost reduction is 29.5 € which is equivalent to 12%. Also, with the MPC strategy the liquid fraction tends to be larger at the end of the solar energy availability period, which indicates a greater utilization of the LTES to store renewable energy in comparison to the rule-based control strategy.

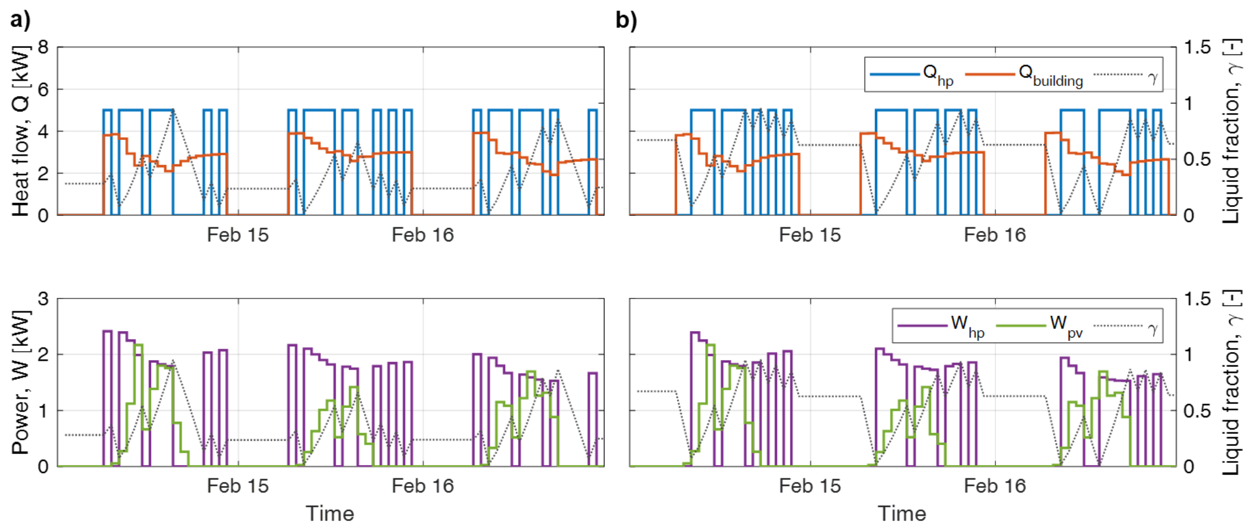

Figure 2: Dynamic behavior of heating system with a) rule-based and b) model predictive control strategy.

3.2. Effect of liquid fraction sensing accuracy

Figure 3 illustrates the behavior of the heating system under MPC considering the effect of underestimating and overestimating the liquid fraction by 0.2. Overestimation and underestimation of the liquid fraction due to sensing limitations lead to a poor utilization of the LTES capacity. When the energy inside the LTES is underestimated, the optimal predictive control generates an operating schedule that does not allow the LTES to be fully discharged and the liquid fraction values are kept between 0.2 and 1.0. Similarly, when the energy inside the LTES is overestimated, the liquid fraction values are kept between 0.0 and 0.8 because the optimal operating schedule for the heat pump does not allow the LTES to be fully charged.

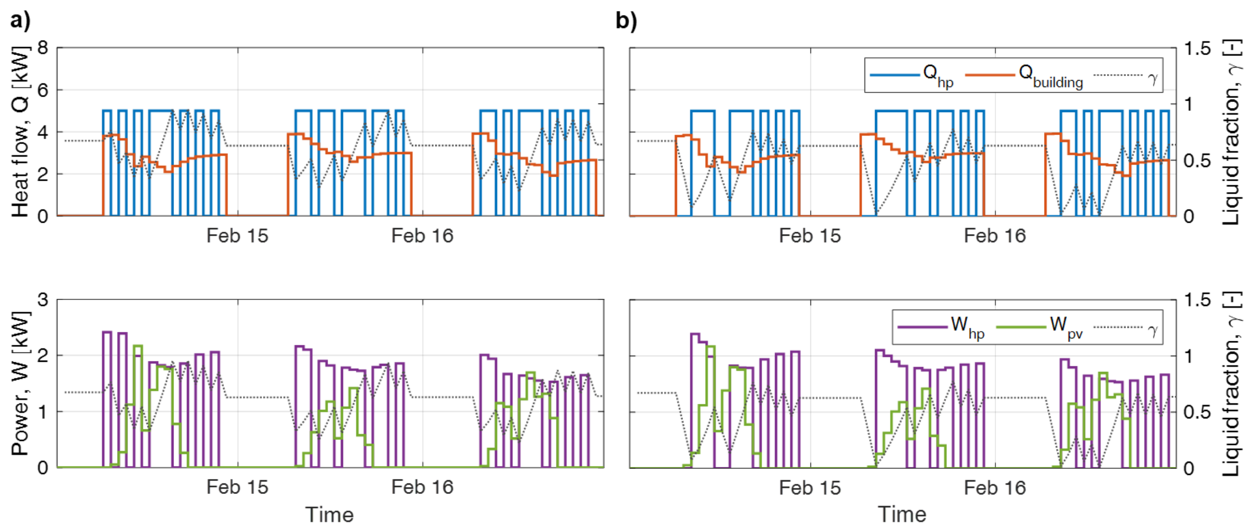

Figure 3: Dynamic behavior of heating system under model predictive control with a) underestimation of the liquid fraction by 0.2 and b) overestimation of the liquid fraction by 0.2.

Figure 4 compares the total heating cost for the rule-based control strategy and the MPC strategy with different fixed values for the error in the liquid fraction. The total heating cost for the MPC strategy proportionally increases with the absolute error in liquid fraction sensing. This increase in cost is due to the underutilization of the LTES capacity that was described earlier. The total heating cost for the MPC strategies becomes larger than the total heating cost for the rule-based controls strategy when the liquid fraction is underestimated or overestimated by 0.3. However, given the added complexity, the error in liquid fraction sensing needs to be much lower to harness the cost reduction advantages of MPC. Probably absolute errors greater than 0.1 may be considered unacceptable.

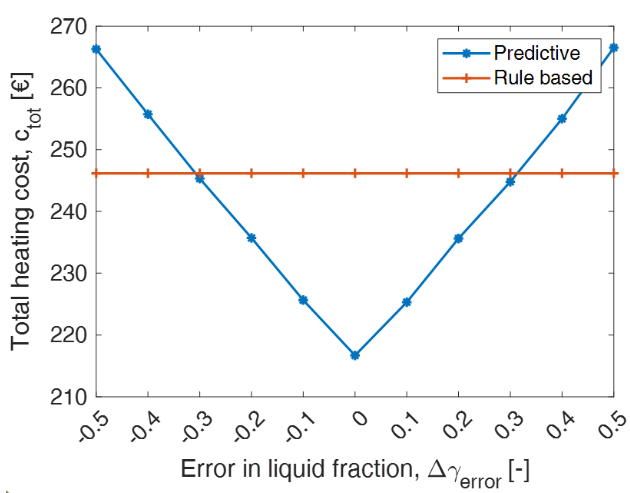

Figure 4: Total heating cost with different fixed error in the liquid fraction.

6. CONCLUSIONS

The operational dynamics and economics of a residential heating system consisting of a heat pump, a latent thermal energy storage, and a photovoltaic array are analyzed considering rule-based and MPC strategies. Also, the effect of liquid fraction sensing accuracy on the performance of the MPC is assessed. The MPC strategy can yield a total cost reduction of 12% in comparison to the rule-based control strategy because the LTES is better utilized to store heat generated with photovoltaic electricity. However, underestimating or overestimating the liquid fraction leads to poor utilization of the LTES capacity and increased heating cost. The total heating cost for the MPC strategy proportionally increases with the absolute error in liquid fraction and surpasses the cost for the rule-based control strategy when the absolute error is greater than 0.3. Hence, to exploit the savings potential of the MPC strategy the liquid fraction needs to be sensed accurately.

NOMENCLATURE

c	cost	(€)
COP	coefficient of performance	(-)
$\dot{Q}$	heat flow rate	(kW)
t	time	(h)
Δt	size of time step	(h)
T	temperature	(°C)
V	volume	(m^3)
$\dot{W}$	power	(kW)
x	on/off state	(-)

Greek symbols

α	threshold fraction	(-)
β	price	(€)
γ	liquid fraction	(-)
$\Delta\gamma_{error}$	error in liquid fraction	(-)
λ	heat of fusion	(kJ/kg)
ρ	density	(kg/m^3)

Subscript

amb	ambient
buy	bought from electric grid
build	building
HP	heat pump
Nom	nominal
PV	photovoltaic
self	self-consumption
sell	sold to electric grid
t	current time
tot	total

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