PHYSICS-BASED MODELLING OF A MILK COOLING SYSTEM FOR INTELLIGENT ENERGY MANAGEMENT

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KEYWORDS

Modelling, Optimization, Parameter Identification, Demand Side Management, Renewable Energy

ABSTRACT

Forecast-based energy management can play a large role in a smarter and more efficient use of renewable energies based on demand side management. Using approaches such as model predictive control, individual consumption devices can be shifted within operation constraints so that their electricity consumption optimally matches generation. In agriculture, large thermal storages make up a sizeable part of electricity consumption, and offer a potential use in the short term shifting of demand. Necessary for this are accurate models to forecast behaviour of such dynamic systems, so that minimal power demand and fulfilment of operation constraints can be ensured when computing optimal controls. This work focuses on the physics-based modelling of a milk cooling storage through parameter identification on real measurement data. Emphasized are the derivation of a suitable model ODE with regards to available data, and evaluation of the model on a rolling horizon. All major features of the measurement data can be recreated by the model forecasts, and model performance values show errors of around 30% relative to mean temperature. Model performance is considered suitable for use in energy management at least on short forecast horizons, while practicability on longer horizons is subject to further research.

INTRODUCTION

One of the main difficulties in the large scale integration of renewable energy sources like solar and wind plants is their varying and uncontrollable generation, dependent on the weather. Sufficient storage solutions are very expensive, and at least currently and in the near future not available on a large enough scale (Pickard et al., 2009). This leads to situations of either over- or underproduction of renewable energies, which on the grid level causes a need for (usually carbon-based) buffer generation, and in some situations also the temporary shut down of plants. Analogue situations also affect individuals generating their own energy, who face expensive import or unprofitable export of energy when self-consumption is not possible. One strategy to mitigate this problem is demand side management (DSM), which comprises strategies of influencing the energy consumption side of the situation, in order to have overall energy demand match the available generation as closely as possible at all times. On the scale of an individual household or enterprise, this can be achieved through an energy management system (EMS). Economic incentives making this worthwhile for individual households can derive from the difference between electricity price and feed-in tariff when producing own renewable energy, or from variable electricity pricing schemes, which are becoming an option with increasing relevance in Germany. Intelligent EMS approaches (sometimes also smart EMS) can include the forecast-based consideration and control over individual devices and storages. Where possible under operation constraints, device start times can be shifted to optimal times, continuous control values adapted or the operation of storage systems optimized, often in a model predictive control (MPC) scheme. Especially the autonomous and optimized management of larger consumers has gained increasing interest in research, including investigation of mathematical solution strategies for the ensuing problems in the fields of optimization, control and modelling. Burda et al. (2023) published approaches for the optimized control of thermal and electrical building energy supply with a Mixed-Integer Non-linear MPC. An agricultural setting stood in the centre of research projects *SmartFarm* and *SmartFarm2*, where a focus was put on the development of lightweight optimization algorithms for data-based modelling, scheduling and optimal control in a forecast-based EMS (Lachmann et al., 2020).

This work examines the modelling of thermal storages, needed for their use in an intelligent, forecast-based EMS. Application example is a milk cooling system, this being a large consumer of electricity on dairy farms. In order to fulfil operational constraints, the temperature behaviour of such a thermal storage needs to be forecast based on the applied controls. Lachmann and Büskens (2021) presented the use of data-based modelling for this and other storage devices, emphasizing the need for a sufficient basis of data when using purely data-based model approaches. Afram et al. (2014) reported good model performance for data-based, first order linear models for thermal storage tank data developed for a similar use case. Other publications on the modelling of thermal storages in this context often base their models on consideration of the relevant physical processes, e.g. for a combined heat and power unit and heat storage tank (Bitner et al., 2021), or for a residential system including heat pump and thermal storage system Schütz et al. (2015). Such models can usually simulate the considered system well, but their application to specific real systems is dependent on expert knowledge, and usually not transferable. This work aims to bridge this gap between the purely data-based modelling of devices based on real-world measurements and the physical modelling of such systems in the context of energy management by employing widely used methods of parameter identification (PI) a for parametrized physical model of the dynamic system. Using the milk cooling system as an application example, approaches outlined in previous work (Kappertz and Büskens, 2023) are investigated and tested for real data. A complete workflow from the derivation of a phyics-based dynamic model, the fitting of its parameters in a PI problem and the evaluation of this model is presented. An emphasis lies on the difficulties of modelling and parameter identification with limited real-life data, and an evaluation of model performance through a simulation scheme motivated by the designated application in a forecast-based EMS.

THEORY AND METHODS

Parameter Identification of Dynamical Systems

This work focusses on the modelling of dynamical systems, whose behaviour is assumed to be representable through an ordinary differential equation (ODE) for the state derivative $\dot{x}(t) = f(x(t), u(t), t, p)$ as a function of current state of the system $x(t) \in \mathbb{R}^{n_x}$, any applied controls (external influences) $u(t) \in \mathbb{R}^{n_u}$, and a set of parameters $p \in \mathbb{R}^{n_p}$ describing the specific properties of the modelled system. An explicit time dependency may be accounted for in this ODE, but is not considered in the following.

Any future state of the system at time $t > t_0$ can then be computed through integration of the ODE from $x(t_0)$ for given controls $u(\tau), t_0 \leq \tau \leq t$, as

$$x(t) = \int_{t_0}^{t} f(x(\tau), u(\tau), p)\mathrm{d}\tau.$$

In order to do this, a reasonably accurate estimate of the 'true' parameters is needed, which is achieved by PI on measured data. Measured data $\{t_i, \bar{u}_i, \bar{x}_i \mid i = 0, 1, ..., n_t - 1\}$ contain control and state values measured at n_t time points. These are used to identify the optimal parameters p^* that minimize the error between measured and predicted state values in a (direct) PI problem of the general form

$$\begin{aligned} p^* = \underset{p \in \mathbb{R}^{n_p}}{\arg\min} \quad & \sum_{i=0}^{n_t-1} \sum_{j=0}^{n_x-1} (\bar{x}_{i,j} - x_j(t_i))^2 \\ \text{s.t.} \quad & \dot{x}(t) = f(x(t), \hat{u}(t), p), \quad t_0 \leq t \leq t_{n_t-1}, \end{aligned}$$

where for the error measure usually the quadratic norm is used, based on an assumed normal distribution of measurement errors. The dynamic model and the necessary integration can make this a non-linear and numerically intensive problem, for which different numerical solution schemes exist (Schittkowski, 2002). In the following, the approach of *full discretization* is used, in which the numerical integration of the ODE is included in the optimization problem as additional equality constraints at a specified number of discretization points (Schäfer et al., 2018). While this approach increases the overall dimension of the optimization problem, it eliminates the need for costly iterative integration steps. The model ODE not having to be fulfilled at all intermediate steps can also make it possible to avoid local minima in search of a better local or even global minimum (Wiesner and Büskens, 2023).

Milk Cooling System

A milk cooling system is a large agricultural thermal storage used on dairy farms to cool and store milk at conditions constrained by sanitary regulations. Its relevance for energy management stems from its large electricity consumption, and the fact that a margin in the temperature constraints allows shifting of this consumption in time. Generally, milk cooling systems have an internal on-off controller set to cool the fresh milk to around $5°$C until it is emptied. In this work, real measurement data previously discussed by Lachmann and Büskens (2021) are used, gathered on a dairy farm in Northern Germany. The milk cooling system is operated such that new milk is input twice per day (around 3500 and 2000 l), and emptied every two days. The data contain measurements of the temperature within the tank, as well as the electrical power used for cooling the milk, both available in minutely resolution. In the following, eight days of data from February and April are used. As visible in the measured power data (Fig. 2), the cooling aggregate kicks in twice per day when warmer fresh milk is entered, then averaging at $11.9\,$kWh. An average daily consumption of $55\,$kWh is observed. The different phases of operation have clear influences on the temperature data, where the small, twice daily peaks of simultaneous milk inflow and cooling are alternated with long periods of no activity, during which ambient warming of the system seems small enough to not warrant additional cooling. Every two days, the cleaning period after the tank is emptied expresses itself in temperature peaks of more than $50°$C, followed by a cooling-down period until the next milking in the morning.

Not all of these processes are covered satisfactorily in the available data. With the two measurements available, many aspects of the state behaviour, i.e. temperature, are not linked to control input, i.e. cooling power. Important external influences onto the system, like the cleaning process, or the adding of milk, are not available as control data. Following (Lachmann and Büskens, 2021) they are therefore substituted by 'auxiliary' controls derived in a preprocessing step from the available data. Since the influence of these processes onto the temperature measurement is straightforward, simple conditions on the available data allow for the generation of additional boolean variables marking e.g. the external influence of milk inflow (defined by a rise in temperature when cooling power is active). Similarly, the filling level of the tank can be estimated based on the number of milking processes since last pickup. In this work, every process phase (like cleaning or milk inflow) is only marked by a single value at the beginning of the process. This assumption of instantaneous processes is made to keep preprocessing and model formulations simple. Overall, four substitute variables are generated, resulting in an augmented dataset of one state and five control measurements.

For external control by an intelligent EMS, a temperature margin for safe operation of the milk cooling system of $1°$C is assumed as a conservative estimate of what food safety permits. Based on a superficial physical consideration of the system, the $1°$C temperature margin for a tank filled for example with a volume of $V = 9000\,\mathrm{l}$ milk corresponds to a margin of approximately $\Delta Q = c \cdot V \cdot \rho \cdot \Delta T \approx 10\,\mathrm{kWh}$ in terms of heat energy Q, where c is the specific heat content of milk and ρ its density. The amount of electrical energy that could on short timescales be shifted to more optimal times depends on the coefficient of performance (COP) of the cooling aggregate used, defined as the fraction of heat removed per applied amount of energy. Generally, COP values can vary between up to 4 down to 1 (Mhundwa et al., 2017), which leaves a potential for short term load-shifting in the order of 2.5 to $10\,\mathrm{kWh}$.

In order to intelligently shift the electrical consumption of the milk cooling system, its behaviour needs to be predictable, to comply with the temperature constraints, and to assess future power demand accurately, as not to waste energy on over-cooling. A physical description of the relevant processes, and thus a basis for a model ODE can be derived from considering energy conservation of the relevant heat flows at time t as

$$\dot{Q}_{\mathrm{m}}(t) + \dot{Q}_{\mathrm{a}}(t) + \dot{Q}_{\mathrm{w}}(t) - \dot{Q}_{\mathrm{c}}(t) = \dot{Q}_{\mathrm{internal}}(t), \quad (1)$$

where $\dot{Q}_{\mathrm{m}}$ denotes the heat inflow when fresh milk is added, $\dot{Q}_{\mathrm{a}}$ the heat exchange with the environment, $\dot{Q}_{\mathrm{w}}$ the heat inflow of the hot water during the cleaning phase, and $\dot{Q}_{\mathrm{c}}$ the outflow of heat achieved by the cooling aggregate. Any accumulated heat flow affects the state of the system, and is 'stored' in form of a change in its internal heat content as

$$\dot{Q}_{\mathrm{internal}}(t) = C(t) \cdot \dot{T}(t) + T(t) \cdot \dot{C}(t),$$

dependent on system heat capacity C and temperature T. Eq. 1 can then be reformulated to yield an ODE for the temperature of the system as

$$\dot{T}(t) = \frac{\dot{Q}_{\mathrm{m}}(t) + \dot{Q}_{\mathrm{a}}(t) + \dot{Q}_{\mathrm{w}}(t) - \dot{Q}_{\mathrm{c}}(t) - T(t) \cdot \dot{C}(t)}{C(t)}. \quad (2)$$

The individual terms of this ODE are approximated to provide a model function to predict temperature behaviour based on the available augmented dataset. Time-dependent physical properties are thus approximated through time series data, but since the further use of the model function only involves numerical operations in a discretized setting, this is not an issue. Heat capacity of the system is approximated as

$$C(t) \approx C_{\mathrm{t}} + c_{\mathrm{m}} \cdot i_{\mathrm{m}}(t) \cdot V_{\mathrm{m}} \cdot \rho_{\mathrm{m}},$$

consisting of a constant term C_{t} for the heat capacity of the tank itself and a second term, varying with the amount of milk in the tank. Since no data on milk level or in- and outflow is available, this is expressed in terms of a 'counter' variable $i_{\mathrm{m}}(t)$, defining how many milking processes (i.e. from zero to four) have taken place since last emptying. For each milking process, a constant volume of added milk V_{m} is assumed, with constant material properties for specific heat content of milk c_{m} and milk density ρ_{m}. The heat flow from adding or removing milk is approximated as

$$\dot{Q}_{\mathrm{m}}(t) \approx (b_{\mathrm{o}}(t) \cdot T(t) + b_{\mathrm{i}}(t) \cdot T_{\mathrm{m}}) \cdot \dot{C}(t)/\Delta t_{\mathrm{m}},$$

relying on boolean variables $b_{\mathrm{o}}(t)$ and $b_{\mathrm{i}}(t)$ to mark times of milk out- and inflow, as well as assumptions of constant values for (fresh) milk temperature T_{m} and milking duration Δt_{m}, and the implicit assumption of perfect mixing. Again the above assumption of the varying milk content being the only time-dependent component of the overall systems heat capacity is used. Ambient heat exchange with the environment is approximated using Newton's law of cooling as

$$\dot{Q}_{\mathrm{a}}(t) \approx (h_{\mathrm{c}} + b_{\mathrm{d}}(t) \cdot \Delta h_{\mathrm{d}}) \cdot A \cdot (T_{\mathrm{a}} - T(t)).$$

Another boolean variable $b_{\mathrm{d}}(t)$ is used to describe times where the tank door is open, leading to an increase in heat exchange coefficient h, whose values in the two situations themselves are assumed to be constant. Also assumed constant is the tank surface area A, and – less likely to match reality – ambient temperature T_{a}. A more realistic approach including either explicit or implicit time dependency is neglected in favour of a simpler model function. Also the heat inflow from hot cleaning water is approximated only in a simple manner as $\dot{Q}_{\mathrm{w}}(t) \approx \frac{Q_{\mathrm{w}}}{\Delta t_{\mathrm{w}}} \cdot b_{\mathrm{w}}(t)$ by using binary variable $b_{\mathrm{w}}(t)$, describing times of active cooling, together with an assumedly constant amount of heat energy Q_{w} of said water delivered within cleaning duration Δt_{w}, also assumed constant. Finally, as described above, the heat extracted by cooling is approximated as $\dot{Q}_{\mathrm{c}}(t) \approx \mathrm{COP} \cdot P_{\mathrm{c}}(t)$, where, analogous to the assumption of constant external temperature, a constant COP is assumed. Using all approximations listed above in Eq. 2, a parametrized model ODE can now be based on the physical relationships as

$$\begin{aligned}\dot{x}_0(t) = \frac{1}{p_3 + u_4(t)} \cdot \Big(& p_4 \cdot u_2(t) - p_5 \cdot u_0(t) \\ & + p_1 \cdot u_3(t) \cdot (p_0 - x_0(t)) \\ & + (p_2 - x_0(t)) \cdot u_1(t) \Big),\end{aligned}$$

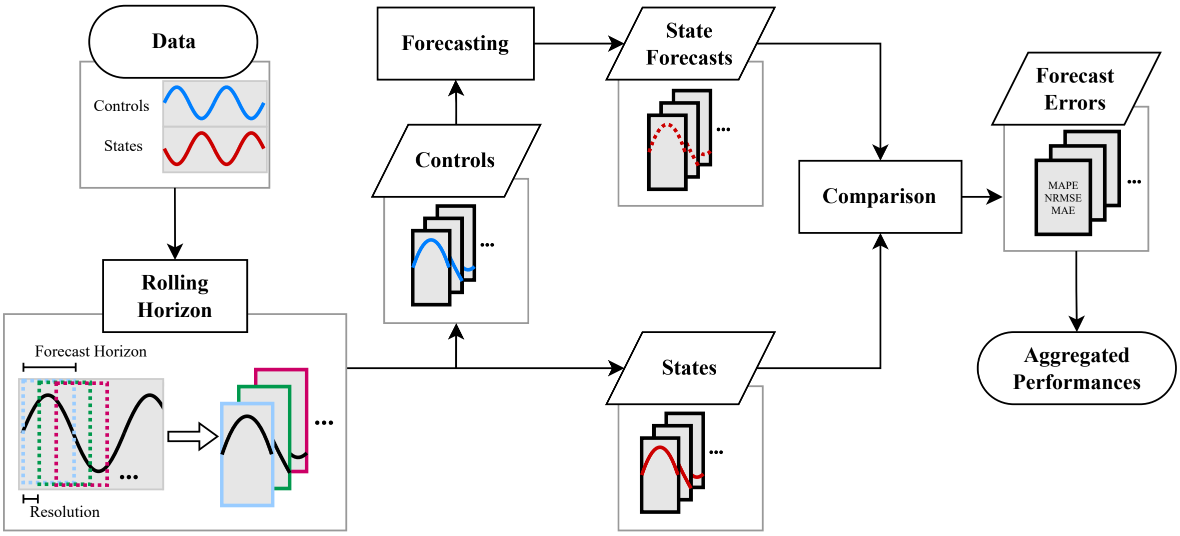

Figure 1: Overview of the Rolling Horizon Scheme for Model Evaluation

where the state $x_0(t)$ of the system is the temperature, and the controls of the system are the inputs of

$$u_0(t) = P_c(t), \quad u_1(t) = b_i(t)/\Delta t_m, \quad u_2(t) = b_w(t),$$
$$u_3(t) = b_d(t), \quad u_4(t) = i_m(t).$$

All physical constants (or variables assumed constant) are covered by six parameters, formulated so that structural identifiability is possible, i.e. such that there are not multiple combinations of parameters leading to the same result. For a complete overview of physical equivalents to each parameter, see Tab. 1.

Methodology

The augmented dataset is used to both fit and validate the presented physics-based model. Since the milk cooling system runs on a periodic cycle of two days, no large variance of behaviour is expected over longer durations. Therefore, only four days of measurement data are used for model training in the parameter identification step, and an equal length dataset is reserved for test purposes. In accordance to the designated use in an EMS, the training set is the data right up to the test set. In application, this should enable the model to account also for slowly varying external influences.

To solve the PI problem, initial parameter guesses are provided based on estimates of the physical properties they are based on (Tab. 1). Arbitrary initial guesses are possible – and would be more practical for real-life application of the forecast-based EMS approach – but can lead to longer computation times and higher risk of getting stuck in local minima. The PI problem is solved using the full discretization scheme implemented in the *Topas Model Fitting* tool (Wiesner et al., 2021). It transposes the problem into a high-dimensional, but sparse non-linear program (NLP), which the local solver *WORHP* solves with a Penalty-Interior-Point algorithm (Büskens and Wassel, 2013).

To use and evaluate the model, simple Euler integration is deemed accurate enough, since the model ODE is linear in its single state. Model evaluation is performed by comparing model forecast and measured data for the test set, but because of the dynamical nature of the model, and mirroring its intended online application in an EMS, this is performed on a rolling horizon. The model is intended for short term forecasts, and evaluation over the longer test set is carried out by iterative forecasting, as shown in Fig. 1. Given a fixed forecast horizon Δt_{fh} and a resolution of the rolling horizon of Δt_{RH}, the test set of length Δt_{t} is split into $n_{\text{RH}} = (\Delta t_{\text{t}} - \Delta t_{\text{fh}})/\Delta t_{\text{RH}}$ windows. For each, a forecast is generated by iterative integration of the model ODE using initial value and control values from measurements over the full forecast horizon. Predicted and measured state values are compared by computing mean average percentage error MAPE, and normalized root mean squared error NRMSE (normalized by mean measured value of the respective period) for the window. An additional error measure more specific to the use case in an EMS is computed as the mean average error of all those durations of interest for demand shifting, denoted as MAE_{EMS}. The durations relevant for energy management are those of normal operation outside of the cleaning and empty phases, and are here approximated as all times where $T \leq 10.0°\text{C}$. Repeating the procedure with the next window from time $t_{i+1} = t_i + \Delta t_{\text{RH}}$, the whole test set is covered, and all n_{RH} performance measures can be averaged into an aggregate performance measure.

For energy management, forecast horizons of 24 h are of interest, since relevant cycles in consumption and (solar) generation usually occur daily. Nevertheless, a running EMS would frequently re-evaluate the situation and therefore only the first time steps of generated control output would actually be applied before calculating new ones. Therefore model performance of the first few minutes and hours (depending also on the frequency with which the EMS updates) is much more relevant than model performance over the full 24 h. To account for this, different forecast horizons

Table 1: Model Parameters with Physical Equivalents and Derived Initial Guesses compared to the Identified Values

	Physical Equivalent	Unit	Initial Guess	Expected Range	Identified Parameter
p_0	T_a	°C	10.0	-10.0 to 30.0	19.1
p_1	$\frac{\Delta h_\mathrm{d} \cdot A}{c_\mathrm{m} \cdot V_\mathrm{m} \cdot \rho_\mathrm{m}}$	$1/\mathrm{s}$	$2.71 \cdot 10^{-5}$	0.0 to $1.81 \cdot 10^{-4}$	$9.60 \cdot 10^{-2}$
p_2	T_m	°C	20.0	10.0 to 30.0	18.8
p_3	$\frac{C_\mathrm{t}}{c_\mathrm{m} \cdot V_\mathrm{m} \cdot \rho_\mathrm{m}}$		$7.34 \cdot 10^{-5}$	0.0 to $1.31 \cdot 10^{-1}$	$2.93 \cdot 10^{-2}$
p_4	$\frac{Q_\mathrm{w}}{\Delta t_\mathrm{w} \cdot c_\mathrm{m} \cdot V_\mathrm{m} \cdot \rho_\mathrm{m}}$	$°\mathrm{C/s}$	$1.03 \cdot 10^{-5}$	$0.26 \cdot 10^{-5}$ to $3.42 \cdot 10^{-5}$	$4.33 \cdot 10^{-4}$
p_5	$\frac{\mathrm{COP}}{c_\mathrm{m} \cdot V_\mathrm{m} \cdot \rho_\mathrm{m}}$	$°\mathrm{C/J}$	$2.05 \cdot 10^{-7}$	$0.52 \cdot 10^{-7}$ to $6.84 \cdot 10^{-7}$	$1.35 \cdot 10^{-7}$

from 24 h down to 1 h are evaluated, with a resolution of the rolling horizon of $\Delta t_\mathrm{RH} = 600\,\mathrm{s}$.

NUMERICAL RESULTS

The parameter identification problem is thus solved with 5760 points of measured data (4 days in minutely resolution). With a number of discretization points chosen as $n_\mathrm{dis} = 0.7 \cdot n_\mathrm{t}$, the NLP resulting from the full discretization scheme consists of 4037 variables, for which an optimal solution is found within $554\,s$. The identified parameters are displayed as well in Tab. 1, together with the initial guesses and expected range. Major displacement from the initial guesses by more than one order of magnitude is present only for p_1 and p_3. This is to be expected, since these parameters account for uncertain and very device-specific properties like heat capacity and heat transfer coefficients of the tank. Only in the cases of p_1 and p_4 do the identified parameters fall outside of the bounds of expected values. Whether this is due to the found local solution differing from a possible 'true' global solution, due to processes not considered in the formulation of the physical model ODE, or simply due to operation of the milk cooling system different to the expectations used in the initial guesses, is unclear.

In general, while the model function was derived using physical descriptions of the relevant processes, the overall model trained on data does not necessarily match these expectations of physical meaning. Processes not considered or unduly simplified in the model formulation, as well as simple measurement noise and other influences, are all included in the fitting of the parameters on the measured data, and can have a large influence on the identified values. The fit model should be checked and evaluated with the same scrutiny as any data-based model. A visual comparison of individual 24 h-forecasts against the measured data is presented in Fig. 2. For both training and test set, out of the $n_\mathrm{RH} = 432$ available forecasts, only those for $i = 0, 144, 288, 432$ are shown, leaving out all overlapping ones in between. The data show an accordance of modelled and observed temperature for all important operation phases.

Main discrepancies between model forecasts and measured temperatures occur during the cooling down phase after cleaning (which would not matter in a real EMS system), during the milking phases, where the simplifying assumption of instantaneous inflow is clearly visible (but this offset is limited to a short duration), and - especially on the test set - as constant offsets after the individual cooling phases. The latter observation is most relevant as a source of error in the overall model performance and especially for use in an EMS, since these are the periods where cooling activity could be shifted, and where an accurate estimate of temperature behaviour is needed. The reason for these offsets lies in the fact that no information about future (or even past) heat inflow from milking is available to the model. The consideration of this inflow with only a constant parameter obviously cannot account for the fluctuations present in the real operation. The different individual model forecasts shown for this period also display the dynamic nature of the model. Since future behaviour of the system depends on its current state, any error within a forecast propagates to all further values. Overall forecast error therefore can also depend on the starting point of the integration, as visible in the second and fourth day of the test period, which produce larger deviations than the first and third.

Tab. 2 shows mean and standard deviation of the performance measures for both training and test set of all individual forecasts within the rolling horizon, for forecast horizons of 24, 12, 6 and 1 h. As expected, model performance on the data in the training set is notably better than for the unseen data of the test set for all error measures. The standard deviations are used as secondary metrics for the distribution of performances, although interpretation is difficult since these are not necessarily normal distributions, but increasingly skewed when average model performance is better. Nonetheless, they indicate that within the set of forecasts of the rolling horizon, there are large differences in performance. This matches the observation of starting time (rather, initial state) having a large influence onto the forecast. Overall, the percentage model performances for full day forecasts of around $30\,\%$ on the test set confirm the visual impression of an adequate forecasting ability with room for improvement. This does however not provide any clear inferences for its designated application in an EMS. Values of the use case-specific $\mathrm{MAE}_\mathrm{EMS}$ provide a more tangible estimate here. Assuming a temperature margin of $1°\mathrm{C}$ for EMS operation, forecast errors should be well below this bound, although there is no definite threshold. This is the case for 1 h forecasts, but the $\mathrm{MAE}_\mathrm{EMS}$ of $1.7°\mathrm{C}$ on the test set observed for 24 h forecasts is very high for beneficial use in an EMS. Notably, the shorter

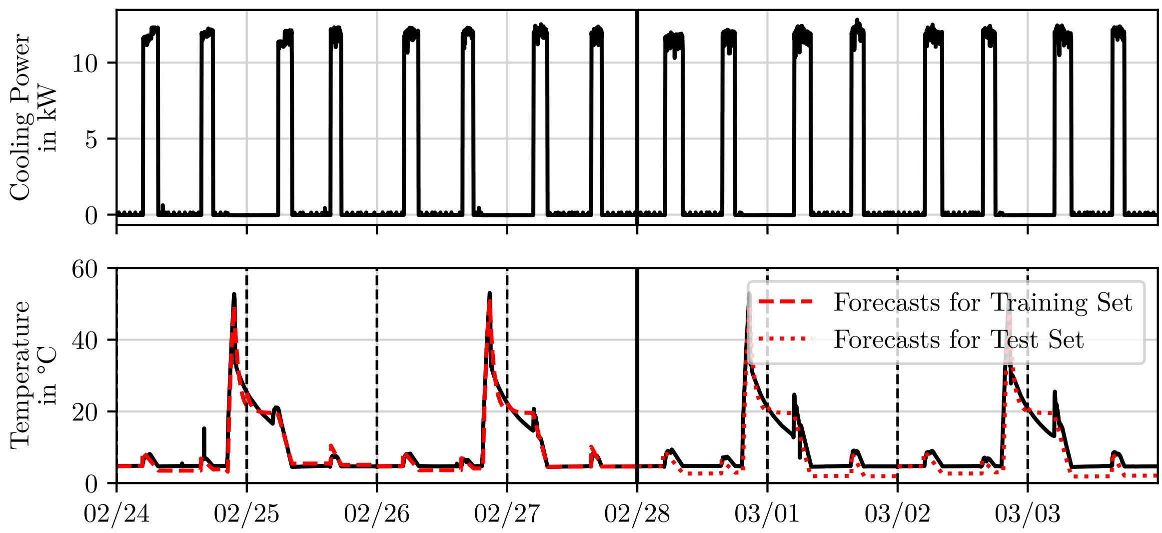

Figure 2: Individual 24 h-Forecasts of the Milk Cooling Model against Measured Data of Training and Test Set

Table 2: Mean Performance Measures of the Milk Cooling Model for Different Forecast Horizons

Δt_{fh}	Set	μ_{MAPE} [%] in %	σ_{MAPE} in %	μ_{NRMSE} in %	σ_{NRMSE} in %	$\mu_{\mathrm{MAE_{EMS}}}$ in °C	$\sigma_{\mathrm{MAE_{EMS}}}$ in °C
24 h	Training	11.55	6.57	15.74	3.92	0.67	0.47
	Test	29.41	13.39	28.86	9.74	1.74	0.91
12 h	Training	10.46	9.07	15.30	7.19	0.54	0.50
	Test	22.44	18.52	25.83	13.58	1.32	1.20
6 h	Training	8.68	8.99	12.45	8.30	0.46	0.55
	Test	15.33	16.99	18.70	14.50	0.98	1.37
1 h	Training	4.28	6.22	5.55	8.51	0.24	0.46
	Test	5.95	8.94	7.59	12.07	0.38	1.08

forecasts generated in the rolling horizon evaluation seem to behave even more diversely than the full-day forecasts. The standard deviations of the performance measures increase with decreasing forecast horizons. This again shows the strong dependency on the starting point of the forecast, which is exacerbated by the additionally generated auxiliary controls being only instantaneous influences, even though in reality these processes last longer. The $\mathrm{MAE_{EMS}}$ decreases as expected with decreasing forecast horizon, and for Δt_{fh} shorter than six hours, the error is below the discussed bound of 1°C also for the test set. This does not necessarily mean that the model already allows for optimal energy management, but it shows the possible use of local models with realistic handicaps in an EMS.

CONCLUSION AND OUTLOOK

Accurate modelling of dynamical systems is a necessary but complex step in the development of a forecast-based EMS. To develop a model usable and transferable in practice, inclusion of device-specific measurement data in the form of PI or similar fitting approaches is unavoidable. The presented work shows that a physics-based approach to this can embed important information in the model to help performance even with lacking data. However, this also means a stronger reliance on expert knowledge, and makes the approach less transferable to other types of devices compared to purely data-based approaches. For the considered milk cooling system, forecasting quality is at least comparable to results from fully data-based methods published previously for the same dataset (Lachmann and Büskens, 2021), where even more information was provided as model inputs from preprocessing. A higher forecast performance through improvements in the model, intermediate model updates, or improvements in data preprocessing may be possible. The main obstacle of the data not containing all needed information about future heat inflow however remains.

The question of what level of model performance is needed for successful energy management cannot be answered definitely, but the constraints to be fulfilled during the operation of the milk cooling system provide some guidance. Assuming a conservative 1°C margin for EMS operation, the $\mathrm{MAE_{EMS}}$ computed for 24 h forecasts is quite large. For shorter forecast horizons, errors well below this goalpost are reached. In a frequently updating EMS, these short term forecasts would be most relevant and flow directly into control values that are actually applied before the next iteration of the system. The question of whether optimizing energy use over a short horizon with good model forecasts, or over a longer horizon with less accurate model forecasts leads to better outcomes provides an interesting setup for further studies. Important future steps also include the direct comparison of models developed without any assumptions on physical behaviour of the system, and the transfer of both approaches to other relevant thermal storages. The development and test of an EMS using these methods hold their own challenges; Already now, however, the practicability and the possible benefits of intelligent energy management of large thermal storages in the agricultural domain can be shown, motivating further research and development.

ACKNOWLEDGEMENTS

This research is funded by the Federal Ministry for Economics Affairs and Climate Action of Germany within the project *SmartFarm2 - Autonomes EMS für den ländlichen Raum* (Ref.: 03EI6046B). Special thanks goes to all who made this work possible, including the technical staff of the University of Bremen.

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