Data-driven Prediction of Optimal Operating Strategies for Residential Energy Systems

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Abstract

Future residential energy system will present much larger complexity caused by decentralized roof-PV generation, electrification of heating, and installation of storages in order to create flexibility of the system. Because of increasing interdependencies, simple rule-based controller falls short of delivering cost-optimal operating strategies. An optimization-based energy management algorithm such as model predictive control, on contrary considers multiple factors to find an optimal operation of the system in terms of generation cost and energy consumption. But it requires complex implementation and intensive computational effort, which builds barriers for a successful market entrance. Concurrently, the detection of interdependencies within multiple variables has improved due to recent expansion of machine learning application. This sheds a light on designing and implementing smart controllers with the help of data analytics.

The aim of this work is to determine whether selected machine learning algorithms could detect a relation between multiple factors in residential energy system and thus improve prediction of an optimal operation of a bivalent heat pump system. Four system configurations are selected. Optimal operating profiles of each configuration are obtained from an energy-planning tool that is developed at Bosch. Inputs of the tool are, beside economical boundary conditions and technical specifications: demand profiles, weather and irradiation conditions.

Impacts of PV installation, thermal storage and battery on operation of the system are analysed. Based on feature analysis three models are designed in order to determine which features could improve the accuracy of prediction. Three machine learning algorithms have been tested to determine the prediction of the system – random forest regression, neural network and long short-term memory network.

The results demonstrate capability as well as potential of implementing ML algorithms for residential energy management. The analysis also shows that the RF and NN outperform LSTM on selected data. Additionally, these algorithms are able to predict the operation of the system with average accuracy of R^2 0.93 for all configurations.

Keywords: Hybrid Heat Pump, Prediction of operation, Energy Management, Machine Learning,

1. Introduction

1.1 Motivation

The strategic long-term vision of European countries is competitive and climate-neutral economy by year 2050. That leads to strong emphasis on the reduction of the CO_2 emission, reduction in energy consumption and efficient energy management. According to data provided by Eurostat, the building sector was responsible for 27.2% of final energy consumption in European Union in 2017. Most of the residential energy consumption was used for space heating (64.1%) and water heating (14.8 %). Additionally, most of the space heating and water heating consumption was covered by gas (up to 42 % and 47 % respectively) [1]. These facts bring a lot of potential for energy savings and CO_2 reduction and, they have also been considered in European legislation. According to the European directive 2010/31/EU [2] on energy performance of buildings, all new buildings built by 2021 are encouraged to be zero net energy buildings. Electrification of the heating sector presents itself as an essential part to meet that goal and to progress in the overall effort to decarbonize energy supply replacing the fossil fuel-based heating systems. The heat pumps are considered energy-efficient and low-carbon alternative to conventional heating systems. The advantage of the heat pumps is that their efficiency is much higher comparing to conventional electrical resistance heaters. That is as heat pumps transfer heat from external environment and only fraction of energy is needed to run the device. The transferred heat can be up to 3-4 times higher than the electric input power of the heat pump. That makes the efficiency of the system, which is defined as coefficient of performance (COP), 3-4 larger comparing to COP of 1 of the electrical resistance heaters. Additionally, the EU Directive on energy efficiency considers heat pump as a renewable heat source [3].

However, transition to electrification of heating would cause steep growth of electricity demand resulting in increase in conventional electricity production and risks for electrical grids. As a transitional solution to tackle these challenges hybrid systems could be considered [4]. Hybrid systems are composed of an electrically driven heat pump paired with a fossil-based heat generator such as gas boiler. Both components can be operated simultaneously or in a serial operation [5]. Connecting heat pump into hybrid system enables reduction in sizing of the heat pump in order to cover partial load of the total maximum thermal load required. Thus, the seasonal coefficient of operation (SCOP) increases as the heat pump can operate during the heating season with higher load factors, reducing the annual cycling losses [6]. Hybrid systems are also appealing from the economical aspect as they decrease the investment cost and can flexibly adjust to current fuel costs. Additionally, the hybrid system could be a solution for implementation of heat pumps into old buildings which require high temperature at the inlet of the heating system.

Operation of the Hybrid system

Currently the operation of the hybrid system is dictated by the ambient temperature. When the ambient temperature drops under certain determined value (bivalent point) heat pump is not able to cover the whole load on its own. Thus, heat pump starts to operate in parallel with the secondary heat generation technology. That is due to decreasing COP of the heat pump with decreasing temperature and presumable increase in heating demand. When the ambient temperature and consequently COP are too low for heat pump to operate then gas boiler provides all the heating supply.

On the other hand, future residential energy systems will present much larger complexity caused by several trends. First is the decentralization of energy generation. Second energy market flexibility that will dynamically shift loads based on the current energy generation. The operation of such complex system depends on multiple factors such as generating technology implemented in the house, available storage technologies, price tariffs, demand profiles, weather conditions, unpredictability of the renewable sources etc. These technologies might shift the optimal operation of bivalent point from being ambient temperature dependent to dependency on multiple variables.

1.2 Objective

The objective of this work is to investigate if the operation of the hybrid heat pump system can be improved using machine learning algorithms which are trained with data obtained from simulation model. The simulation generates the optimal operation of the system by calculating the energy balance at the time step nodes having all relevant information in defined time frame including past, current and future time steps. The thesis investigates if the ML algorithms can capture the relations between the variables and learn the optimal operation of the system in order to be able to predict the operation of the system in next time step with the data available at current and past steps.

1.3 Contribution of This Work

The main purpose of this work can be divided into two parts:

I. First one is to analyze how various factors influence the optimal operation of the hybrid heat pump system. As factors are considered the price of electricity, installation of photovoltaics panel, battery storage and thermal storage.

II. Secondly, the work investigates the potential implementation of machine learning algorithms into the control of hybrid generation system operation in relation to energy management of the house. The aim is to select appropriate machine learning algorithms, analyze which algorithm would be the most appropriate for this purpose and what features are relevant for the performance of the algorithms.

2. Fundamentals

2.1 Heat Pump

Heat pumps is a form heat engine that uses mechanical work to transfer heat from a low temperature source to a higher temperature sink. The heat transfer occurs by extracting the heat from the external environment (source) and providing that heating to the building (sink). The process reserves natural heat transfer using refrigerant [7].

The efficiency of the heat pump operation is denoted as coefficient of performance (COP).

Carnot Efficiency

Carnot Efficiency is defined as a coefficient of performance of a reversed Carnot cycle and it is theoretical maximum COP limited by the absolute temperature of the sink (T_{sink}) and source (T_{source}). This implies that the efficiency of the heat pump is higher when the temperatures of the sink and source are closer [7]:

$$COP_{Carnot} = \frac{T_{sink}}{T_{sink} - T_{source}} \qquad (1)$$

Theoretical COP

COP_{carnot} indicates the maximum theoretical potential performance of the system given by the environments, however in real operation such performance will never be achieved. The operational performance corresponds better to theoretical COP_{th} which takes into account efficiency of the system [7]:

$$COP_{th} = \eta \cdot COP_{Carnot} \qquad (2)$$

For which is η evaluation of heat pump system performance. it is related to particular heat pump model and it is given by the manufacturer. It is dependent on modulation of the compressor, losses in the hydraulic system etc.

Coefficient of Performance

COP can also be defined as a ratio between quantity of the heat delivered by the heat pump and the electricity input power of the heat pump [7]:

$$COP = \frac{Q_{HP}}{W_{HP}} \qquad (3)$$

Seasonal Coefficient of Performance (SCOP)

Seasonal Coefficient of Performance is defined as an average COP during the heating season.

2.2 Control of Heat Pump Systems

Control is method of operating device in a consistent, economical and safe way which could not be achieved by human manual control. [8]

2.2.1 Base Control

Control of the heat pump system consist of the decision and action agent. The decision agent is an operational system, which analyses the current state of the system and makes decision-making process. Action agent implements the required change on the device. In case of the heat pump, the action agent is the operational speed of compressor [8].

The control of the heat pump system is implemented by the operation of the compressor. There are two approaches to operate the compressor:

On/Off compressor operation – the operation of compressor is driven by the on and off state of the constant speed motor, any adjustment in change of the heat load can be only done by intermitting of the motor. [8]

Inverter adjusts variable compressor speed **–** the speed of the compressor motor in order to meet the demanded heat load [8]

2.2.2 Energy Management Strategies

There are several strategies which are used for control of the operation system which can be divided into two groups - non-predictive methods and predictive methods.

Non-predictive methods

Rule Based Control (RBC) – the most widely used control for heat generation systems. The control principle is based on simple *if condition – then action* rule-based mechanism. Operation of most rule-based controllers for energy management is determined by the ambient temperature, which is used as set point for the operation of the heat pump or secondary generation source. Additionally, ambient temperature is also used to determine required supply temperature to heating distribution system – heating curve function. The drawback of the rule-based controller is that the action is determined by current state of the system. The current state is defined by the output of sensors in real time or its average along the determined past time period. However, it does not predict the possible future behavior of the system with respect to future heating demand, change of the heat inertia of building, occupancy, time of the day or irradiation. This can lead to overheating or overcooling of the dwelling and therefore it is not considered as the most economical way to operate energy management system. [8]

Model Predictive Control

Model predictive control (MPC) is an advance method of control which can manage complex dynamic systems. The principle of the MPC is to optimize the current timeslot while considering the following future time slots. MPC can be divided based on the complexity of computation and input data into:
Model based predictive control is model based meaning that model of an actual physical system is designed and improved with the data obtained from the real measurement or the real system. Modelling approach which considers both the physical model of the system and measured data is known as gray box modelling. [8]
Model free predictive control is based on purely the data from the real system measurements which are used to determine the operation of the system. The physical model of the system is not implemented.
Stochastic Predictive Control is a model which is based on taking into account the uncertainty of the prediction of the model. [8]

The data provided for the MPC prediction can be provided entirely from the system (autonomous system) or from third parties. External values such as ambient temperature, irradiation or market price can be very accurately obtained from third party provider. Additionally, ambient temperature and irradiation are used for predicting the thermal demand of the building (heating curve) and PV generation and are determined individually for each household. The prediction of the energy demand for hot water and space heating demand is based on the internal historic data with pattern recognition. If data from the third parties are not available or the system aim to be autonomous various statistical methods are used such as auto regressive method, moving method, ANN, generalized mixture models and others. [8], [9] .

2.3 SystemFinder

The data provided for this thesis was obtained using an optimization-based energy-planning tool called SystemFinder, which was developed by Bosch. SystemFinder was created in order to provide optimal sizing, configuration and operation of the system for the residential housing taking into consideration interdependencies between end-use domains of electricity, hot water and space heating. The optimization of the operation mode is calculated by meeting the end-use demand with combination of power flows of various generation units and storage technologies in each time step. Target function of the optimization is the minimization of total annualized discounted costs of an entire house energy system including the fixed, variable operational cost and investment cost.

The input information can be divided into three main groups – demand profiles, technology input and economic information.

There are two main outputs that the system can provide with respect to demand profile and fixed and operational cost. First one is an optimal sizing of technologies and storages for a given house. Second is an optimal operation of the given system.

The specific constrains of modelling

Optimization time steps

There are two different time steps implemented in the system with the respect to different demand behavior. The optimization of the power flows is modeled in the step of 5 minutes whereas the time step for space heating demand is optimized in 60 minutes times step taking into consideration the inertia of the building and the heat transfer system. At each time step, the end-use demand (load) must be met.

Variable Flow Temperature

When modelling the temperature dependent demand profiles – (hot water demand and space heating demand) not only the load at each time step must be fulfilled but also the temperature demand.

When there is more than one source providing the heat supply simultaneously, it assumed that the all units provide the same temperature level for the simulation purposes of linear operation (parallel connection). However, in the real operational system it is more beneficial to use a serial connection of technologies in order to make use of the high COP of the lower flow temperature of the heat pump. Therefore, in order to make the model more corresponding to the actual physical state, discretization of the temperature levels is introduced for the technologies with non-linear behavior with respect to flow temperature.

The required heat demand is divided on three levels at each time step and consequently the required temperature at each level and COP of heat pump is calculated. Consequently, each generation technology can supply the heat up to the temperature level which is currently most economical.

Indoor Temperature

SystemFinder does not take into consideration indoor temperature as it only calculates with energy flows. Therefore, if the final energy demand of space heating is met, it is considered as indoor temperature being achieved.

General Economic Parameters

The optimization of dimensioning of the technologies and investment will be not discussed further as there are not objective of this work. However, as the optimization of the system operation is dependent of the target function of the simulation it is necessary to state cost for investment and operation.

Further assumptions

Comparing to data obtained from real system there are assumptions that are not necessary to be taken into account. Those would be delay of the measurement system and disturbances caused by weather and house occupancy.

2.4 Machine Learning

Machine learning (ML) is statistical algorithm method which can perform a specific task without being explicitly programmed by capturing patterns between the input variables during training period.

2.4.1 Correlation Analysis

Correlation analysis is an essential tool in order to determine the eventual linear relationship between variables (features). If two variables present close correlation, they can be predicted one from another. This can potentially eliminate the number of features and simplify the model. Second, certain algorithms might give misleading results for cases when several features possess perfect correlation. Additionally, the correlation analysis provides us with better perspective to understand the data. It ranges between - 1 to 1. Correlation acquires negative values when the relation between features is indirect, meaning that when one variable increases the other one decreases. Variables present no correlation if result value is approaching 0 [10].

Covariance

Covariance determines if two variables present linear relationship. However, it does not establish how strong the relationship is. Covariance is calculated as following [11]:

$$COV(X,Y) = \frac{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{n-1} \tag{4}$$

where *Xi, Yi* present the sample *X,Y* in observation *i* respectively; *X,Y* present mean of samples respectively and *n* represents number of samples.

Correlation

Correlation build on covariance principle and additionally determines how strong the linear relationship between two variables is [11]:

$$COR = \frac{COV\ (X,Y)}{\sigma_X * \sigma_Y} \tag{5}$$

where COV (X,Y) is the covariance calculated in Equation 4. and σ stands for standard deviation.

Pearson correlation

Pearson correlation indicates linear relation (strength and direction) between two continuous variables. It seeks a line that best fits between the data points of two features and consequently calculates the distance of each point to the line. The relationship is linear only when the change in one variable is proportional to the change in another variable [12]:

$$r = \frac{n\left(\sum xy\right) - \left(\sum x\right)\left(\sum y\right)}{\sqrt{\left[n\sum x^2 - \left(\sum x\right)^2\right]\left[n\sum y^2 - \left(\sum y\right)^2\right]}} \tag{6}$$

X,Y represent the respective variables, and n stands for number of samples.

2.4.2 Supervised machine learning

Supervised machine learning is task of machine learning that trains the interdependencies between inputs based on given output. In other words, the predicted output of the given inputs is known during the training phase and directly affects the training process [13].

Random Forest

Random forests are a type of ensemble learning algorithm in which each model (tree) is trained individually with different subset of dataset and different features. Comparing to other models each tree is trained individually and there is not weighing scheme in between the trees. The final prediction is an average of prediction of several independent base models - trees. The working principle can be explained as following. Firstly, n samples of dataset is used for training set for k trees. Secondly, decision tree is built on the randomly selected d features. Then, steps 1 and 2 are repeated k times. Final prediction is a result of overall average of trees output.

There are several advantages of using random forest model. Firstly, RF is very easy to implement. Secondly, decision trees are non-parametric meaning that it can model complex relations between inputs and outputs without any previous assumption [10]. Additionally, RF does not require complex data processing. It can work with both categorical and continuous data even combined in one dataset. Moreover, RF works with certain in build feature selection which eliminates noisy variables and therefore it makes RF robust to outliners.

Artificial Neural Network (ANN)

The artificial neuron works on a following principle. The network consists of signal inputs, which are fed into artificial neuron, processed in neuron and forwarded as an output value. The independent input variables are processed by the weight function and feed into neuron layer. In the neuron layer all the weighted inputs are added up and activation function is applied. The processed value is forwarded as an output value ŷ. This process is called a forward propagation when the input variable is process by the neuron resulting into output variable ŷ. This output variable is then compared with the actual value using the cost function. The aim of the optimization of the neural network is the minimization of the cost function which represents the error between the prediction of ANN and the actual value. The result from the cost function is then feed back into network and back propagated. During backpropagation the weighted functions are updated based on the output from the cost function. This process of forward and back propagation is repeated until the values of the weighted functions are optimized and the error is minimized [14].

Long Short-Term Memory Network (LSTM)

Long Short-Term Memory network is a type of recurrent neural network (RNN). RNN is a class of neural networks that allow previous outputs to be used as inputs while having hidden states. RNN might be affected by short memory while processing long sequence of data. Consequently, an important information might get lost while processing a longer sequence. Additionally, RNN might suffer from vanishing gradient problem during back propagation. That means that the function reaches local minimum and the network stops updating value of the weights. As a solution to this LSTM have been created with a system of gates which regulate the flow of information by selecting information based on its relevance [15].

2.4.3 Feature Scaling

Scaling is important for gradient-based models as these are designed to work with data close to zero. Using unscaled data for such algorithms might results in longer computing times or even caused the algorithm not to converge. The models which are not gradient based do not require features scaling – for example Random Forest [10].

Standard Scaling

Standard scaling was used in order to scale the features for ANN and LSTM models [10]:

$$x' = \frac{x - mean\ (x)}{\delta} \qquad (7)$$

where x is the current value, mean (x) is the mean of the training samples or zero and δ is the standard deviation of the training samples.

2.4.4 Model Evaluation Metrics of Regression Problems

In order to evaluate the accuracy of the regression model these metrics are used to measure the accuracy for continuous variables.

Mean Absolute Error (MAE)

It is determined as an average over test sample *n* of absolute difference between each predicted value (P_j) and actual observation (O_j). All the individual differences are weighted equally in average that means that the error for outliners is not additionally penalized. MAE describes the average error [16].

$$MAE = \frac{1}{n}\sum_{j=1}^{n} |P_j - O_j| \qquad (8)$$

Mean Square Error (MSE)

It is defined as an averaged squared difference between predicted value (P_j) and actual observation (O_j) over the test sample *n*. Higher the value of MSE the worse the performance of model is. The perfect model would have a value of MSE equal to zero [16].

$$MSE = \frac{1}{n}\sum_{j=1}^{n} (P_j - O_j)^2 \qquad (9)$$

Disadvantage of this metrics MSE is that it gives higher weight (penalty) to bigger errors, which may lead to misevaluation of a good model when outliners in dataset occur.

Coefficient of Determination (R^2)

Coefficient of Determination is defined as ratio between how good the prediction of the model is comparing to the model predicting the mean.

$$R^2 = 1 - \frac{\sum_{j=1}^{n} \left(P_j - O_j\right)^2}{\sum_{j=1}^{n} \left(O_j - \bar{O}_j\right)^2} = 1 - \frac{MSE\ (model)}{MSE\ (baseline)} \qquad (10)$$

where O_j is mean of predicted and observed data

It usually ranges between 0 to 1 with 1 being the perfect model. However, it might also score negative values of R^2 for very poor models when the model is worse than predicting the mean. Advantage of this model is that it is scale free model which means that its evaluation is independent of whether the output values are very small or large [16].

3. Methodology and Program Development

3.1 Methodology

I. State the objective and determine required data

At first, a scope of required data must be selected based on a determined objective. The objective is to analyze how various factors affect the optimal operation of a hybrid heat pump system and how to predict its operation based on selected machine learning algorithms. To conduct such analysis, a set of typical household energy demand profiles are selected over one year. Dimensioning is conducted using SystemFinder. The simulation enables to find the optimal sizing of generation technologies and storage elements tailored to house demands.

To analyze how various technologies and storage elements affect the operation of the hybrid heat pump operation, configurations using different technology setups have been designed. The basic configuration is designed consisting only of a hybrid heat pump system. Photovoltaics, battery and thermal storage are added one by one to the other three configurations, respectively.

Next, SystemFinder is performed for each configuration using demand profiles of selected household and sizing of technologies as input parameters. The output of the simulation are optimal operating profiles of the hybrid heat pump system for the given year. Additionally, parameter variations on price ration between electricity and gas are conducted since it has significant influence on the optimal operation.

II. Exploratory Data Analysis and model determinations

The generated data are object to analysis, which enables to understand properties of various attributes and the interdependencies between them. This analysis is also conducted in order to determine which features are crucial for model implementation. At first, Pearson correlation analysis is carried to establish linear relationship between the features. Additionally, data visualization is performed in order to obtain the specificity of the data and to discover previously invisible patterns. Three models varying in features are designed for all configurations as a result of the performed analysis. These models are designed to analyze how features improve the performance of the prediction.

III. Machine Learning Algorithm development

Based on the literature review, three machine-learning algorithms are selected based on their implementation on similar applications.

Random Forest – for its easy implementation and good results [17], [18], [19]
Neural Network – for its common application for prediction of operation and good results [20], [21], [17].
Long short-term memory – to determine the dynamics trends in prediction based on [20] and [21].

IV. Data Preparation

The performance of the machine-learning model is highly dependent on the quality of the data provided. It is essential that the algorithm is provided with filtered, processed data with consistent input and output data at each time step. Since data are provided from simulation, datasets are coherent and no disturbance such as delay of measurement or error in measurement is existing. Steps to be taken to prepare the data for implementation:

A. Outliners elimination
B. Feature construction
C. Feature scaling
D. Division of the dataset into training and testing data

V. Evaluation Metrics

In order to being able to compare the models among each other, a metrics of evaluation must be determined. The description of each metrics is provided in chapter 2.4.4.

VI. Implementation of models

Selected machine learning algorithms are implemented in python script using selected libraries for neural network development.

Consequently, algorithms are fed with features based on the model's setup design in step II.

VII. Parameter optimization

To increase the accuracy of the algorithms, the right set of parameters of each algorithm to a given model must be determined. Despite many expert discussion and recommendation, there are no universal rules of thumb to determine optimal parameters for each algorithm before being tested on actual data. Therefore, parameter grid optimization must be conducted, testing various combination of preselected parameters, in order to improve the performance and accuracy of the models and to avoid both underfitting and overfitting of the data.

VIII. Training and testing optimized models

Algorithms with optimized parameters are trained with training dataset and subsequently the trained models are tested with testing dataset.

IX. Evaluation and Interpretation

The output models are evaluated using the metrics selected in step V. The results are interpreted and presented visually and numerically.

3.2 Program Development

Description of input profile variables

Ambient temperature

The input temperature profile is an average hourly temperature for the year of 2013 in area of Stuttgart, Germany.

Space heating demand and supply temperature

The offset temperature for switching off space heating operation is the ambient temperature of 20 °C. For the period between months June, July and August, space heating is off despite the occurrence of cold days with an ambient temperature below 13 °C.

Hot water demand

The input profiles of hot water demand of the household is assumed identical for every single day in a year. During the periods without hot water demand, hot water storage is still maintained in operation, thus requiring heating power supply.

Electricity demand

The dataset has an average hourly electricity consumption of 0.45 kW and maximal electricity consumption 3.7 kW.

Irradiation profile

Irradiation profile for the Stuttgart area is used as an input for configurations with photovoltaics installation.

3.3 Description of Configurations

Dimensioning of generation and storage technologies

Based on the input demand profiles of the household, dimensioning of generation technologies and energy storage elements have been conducted using the SystemFinder. The final sizing of the technologies is presented in Table 1

Table 1 Dimensioning of the technologies

Parameters	
Maximum Heat Pump Power Input [kW]	0,96
Gas Boiler Nominal Power [kW]	8,9
Bivalent Storage Capacity [l]	200
Photovoltaics Maximum Power [kW]	5
Capacity Battery [kW]	5
Capacity Thermal Storage [l]	400

Configuration setup

Four different configurations have been selected in order to investigate the influence of various factors. Firstly, basic configuration (Configuration 1) is designed consisting only of the hybrid heat pump system. This configuration is used as baseline model to compare with other configurations having additional PV installation and storage units as presented in Table 2. All configurations also include bivalent water storage. For generating data for all configurations, the component size of each generation technology remained constant. Each configuration is generated for two gas/electricity price ratios.

Table 2 Configuration setup

	Gas Boiler	Heat Pump	PV Panel	Battery	Thermal Storage
Configuration 1	x	x			
Configuration 2	x	x	x		
Configuration 3	x	x	x	x	
Configuration 4	x	x	x		x

3.4 Analysis of Configuration

3.4.1 Configuration 1

Configuration 1 explores operation of the hybrid heat pump system. Within such systems, it is usually the ambient temperature, that determines the switching between heat pump and gas boiler.

Taking the correlation matrix for dataset 1 [see Figure 1], it can be observed that ambient temperature has a strong negative correlation in relation to gas consumption (-0.83). Heat pump operation presents slight negative correlation with respect to ambient temperature (- 0.28). The linear relation is not that straight forward as the heat pump operation increases with increasing temperature. However, once crossing below the threshold temperature, the operation of heat pump decreases caused by decreasing COP.

Additionally, there is an almost perfect negative correlation between ambient temperature and the temperature at the inflow of the space heating (T_sh_flow) 0.99 and also between ambient temperature and space heating demand (D_sh) 0.9. This implies that the space heating demand can be determined using these two variables (T_sh_flow and T_amb). Similarly, one can also verify this relation as control by using the heating curve function of house. Heating curve function of the

	T_amb	Gas_consum	HP_consum	D_sh	T_sh_flow
T_amb	1.0	-0.83	-0.28	-0.9	-0.99
Gas_consum	-0.83	1.0	-0.054	0.89	0.84
HP_consum	-0.28	-0.054	1.0	0.37	0.3
D_sh	-0.9	0.89	0.37	1.0	0.91
T_sh_flow	-0.99	0.84	0.3	0.91	1.0

Figure 1 Correlation table for Configuration 1

house is a relation between the ambient temperature and the required supply heat that needs to be provided in order to allow the heating system to meet the building thermal loads.

It can be assumed that the gas generation contributes the most to the heating demands of the house from the correlation 0.84 between the gas consumption (Gas_consum) and the inflow of the space heating (T_sh_flow). To conclude, the correlation analysis shows that ambient temperature is an important feature with respect to control of the bivalent system. Additionally, the relation between the flow temperature of space heating and ambient temperature can determine the space heating demand for respective house.

3.4.2 Configuration 2

Configuration 2 investigates the impact of photovoltaics installation on the operation of hybrid heat pump system. The electricity generated from the photovoltaics is primarily used to cover the electricity demand of the household. When residual electricity from PV is available, it is used for heat pump operation or feed back into grid as feed-in tariff respectively. The flow of the PV generation is depicted on Figure 2.

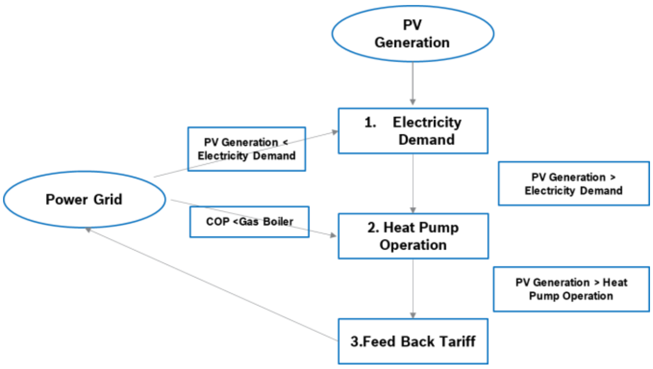

Figure 2 Priority chart of PV generation flow

Comparing Figure 3 with the correlation table of configuration 1 [Figure 1], where PV was not implemented, there is a significant negative correlation between heat pump input power and both ambient temperature and space heating demands. This implies that PV generation has an impact on the operation of heat pump for space heating generation at lower temperatures where the COP is low, and the operation of heat pump powered by grid electricity is hence not justifiable. On the contrary, the operation of heat pump for hot water trajectory does not increases proportionally with the PV generation.

Besides the features used for configuration 1, configuration 2 will also take into account two more feature variables. The photovoltaics generation of the system (PV_total) and the electricity demand of the household (D_ele). Electricity demand must be considered in order to determine how much electricity would be available for other applications (HP, Feed-in).

Besides the features used for configuration 1, configuration 2 will also take into account two more feature variables. The photovoltaics generation of the system (PV_total) and the electricity demand of the household (D_ele). Electricity demand must be considered in order to determine how much electricity would be available for other applications (HP, Feed-in).

	T_amb	Gas_consum	HP_consum	D_sh	D_hw	PV_total	Storage_hw
T_amb	1.0	-0.82	-0.75	-0.9	-0.019	0.35	0.39
Gas_consum	-0.82	1.0	0.58	0.89	0.061	-0.31	-0.33
HP_consum	-0.75	0.58	1.0	0.84	-0.0078	-0.23	-0.32
D_sh	-0.9	0.89	0.84	1.0	-0.013	-0.39	-0.31
D_hw	-0.019	0.061	-0.0078	-0.013	1.0	-0.061	0.1
PV_total	0.35	-0.31	-0.23	-0.39	-0.061	1.0	-0.18
Storage_hw	0.39	-0.33	-0.32	-0.31	0.1	-0.18	1.0

Figure 3 Correlation table for Configuration 2

3.4.3 Configuration 3

Configuration 3 explores the impact of battery on the operation of hybrid heat pump system with photovoltaics installation. Battery is used to better distribute the difference between the over production of electricity during the day and the household electricity demand during the evenings. Battery at this configuration can be only charged from the photovoltaics installation and the charging directly from the grid is not considered due to the constant price. Discharging of the battery is related to minimize supply of electricity from grid to cover electricity demand without taking into account the heat pump generation.

Therefore, the installation of battery does not impact the operation of heat pump. The limitation of the battery is also the limited discharging energy rate which is 0.3 kW per hour. Observing the correlation matrix for configuration 3 [Figure 4], it can be concluded that battery discharging has a very low correlation -0.23 with heat pump operation.

	T_amb	Gas_consum	HP_consum	D_hw	D_sh	Storage_hw	PV_total	Bat_dischar
T_amb	1.0	-0.83	-0.75	-0.019	-0.9	0.4	0.35	0.17
Gas_consum	-0.83	1.0	0.58	0.062	0.89	-0.34	-0.31	-0.23
HP_consum	-0.75	0.58	1.0	-0.0087	0.84	-0.33	-0.23	-0.23
D_hw	-0.019	0.062	-0.0087	1.0	-0.013	0.097	-0.061	-0.043
D_sh	-0.9	0.89	0.84	-0.013	1.0	-0.32	-0.39	-0.2
Storage_hw	0.4	-0.34	-0.33	0.097	-0.32	1.0	-0.2	0.19
PV_total	0.35	-0.31	-0.23	-0.061	-0.39	-0.2	1.0	-0.28
Bat_dischar	0.17	-0.23	-0.23	-0.043	-0.2	0.19	-0.28	1.0

Figure 4 Correlation table for Configuration 3

3.4.4 Configuration 4

Configuration 4 studies the impact of thermal energy storage on the optimal control trajectory of heat pump. Thermal storage accumulates heat when heat pump operation is optimal and discharges when the demand for space heating is requested. In SystemFinder, the thermal storage is modelled in such way that it is regarded as low-value and thus need to be paired with a certain portion of high-value heat from gas boiler. The limitation of SystemFinder is that it calculates only with energy flows, but it does not take into account temperature variable. Therefore, the model charges the storage when the ambient temperature is high and temperature at the inflow to space heating is low. And the heat is released when the efficiency of the system is low.

The correlation 0.3 between space heating demand (D_sh) and discharging of the thermal storage (PS_dischar) is low. No other correlations between the level of thermal storage, its charging and discharging present any significant correlation as depicted in Figure 5.

	T_amb	Gas_consum	HP_consum	D_sh	T_sh_flow	PV_total	PS_level	PS_char	PS_dischar
T_amb	1.0	-0.79	-0.73	-0.9	-0.99	0.35	-0.043	-0.075	-0.24
Gas_consum	-0.79	1.0	0.52	0.81	0.79	-0.27	-0.18	0.2	0.025
HP_consum	-0.73	0.52	1.0	0.8	0.75	-0.18	0.18	0.2	0.22
D_sh	-0.9	0.81	0.8	1.0	0.91	-0.39	0.088	-0.01	0.3
T_sh_flow	-0.99	0.79	0.75	0.91	1.0	-0.35	0.043	0.073	0.25
PV_total	0.35	-0.27	-0.18	-0.39	-0.35	1.0	-0.11	0.12	-0.12
PS_level	-0.043	-0.18	0.18	0.088	0.043	-0.11	1.0	-0.0077	0.22
PS_char	-0.075	0.2	0.2	-0.01	0.073	0.12	-0.0077	1.0	0.13
PS_dischar	-0.24	0.025	0.22	0.3	0.25	-0.12	0.22	0.13	1.0

Figure 5 Correlation table for Configuration 4

3.5 Data Preparation

Features Construction

Timestamp conversion

The data is generated with hourly timestamp, which indicates the hour of the year. In order to handle better the data analysis, the timestamp is transformed into month of the year, day of the month and hour of the day.

Time of the day

The dataset is divided into hour of the day and a feature day/night is added in order to more precisely model the dependency of solar irradiation.

Operating Modes

Operating mode of each hour is added into dataset to determine current state of the system. This feature is mostly used for data visualization or classification. The modes are divided as listed inTable 3.

Table 3 Operating modes

GB mode	Gas Boiler operation only
Bivalent mode	Gas Boiler and Heat Pump operation in parallel
HP mode	Heat Pump operation only

Off	No operation

Price

Price of the heat pump operation at each hour is added with respect to electricity price and current COP at each hour.

Rolling averages

It is used for several features in model 3, in order to represent the time sequence of the feature. It uses several prior time steps of a feature and creates a new feature which is an average of these prior step's values.

Space heating on/off

It is used to determine if the space heating is on or off.

Labels Construction

As the model objective is to predict operation of the hybrid system both gas boiler and heat pump operations are considered as labels.

Gas consumption – considers consumption for both space heating demand and hot water demand

Heat Pump input power – Input power of heat pump is considered to determine its operation. This label has been selected instead of delivered heat since it is not dependent on fluctuating COP.

Feature Scaling

Feature Scaling - Scaling of the features is necessary to implement on the gradient-based algorithms. The features were scaled using the standard scalar (chapter 2.4.3) for the application of NN and LSTM.

Division of the dataset into training and testing data

Division of the dataset into training and testing data. The ratio between training and testing data has been divided into ratio 75 to 25 percent. In case of RF and NN, shuffling of data has been applied contrary to LSTM, which has been used as time series.

Implementation of models

Based on the analysis of the configuration 1 three models have been designed in order to analyses how features impact the accuracy of the prediction.

Model 1: only considers ambient temperature as a feature. It is a baseline model used for benchmarking.

Model 2: uses features which are determined as relevant from the explanatory analysis for each configuration.

Model 3: uses features from *Model 2* and additionally it is extended for time sequence of selected features.

3.6 Parameter Optimization

Determining proper parameters of the algorithm is an essential task in order to obtain the best possible performance of the algorithm. Based on theoretical basis parameters are selected for grid parameter search with an aim of lowest mean absolute error.

Final Parameters

The results of parameter grid search are set of optimized parameters achieving the lowest mean absolute error from given combinations. Table 4 and Table 5 present the results of the grid search of the optimal parameters for each model and each algorithm. These parameters are used to construct the algorithms.

Table 4 Optimized parameters for algorithms development Configuration 1 and 2

		Configuration 1			Configuration 2		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
RF	Number of estimators	394	158	158	394	158	158
	Max. Features	Sqrt	sqrt	Sqrt	Sqrt	Sqrt	Sqrt
	Max leaf Nodes	30	45	45	30	45	45
	Min samples leaf	4	4	4	4	4	4
	Min samples split	5	2	2	5	2	2
	Bootstrap	True	False	False	True	False	False
NN	Hidden Layers	1	2	2	1	2	2
	Neurons Input L.	2	9	14	1	13	31
	Neurons L1	2	30	37	2	9	26
	Neurons L2	-	36	28	-	64	32
	Activation Function	Linear	tanh	Linear	Linear	Linear	Tanh
	Learning Rate	0.001	0,001	0.001	0.01	0.01	0.01
	Batch	10	30	20	80	60	90
LSTM	Neurons Input L.	13			12		
	Neurons L1	18			16		
	Neurons L2	30			16		

Table 5 Optimized parameters for algorithms development Configuration 1 and 2

		Configuration 3			Configuration 4		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
RF	Number of estimators	394	158	158	368	158	158
	Max. Features	Sqrt	Sqrt	Sqrt	Log2	Sqrt	Sqrt
	Max leaf Nodes	30	45	45	25	45	45
	Min samples leaf	4	4	4	4	4	4
	Min samples split	5	2	2	10	2	2
	Bootstrap	True	False	False	True	False	False
NN	Hidden Layers	1	2	2	1	2	2
	Neurons Input L.	1	14	35	1	15	36
	Neurons L1	2	28	70	2	45	36
	Neurons L2	-	28	93	-	30	36
	Activation Function	Linear	Linear	Tanh	Linear	Tanh	Tanh
	Learning Rate	0.01	0.001	0.01	0.01	0.001	0.01
	Batch	10	40	70	60	50	60
LSTM	Neurons Input L.	13			13		
	Neurons L1	18			18		
	Neurons L2	30			20		

4. Results

Results part can be divided into three summary parts:

I. Overview of factors influencing the operation of the hybrid heat pump system.

II. Evaluation of models and importance of selected features.

III. Evaluation of machine learning algorithms for the purpose of predicting the operation of the hybrid heat pump system (Gas Boiler and Heat Pump).

I. Overview of factor influencing the operation of the hybrid system

From analysis carried in Chapter 3 it can be concluded which parameters should be included or considered when building a model for predicting operation of the system.

For the analysed system, space heating takes major part of the energy consumption of the household. Therefore, it is necessary to determine which features can improve accuracy of space heating consumption prediction. *Ambient temperature* and *inflow temperature of space heating* are the two essential variables considered when predicting the consumption for space heating demand. *Ambient temperature* is necessary for determining the proportion of generation between technologies in hybrid system. That is due to the optimal operation of heat pump being dependent on the temperature gradient between the sink and source. The inflow temperature at space heating can be used to model the approximate heating demand of the household with respect to ambient temperature.

Based on the analysis of Configuration 2, it can be deducted that photovoltaics installation has an impact on the operation of the heat pump in hybrid system. The occurrence of the operation becomes higher especially when compared to system with increasing electricity cost. PV generation also increases the input power resulting in higher heat pump production. PV generation and electricity consumption are considered as features in order to improve prediction of operation of such system. In real-time system forecasting of irradiation from a third parties would be necessary in order to estimate the approximate generation in next hour. Alternatively, separated model for predicting the PV generation would be necessary to determine the potential production in next hour for an actual installed system based on the historical data. However, the accuracy of such model would be necessary to test due to many factors influencing the PV generation locally.

From the analysis of Configuration 3 it has indicated that the battery system does not influence the operation of the heat pump in the system. The operation exhibited similar tendencies as the system without battery included. However, battery decreases the amount of electricity feed back into grid and increases the self-consumption of the household.

The effect on the thermal storage with respect to the optimal operation of thermal storage is not very comprehensible due to simplifications on modelling temperature behaviour in SystemFinder.

Additionally, thermal storage is often charged with gas boiler generation and it is in operation for periods when heating demand is not requested.

Finally, determining COP and consequent price for generation of each technology are features that enable to improve prediction of bivalent heat pump systems.

II. Evaluation of Models

Based on the exploratory analysis conducted in prior steps, three models have been designed to evaluate the importance of the features on the algorithm performance. There are three models designed for each configuration. First model considers ambient temperature at current time step as the only variable used to predict the operation of the hybrid heat pump system. That feature is selected as it is used to determine the ratio of operation between the generation technologies in current hybrid heat pump systems. Second model operates with features at current time step which are selected as relevant from the exploratory analysis provided in Chapter 3. Third model is an extension of the second one with additional time series for selected relevant features. The final results and comparison of each model and each configuration are presented on Figure 6 for MAE, Figure 7 for MSE and Figure 8 for R^2.

Observing the results of Model 1 of each configuration, it can be concluded that ambient temperature is an important feature as it presents descent performance of R^2 above 0.67, and errors in prediction for MAE and MSE below 0.4 kW. Model 1 presents a good baseline for comparison to more advance models (Model 2 and 3). Comparing Model 1 for each configuration it can be observed that Model 1 gives the best performance for Configuration 1. That can be explained as the Configuration 1 consist of basic hybrid heat pump system only and no other factors such as PV or storage systems are considered. When other technologies are introduced, the accuracy of the model using ambient temperature decreases as the operation is influenced by these factors.

Examining the results of Model 2 for all configurations, it can be concluded that selected features improved the prediction of model for all configurations as expected. Observing the evaluation results for the first three configurations we could conclude that the accuracy of prediction of operation of the system is quite high. The coefficient of performance R^2 is above 0,91 and error of the MAE and MSE is below 0,17 kW and 0,07 kW respectively. The operation of storages in Configuration 3 and 4 adds extra complexities, which deteriorate the final results, especially in M1 of Configuration 3 and all models in Configuration 4. Model 2 of Configuration 4 does not perform as good comparing to previous three configurations. Possible reasons are the inconsistency of the data for that given configuration; inappropriate selection of features or parameters; or necessity to include time series for this configuration with thermal storage.

Model 3 presents the best results for all configurations, giving R^2 of approximately 95 for neural network algorithm (NN) and above 90 for random forest algorithm (RF). Its error of prediction of MAE are below 0,118 kW for NN and 0,137 kW for RF while MSE below 0.06 kW for NN and 0.07kW for RF (with an exception of Configuration 4).

It can be concluded that proper selection of the features has a significant impact on the performance and accuracy of the algorithm prediction. Adding past time series for selected features improves results. However, the difference in result is not that significant. When selecting the features for the algorithm, it must be always taken into account the availability and accuracy of such data in real time.

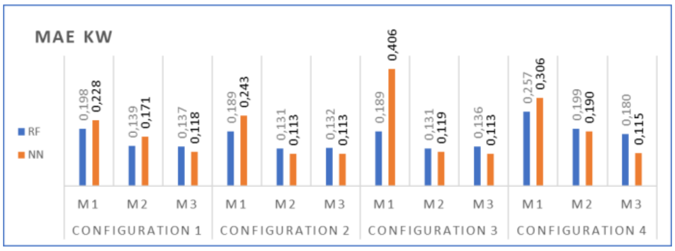

Figure 6 Result evaluation of Mean Absolute Error (MAE) for each model at each configuration

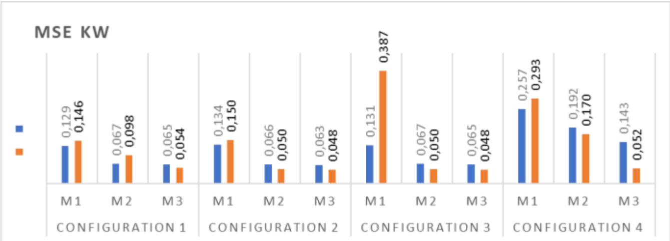

Figure 7 Result evaluation of Mean Square Error (MSE) for each model at each configuration

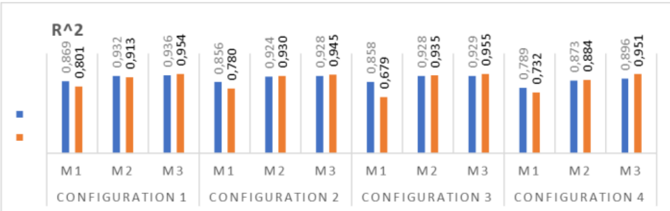

Figure 8 Result evaluation of coefficient of determination (R2) for each model at each configuration

III. Evaluation of machine learning algorithms

Three ML algorithms have been selected in order to analyse its suitability for the problem of prediction of the operation of the hybrid system. Random Forest Regression (RF) as an ensemble method easy to implement on tabular data, Neural Networks (NN) for its capability of capture complex relations between the features, and Long-Short Term Memory network (LSTM), that can process the interdependencies in long time sequences.

RF and NN have been applied on all three models and configurations. The results can be observed on metrics charts depicted on Figure 6, Figure 7 and Figure 8..

In order to compare the metrics of all three algorithms, Model 3 has been selected. That is due to the fact that model 3 applied on RF and NN includes time series for relevant features and LSTM processes all features as time series. The comparison of results for Model 3 of all three algorithms are depicted on Figure 9, , and **Error! Reference source not found.**.

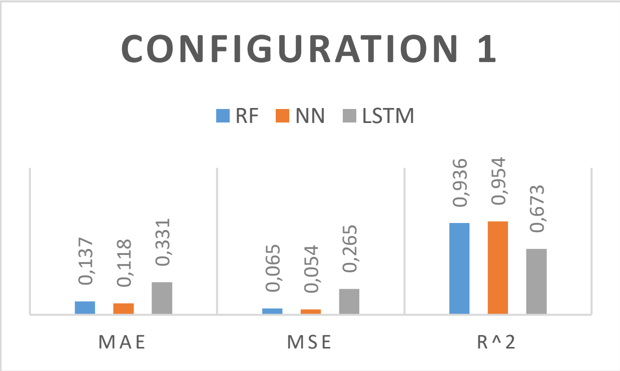

Figure 9 Comparison of results of each algorithm for Configuration 1

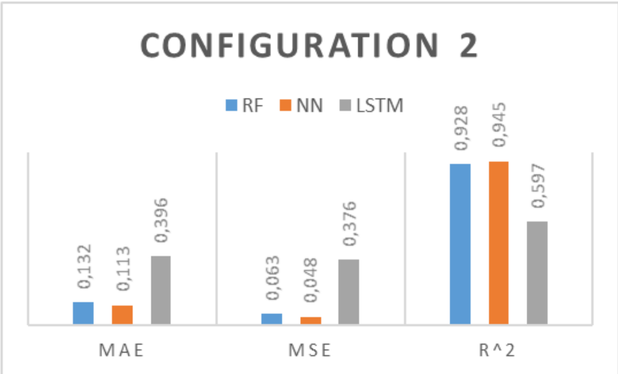

Figure 10 Comparison of results of each algorithm for Configuration 2

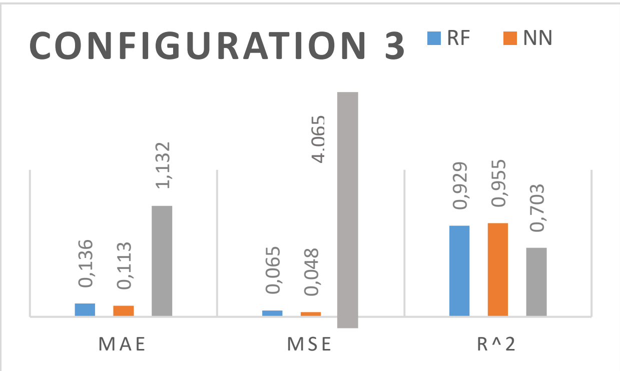

Figure 11 Comparison of results of each algorithm for Configuration 3

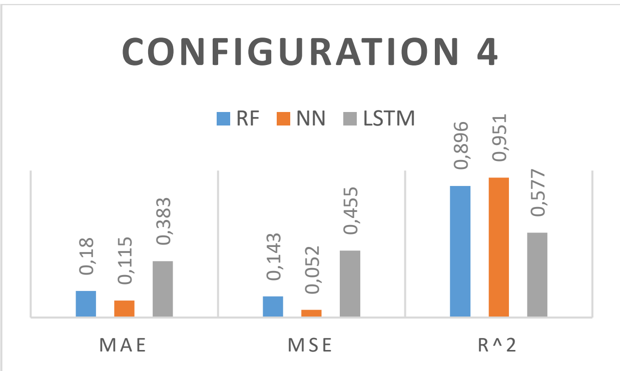

Figure 12 Comparison of results of each algorithm for Configuration 4

Random Forest (RF) Regression

The advantage of this algorithm is that it is very easy to implement as it does not require complex pre-processing, data scaling and works well on incoherent data. Also, it is very fast to optimize and to train. The disadvantage of the algorithm is that it is not able to capture complex relations between features as it works as an ensemble method.

For the Model 1, where only ambient temperature is considered, RF gives significantly better results comparing to NN results. The ensemble decision process behind the RF can capture the relation between one feature of ambient temperature and operation of the system in detail.

For Model 2, where more features are considered at current time step, RF can predict the operation of the generation technologies equally good as neural networks. In model 3, for which also time series of certain features are included, the performance of RF is slightly worse comparing to NN. However, the difference is not that significant. RF might not perform as good as NN for cases when the number of features increases and complexity of the relation between the features increases.

Observing the results achieved, it can be concluded that RF gives consistent results. Interestingly, the random forest algorithm can predict the operation of the heat pump more accurately compared to neural networks. On the other hand, the prediction of gas boiler operation is better predicted with NN.

Neural Network (NN) Regression

The advantage of NN is the capability of capturing complex interdependencies between the features. On contrary, this is redeemed by longer training time and parameter optimization.

For model 1, where only one feature (ambient temperature) is considered, the NN algorithm underperforms compared to RF. For this model, NN uses one hidden layer in order to detect the functional relation between the feature (Ambient Temperature) and labels (Gas consumption and Heat Pump input power). Adding more hidden layers worsens the performance of the algorithm. NN presents more inconsistences in performance comparing to RF. One particular case can be observed for Model 1 configuration 3, which demonstrates notably high error. However, the algorithm performs according to expectations when being tested with the dataset 2 of the same configuration.

NN improves its performance with respect to RF algorithm when increasing the number of features. That is due to the capability of NN to detect complex interdependencies between the features. Therefore, NN can predict operation of the system comparably well for Model 2. When the time series are taken account as for Model 3, NN present the best performance out of all three algorithms.

Long Short-Term Memory (LSTM) Network

Long short-term memory network processes each feature in the time series sequence. LSTM has been selected in order to determine if the model is able to capture the temporal aspect of configuration using storage elements. Based on the total one-year data provided, the model uses sequence of 28 days with the batch size of 4 months after. LSTM does not shuffle data for training and testing as RF and NN do. Instead, it uses sequence of data for training the algorithm and following sequence of data for testing.

The performance of LSTM is very inconsistent with R^2 between 0,577-0,703, error MAE between 0,331-1,132 and error of MSE between 0,206-4,065. This algorithm has not been proven as suitable for such problem primarily for two reasons. Firstly, the training of such model is lengthy as the number of features is high. Secondly the performance of the LSTM is very low comparing to both RF and NN. LSTM might improve its performance by providing longer period of data in order to detect seasonal specificity.

5. Conclusion

The aim of the presented thesis was to analyze the optimal operation of the hybrid heat pump system based on various variables and pricing using selected machine learning algorithms. At the same time, the potential of the algorithms was evaluated in order to enable the prediction of the optimal operation of the hybrid systems.

From the analysis and results achieved, it can be concluded that regression machine learning models have potential to be a significant part of the energy management activities for the future energy household management. It is necessary to always make sure what data are available in real time to be considered as feature for the algorithm.

The results of the evaluation of the machine learning models show that both random forest and neural networks with optimized parameters are suitable algorithms to predict the operation of the hybrid heat pump systems. On the other hand, the LSTM algorithm performed poorly for all configurations. Implementation of random forest algorithm should be considered for cases when easier implementation, faster training and optimization times are preferred and for cases with fewer features. Neural network is more recommendable for cases with large number of features and when accuracy is being prioritized.

SystemFinder model could be used as a tool in order to obtain training data for prediction of an optimal operation of the system by inserting household demand profiles and technology dimensioning as an input. The data generated from SystemFinder would be suitable to predict the operation with accepted accuracy. In order to verify if SystemFinder could be utilized for generation of such data, an implementation and data collection in an actual physical house would be necessary to conduct. Such verification would consist of data collection from sensors in real system in order to implement them as an input variable to generate the optimal operation. Consequently, an analysis of the optimal operation and training of the algorithms would be carried and evaluated. Such implementation of the predictive algorithm into control of hybrid heat pump would be the next step.

Based on the results in this work, recommendations for the future research and implementation are listed as follows:

1. Data for longer period of time than one year for selected household should be provided in order to improve the accuracy of the algorithm and at the same time prevent algorithm from overfitting.
2. Additionally, to establish if the approach is adaptable, the algorithms should be testes on data for various households and location profiles.
3. Consider smaller time interval of prediction (20 minutes or 30 minutes interval) as well as larger time intervals to improve the accuracy of the model.
4. Adding indoor temperature as feature would open the approach also for other methods such as reinforcement learning.
5. As a next step would be recommendable to implement predictive model into controller which also takes into account the user preference as a respond value and test the prediction in real settings to verify its functions.

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