Application of Support Vector Machines for Predicting the Performance of Air-Source Domestic Hot Water Heat Pump Systems

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Abstract

A compact air-to-water heat pump (AWHP) is a novel technology that combines a domestic hot water (DHW) system with an air conditioning system. Its main application focuses on residential houses and apartments. However, the performance of the DHW AWHP is widely unpredictable. Additionally, occupant's behavior is one of the main reasons for the widely variable system's coefficient of performance (COP). For that purpose, different support vector machines (SVM) are trained to recognize the patterns of the hot water consumption and to predict the resulting COP. The predictions are made in a discrete and independent time domain. In the following step, the predicted DHW consumption in sub-hourly intervals will be integrated per week, and the resulting weekly COP will be computed. As the result, operation of AWHP system over 51 weeks can be evaluated, and the predicted COP will be compared to the measured performance. The results pointed out comparable performance as detailed calibrated thermal simulations, while the computational costs of the evaluation process remained lower in comparison to the physical system's modeling. Since no AWHP system specific information are required, this method is applicable for a wide range of DHW AWHP systems.

Introduction

Heat pumps are used for recovering heat from different sources. They are used for heating, cooling, DHW as well as for air conditioning (Bonin, 2015). In case of the compact AWHP, the water storage is connected with a heat exchange unit, which leads to minimizing the distribution heat losses. However, user behavior influences the system's COP, and it may cause a poor efficiency of the system.

Occupant behavior is identified as one of the main sources of discrepancy between the predicted and actual building energy consumption (Demeester et al., 2013), (Hoes et al., 2009), (Yu et al., 2011). In case of the DHW, the systems energy consumption and performance are conventionally predicted based on synthetic hot water consumption profiles. George et al. (2015) concluded that a drawback of synthetic profiles is their inability to capture the true temporal variation in consumption patterns, as they rely on engineering judgment and expectation. In addition, Ahmed et al. (2015) pointed out that an hourly schedule of DHW consumption is strongly cultural and user sensitive. For instance, they showed that an average user in Germany has a peak consumption during morning hours, opposite to the average user in neighboring Netherlands, who uses the maximal DHW water amount in the evening and early night hours. In contrast, Calì et al. (2016) presented the data collected from 90 apartments in Germany and pointed out that the vast proportion of DHW is consumed in the late afternoon hours. Based on that, applying a general DHW system's operating schedule could lead to poor system performance and raised occupants dissatisfaction.

The start hypothesis of this work is that modeling the DHW consumption based on the data including indoor air temperature, outdoor air temperature and household's electrical energy consumption may lead to more accurate thermal building simulation and AWHP performance estimation, compared to the implementation of temporally repeated, measured DHW consumption and generic DHW consumption profiles.

Another issue in case of modeling the DHW consumption and DHW systems performance arises in modeling the apartments with occasional occupancy or in cases where extensive DHW consumption (showering, bath etc.) occurs in wide ranges of frequencies in time domain. In this case, a deterministic model such as the thermal simulation of the DHW HP system may provide insufficient accuracy. For that purpose, a data driven prediction of the systems performance is developed based on occupant behavior, using the in-situ monitored air temperatures and electrical energy consumption as inputs. By applying machine learning methods, DHW consumption profiles and resulting weekly system performances are generated as outputs. Due to the high level of unpredictability of the occupant behavior in the time domain, temporal distribution of the DHW consumption is not taken into account.

 https://doi.org/10.26868/25222708.2017.156

Related Research

Although there is an increasing number of publications on the performance of ground source heat pumps (GSHP), there are few studies about the performance of compact ASHP for DHW. Hadorn, J.C. (2015) made a detailed summary of the results of eighteen major heat pump studies conducted in Europe between 2010 and 2014. The study included five DHW photovoltaic systems, but there was no research about compact heat pumps. Safa et al. (2015) compared an ASHP to a GSHP, and concluded that opposite to a GSHP, an ASHP has a higher unpredictable performance, basing his study on monitoring data of both systems over three weeks. Xu, G. and Zhang, X. and Deng, S. (2006) concluded that an air source solar heat pump in cold and rainy weather operates like an ASHP. The test results for that case pointed out that lower air temperatures have a negative impact on the COP, compared to summer weather conditions.

Fraunhofer ISE (2011) conducted a vast research on the heat pump performance based on the monitoring data of 112 HP systems, including 18 ASHP systems. They concluded that air-to-water HP systems have little seasonal performance oscillations compared to GSHP. In addition, they found out that ASHP systems have a peak performance in transitional months (spring and autumn), while the lowest performance is achieved in July and January.

Machine learning methods, including artificial neural networks (ANN) and SVMs are widely used for the prediction of building energy consumptions (Neto and Fiorelli, 2008), (Khosrowpour et al., 2016), (Li et al., 2009b), (Li et al., 2009a), (Yu et al., 2016), (Dong et al., 2005). They found a wide range of applications for predicting both buildings' systems performance, as well as long and short term energy consumptions.

SVMs were applied for predicting the performance of ground source heat pumps (GSHP), while applications for ASHP systems have been rare. Esen et al. (2008) concluded that a SVM outperforms ANN in the case of modeling the performance of the GSHP. Furthermore, Mathioulakis et al. (2016) predicted the performance of AWHP for domestic hot water using an ANN. They stated that an ANN could represent an effective tool for the prediction of the AWHP performance in various operation conditions.

System Description

The investigated AWHP system is presented in Figure 1. It consists of a ventilator used for the air conditioning, heat exchange cycle containing the evaporator, compressor, liquefier and water storage tank. In addition, it is equipped with an electric smart controlling unit that aims to minimize the electrical energy consumption.

The ventilator (1) forwards air to the heat exchanger where the thermal energy of the air is retracted in a process of evaporation (2). The thermal energy is transferred with the refrigerant to the electrically driven compressor (3), where it is compressed to higher pressure. At the liquefier (4), the heat is transmitted to the water medium through heat exchange. Eventually, an expansion valve (8) depressurizes the liquid heat exchanger.

Hot water is stored in the hot water storage tank (5), until it is consumed at the tap station. Due to hygiene reasons, a heater (6), controlled by a temperature controlling unit (7), is installed in the water tank. The ventilator uses indoor air in the

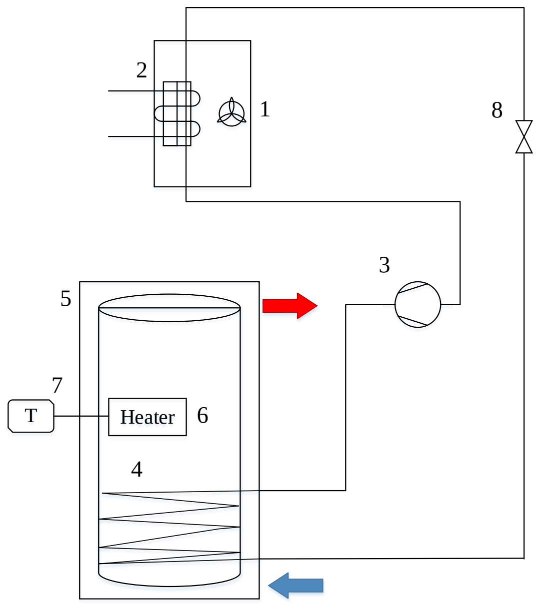

Figure 1: Schema of the investigated system.

months when the indoor temperatures are higher than outdoor air temperatures, and switches to outdoor air during the warm months. As a compact decentral hot water unit, it produces hot water for a single household, consumed in bathroom and kitchen.

The system's performance is evaluated by the weekly performance, which is defined in equation 1

$$COP = \frac{Q_{DHW}}{W_{electrical}}, \qquad (1)$$

where Q_{DHW} is the overall consumed thermal energy and $W_{electrical}$ is the sum of the electrical energy consumption per operating cycle. The electrical energy consumption includes the consumption caused by compressor, heater and ventilation during compressor operation and basic operation. Since a single sensor registers electrical consumption by all system's components, an exclusion of the consumption caused by heater and basic ventilation was not applicable, which may lead to lower performance values compared to COP defined by DIN EN 16147 (2011).

Data Set

Data are collected minute-wise as a part of an energy-monitoring project of two identical apartments in the South of Germany. Sensor data include consumed thermal energy in form of DHW, electrical energy consumption, indoor air temperatures as well as outdoor air temperatures.

Sensor data are imported from the project's database. A time synchronization is realized by joining the data points collected through the different sensors within the same minute. For this purpose, a nearest neighbor algorithm is implemented. Outlier removal is performed by a range check. As a result, the data points outside of the plausible measuring range are excluded from further evaluation. Possible outliers caused by system measuring inaccuracies within the plausible range have not been handled. This sort of outliers may be caused by hypothetical sensors inaccuracies and will be ignored in the course of this work. Electrical energy consumption per fifteen minutes is computed as the derivative of the electrical energy in time domain discretized per 15 minutes, while the electrical consumption of the heat pump is computed by integrating the HP electrical power.

Indoor air temperature is measured as a dry bulb temperature using a temperature sensor placed on the wall at 1.0 m height. Change in the indoor air temperature is computed as the difference in temperature per fifteen minutes while the outdoor air temperature is measured by a weather station on site.

Thermal energy is computed by integrating thermal power consumption measured each minute over fifteen-minute intervals. Due to data loss caused by sensor failure, thermal consumptions between October 2015 and the middle of December 2015 are computed using measured water mass flow, inlet- and outlet temperatures.

Classification of DHW Consumption

Monitored DHW consumption consists of tapping events, where a tapping event is defined as hot water consumption of variable duration with possible interruptions shorter than one minute, registered by a sensor on the hot water outlet. The mean duration of a tapping event is 16.41 minutes. There are around 1000 consumption events recorded over thirteen months. Due to the sensor's technical features, events with the duration of under four minutes were not registered. In the next step, data is discretized in the time domain, and the tapping events are integrated per time step. For that purpose, the discretization is performed for 15, 30 and 60 minutes time intervals. A histogram of the DHW consumption for varied time discretization is presented in Figure 2.

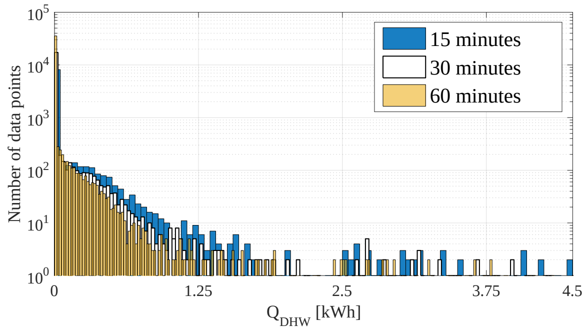

Figure 2: Histogram of the DHW consumption for varied time discretization

Classes of the different consumption activities for varied time discretization are established. Since the distribution of the consumed thermal energy does not show significant differences for the varied time intervals (Figure 2), it is opted for a unique labelling for all cases of performed time discretization. Data points where no DHW consumption took place are labelled as class 0. Class 3 consists of data points with consumption above 2.5 kWh, due to their clear separation from the lower thermal energy consumption. In order to make a meaningful differentiation in DHW consumption range between 0 and 2.5 kWh, the DHW consumption is clustered using the Euclidean distance. The motive behind the clustering of DHW consumption is to establish the border between the different consumption units that are applicable for different time intervals, while maximizing the number of points in the higher class.

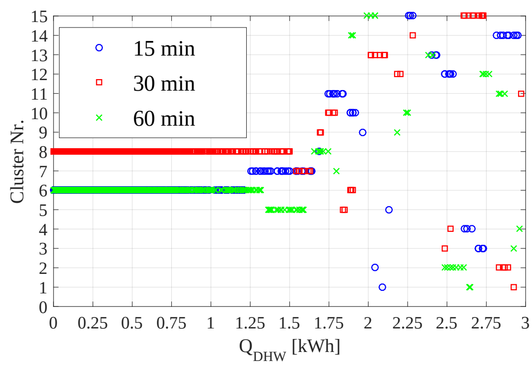

Figure 3: Clustering DHW consumption into different subgroups, based on the amount of consumed thermal energy

The final amount of clusters is established through an iterative process over the number of clusters. It was aimed for a minimum number of clusters, for which an unique labelling in case of all three time discretization intervals would be possible (15-, 30-

and 60-minutes intervals). By clustering the data in 15 clusters (Figure 3), it is opted to define the class 1 as the consumption in the range under 1.25 kWh, and to join the further minor clusters into class 2, which resulted in approximately 0.5 % of incorrectly labeled data points.

Since over 80 % of the data points consist of data where no DHW consumption occurred, there is no proportional distribution of data points per each class. Such a property of a data set is commonly referred to class imbalance and the classes presented by a significantly smaller proportion of data points are defined as under-represented classes.

In case of the imbalanced data sets, there exist two possible approaches proposed by Akbani et al. (2004), He and Garcia (2009) and Tang et al. (2009) in order to improve the model's performance. Firstly, having the equal proportional of each class in the training sample is a widely used method in case of unbalanced data sets. On the other hand, increasing the penalty factor for the under-represented classes is an alternative approach to deal with unbalanced samples, which is common in machine learning classification problems. In this case, it is opted for adjusting the higher penalty factor in case of the classes with the lower proportion of representation.

Eventually, the classified thermal energy consumption is presented in Table 1. The activities that possibly led to different consumption classes are assumed based on DHW consumption events definition proposed by Balke et al. (2016) and DIN EN 16147:2011.

Table 1: Overview of the modelled SVM classifiers.

Class	$Q_{thermal}$ **[kWh]**	**Assumed activities**
0	0.00	no DHW consumption
1	0.00-1.25	hand washing, cooking
2	1.25-2.50	showering
3	above 2.50	bathing

In the following step, five dimensions were projected into two dimensions with the aim of answering the question if there is a pattern behind the measured air quality values and electrical energy consumption, identifying possible DHW consumption in real time?

For that purpose, the DHW consumption is visualized using the t-SNE algorithm. t-SNE is a technique that visualizes high-dimensional data by giving each data point a location in a two or three-dimensional map (van der Maaten, L., Hinton, G., 2008). It is a powerful tool for visualizing high dimensional data sets and it gives good embedding results with comparably low computational costs in case of lower dimensional problems, such as DHW. As presented in Figure 4, sensor data collected in the household, which is not directly associated with the thermal energy consumption could be clustered based on the ongoing DHW consumption.

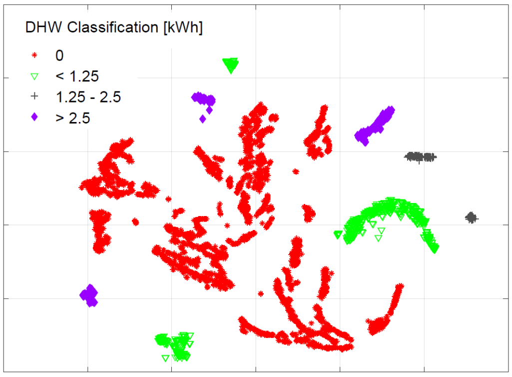

Figure 4: Projection of DWH consumption (5D) per 15 minutes in two dimensions using t-SNE

Feature Selection

Models are created using the features derived from the collected data:

- household's electrical energy consumption,
- heat pump's electrical energy consumption,
- measured air temperature in kitchen,
- measured air temperature in bathroom,
- summed air temperature changes in the in kitchen,
- summed air temperature changes in the in bathroom,
- outside air temperature.

For each data point, the features on the current and previous time step are taken into account, which resulted in a fourteen-dimensional feature space.
In order to avoid numerical problems during the following computation processes, feature scaling of the predictor data is performed. Table 2 lists the minimal and maximal values registered per 30 minutes for each feature.

Table 2: Minimal and Maximal feature values.

Feature	**Unit**	**Min.**	**Max.**
$Q_{Household}$	kWh	0.003	1.297
Q_{AWHP}	kWh	0.08	0.913
$\Delta\ T_{bathroom}$	$^\circ$ C	0	3.8
$\Delta\ T_{kitchen}$	$^\circ$ C	0	4.1
$T_{bathroom}$	$^\circ$ C	17.9	25
$T_{kitchen}$	$^\circ$ C	16.4	25.1
$T_{outdoor}$	$^\circ$ C	-9.9	34.2

Training Set

The data set is split into a training set and an evaluation set. The training data consists of blocks of data points from each month of monitoring. In order to exclude the time dependence of the data points, the training set is shuffled prior to the model training.

For that purpose, a Gaussian SVM is trained with a varied training set size, prior to a parameter tuning. An estimation of the optimal training set size is based on the evaluation of the training error.

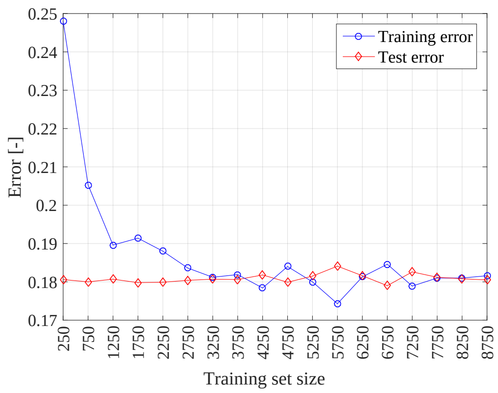

Figure 5: Training- and evaluation error.

The training set size is depending on the chosen step size. In case of modeling per fifteen minutes, an optimal training size consists of 22000 data points. In case of a step size of 30 minutes, the training error converged around 1500 data points, resulting in significantly smaller training size.
In case of the 15 minutes time steps, training data points are chosen as data collected during approximately three weeks from each monitored month. For classification of the 30-minutes data points, the training set consists of monitoring data collected during one week of January, April, July and October.

Evaluation Set

In case of 15 minutes time steps, the evaluation set consists of approximately 13000 data points that were not included into the training set. It consists of the time series where each data point presents measured features over fifteen minutes. Each time-series has approximately 1000 data points, for which the classification of the thermal energy is performed, and eventually integrated over the time domain.

Method Description

SVMs Theory

SVMs classifiers are a set of methods that extract models or patterns from data (Magoulès, 2016) which try to find a hyperplane that maximizes the margin between the different classes. For a detailed theoretical background, the reader is referred to Bishop (2009). In case of a linear, two class problem, the classification has the following form:

$$y(x) = w^T \phi(x) + b, \tag{2}$$

where $\phi(x)$ denotes a fixed feature space transformation and b is the explicit bias parameter. The training data include N input vectors $x = x_1 ... x_N$, with corresponding target values $t = t_1 ... t_N$. In SVMs, the decision boundary is chosen to be the one for which the margin is maximized. The margin is given by the perpendicular distance to the closest point x_n from the data set and optimize w and b in order to maximize the distance

$$\arg\max_{w,b} \left\{ \frac{1}{\|w\|} \min_n \left[t_n \left(w^T \phi(x) + b \right) \right] \right\}. \tag{3}$$

Since there is always a closest point to the margin, the distance is maximized as $\|w\|^{-1}$, which is equivalent to minimizing $\|w\|^2$:

$$\arg \min_{w,b} \frac{1}{2} \|w\|^2. \tag{4}$$

Lagrangian multipliers are introduced to solve this constrained problem in form of the following Lagrange function:

$$L(w,b,a) = \frac{1}{2}\|w\|^2 - \Sigma_{n=1}^{N} a_n \{t_n(w^t \ \phi(x_n) + b) - 1\} \tag{5}$$

By setting the derivatives of $L(w,b,a)$ with respect to w and b, the following conditions are obtained:

$$w = \Sigma_{n=1}^{N} \ a_n \ t_n \ \phi(x_n) \quad \text{and} \quad 0 = \Sigma_{n=1}^{N} \ a_n \ t_n. \tag{6}$$

Eliminating w and b from $L(w,b,a)$ using these conditions gives a dual representation of the maximum margin problem in which $L(a)$ is maximized.

$$L(a) = \Sigma_{n=1}^{N}(a_n) - \frac{1}{2}\Sigma_{n=1}^{N} \ \Sigma_{m=1}^{N} a_n a_m t_n t_m k(x_n, x_m). \tag{7}$$

The sign of $y(x)$ is evaluated in order to classify the new points. This is expressed in terms of parameters a_n and a kernel function by substituting w:

$$y(x) = \Sigma a_n \ t_n \ k(x, x_n) + b. \tag{8}$$

This is a constrained optimization problem that has to satisfy the Karush − Kuhn− Tucker conditions:

$$\begin{aligned} a_n &\geq 0, \\ t_n y(x_n) - 1 &\geq 0, \\ a_n t_n y(x_n) - 1 &= 0. \end{aligned} \tag{9}$$

with $a_n = 0$ not appearing in the SVMs, while the remaining points are the support vectors. SVMs have to be allowed to misclassify some points with a penalty that increases with decreasing distance to the margin. As a result, ξ is introduced, while further conditions remained unchanged (equation 9). The exact classification is now

$$t_n \ y(y_n) \geq 1 - \xi. \tag{10}$$

The points $0 \leq \xi \leq 1$ lie within the margin but on the correct side of the decision boundary.

The goal is to maximize the margin while softly penalizing the points on the wrong side:

$$C\ \Sigma_{n=1}^{N}\ \xi_n\ +\ \frac{1}{2}\|w\|, \tag{11}$$

where C controls the slack variable penalty and the margin. Now, the Lagrange function is minimized with respect to constrains:

$$\begin{aligned} L(w,b,a,\xi,\mu) = \frac{1}{2}\|w\|^2\ +\ C\Sigma_{n=1}^{N}\xi \\ -\Sigma_{n=1}^{N}a_n\{t_n\ y(x_n - 1 + \xi_n)\} - \Sigma_{n=1}^{N}\ \mu_n\ \xi_n, \end{aligned} \tag{12}$$

By eliminating w, b, ξ_n, the Lagrangian form is obtained

$$L(a) = \Sigma_{n=1}^{N}(a_n) - \frac{1}{2}\Sigma_{n=1}^{N}\ \Sigma_{m=1}^{N}a_n a_m t_n t_m k(x_n, x_m). \tag{13}$$

with the constraints

$$0 \le a_n \le C\ \ and\ \ \Sigma_{n=1}^{N}\ a_n t_n = 0. \tag{14}$$

SVM Classification of Thermal Energy Consumption

Different SVM classifiers are trained with the aim of obtaining the method with the best performance in terms of prediction accuracy. Eventually, results are evaluated and the performance of individual classifiers is compared. An overview of the tested models is listed in Table 3.

Table 3: Overview of the trained SVM classifiers.

	Method	Description
Case 1	Linear Quadratic Cubic Gaussian	classifiers generated and trained using the MATLAB Classifier Toolbox
Case 2	Gaussian	joined binary classifiers with adjusted parameters for under-represented labels
Case 3	Gaussian	hierarchical joined binary classifiers

Case 1: Application of SVM Algorithms

SVM classifiers are trained using the MATLAB Classification Toolbox, which includes supervised learning algorithms for binary and multi-class problems. Parameter tuning for the generated models is performed using a grid search, where the penalty parameter C is varied between 2^0 and 2^{10}. In case of a radial basis function (RBF) kernel, σ is varied between 0.05 and 1.00. A one-versus-all classification method based on the early training results is chosen. An overview of the trained models and tuned parameters is presented in Table 4.

Table 4: Classifiers generated using the MATLAB Toolbox.

Method	Parameters (15 min.)	Parameters (30 min.)
Linear	C=64	C=256
Quadratic	C=16	C=512
Cubic	C=8	C=512
Gaussian	C=8, σ= 0.122	C=16, σ= 0.500

Case 2: Treating Under Represented Classes with Joined Binary Classifiers

In case of a thermal energy consumption, the classification problem is an imbalanced data set with four possible labels. For that purpose, it is opted for one-versus-all method, and four binary classifiers are implemented. The predictions made by all four classifiers were ensembled. In case of a classification of one of the same points in the multiple classes by each classifier, the advantage is given to the under-presented label. Eventually, the remaining unclassified points were treated and the performance is evaluated. The training algorithm is presented in Figure 6.

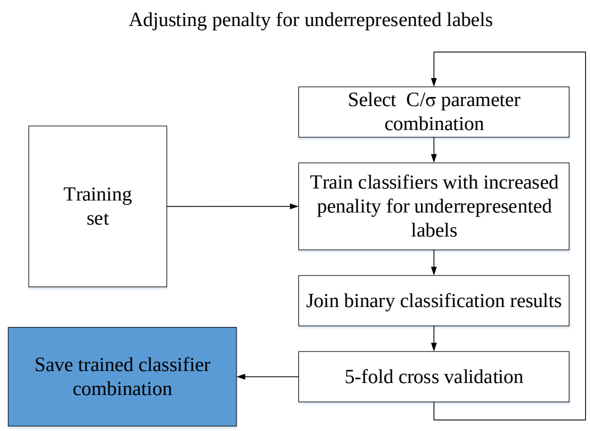

Figure 6: Implemented algorithm with higher penalty for under-represented labels.

Parameter tuning is performed by implementing a grid search for parameters σ and C, with taking an increased penalty factor for the under-represented classes into account. A five fold cross validation is performed during model training in order to avoid over-fitting, and a mean misclassification rate per each training combination of σ and C parameter is computed. The results of the grid search are presented in Table 5.

Table 5: Parameter combination for the hierarchical classifers.

Classifier	C	σ
0	2	0.125
1	8192	0.167
2	2048	0.500
3	2048	0.250

Case 3: Hierarchical Classifier

Two layer classifier is developed by merging four binary one-versus-all classifiers and training sets divided into two subsets. The first subset consists of all training data points, while the other subset contains only labels indicating the presence of the water consumption (labels 1/2/3). In the first layer, binary one-versus-all classifier is trained to distinguish whether a DHW consumption is present. The second layer consists of three one-versus-all classifiers predicting the amount of DHW consumption by sorting the data points in classes one, two or three. Eventually, by assembling the results of all four classifiers, the output data is created. The training procedure of the merged classifiers is validated using a five-fold cross validation. A representation of the implemented algorithm is presented in Figure 7.

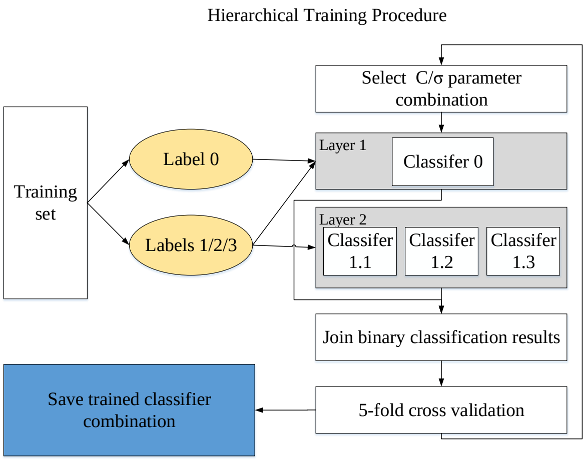

Figure 7: Hierarchical SVM algorithm.

Parameter tuning is performed using a grid search for C and σ combination separately for each of binary classifiers, with the highest performance achieved in case of the parameter combination presented in Table 6.

Table 6: Parameter combination for the hierarchical classifers.

Classifier	C	σ
0 vs. 1/2/3	64	0.500
1 vs. 2/3	256	0.167
2 vs. 1/3	4	0.250
3 vs. 1/2	16	0.125

Estimation of the System's COP

In order to compute the AWHP system's COP, the predicted thermal energy consumption is divided by measured electrical energy. For that purpose, predicted thermal energy consumption is integrated in the temporal domain and grouped on a weekly basis. Additionally, a hard constraint is added, in form of maximal uninterrupted low thermal energy consumption duration of 2.5 hrs (example: maximal 5 consecutive 30 minutes intervals where at least one sink activity was present).

Model Evaluation

Thermal Energy Classification

In case of the supervised learning models on the unbalanced data sets as presented in this paper, the conventional evaluation practice of using singular assessment criteria, such as the overall accuracy or error rate, does not provide adequate information in the case of unbalanced learning (He and Garcia, 2009). In order to reliably represent the performance, the evaluation criteria has to take the accuracy of the under-represented labels into account. This is done by analyzing the prediction accuracy for each separate label, which can be achieved using the confusion matrix, where columns and rows represent the predicted and real labels respectively. As a result, the accuracy for each modelled class can be analyzed. Furthermore, an overview of the misclassification cases can be achieved, since it is presented in which class the data points are misclassified.
Another widely used metrics in case of the evaluation of imbalanced data sets is balanced accuracy.

The balanced accuracy for each class i is computed as the arithmetic mean of the sensitivity and specifity (Brodersen et al., 2010), while the overall balanced accuracy is computed using the average values of the balanced accuracy of all possible classes.

$$B_i = \frac{1}{2}\left(\frac{TP_i}{TP_i + FN_i} + \frac{TN_i}{FP_i + TN_i}\right), \tag{15}$$

with: TP_i- true positive rate for label i, TN_i- true negative rate for label i, FP_i- false positive rate for label i, FN_i- false negative rate for label i.

Estimation of the COP

Prediction of COP per operating cycle is quantified using the mean absolute error (MAE) and standard deviation between the predictions and measured performance. MAE is computed using the following equation:

$$MAE = \frac{1}{n}\sum_{i=0}^{n} \text{abs}(COP_{measured} - COP_{predicted}), \tag{16}$$

while standard deviation is computed as follows:

$$\sigma = \sqrt{\frac{\sum_{i=0}^{n} \mathrm{abs}(COP_{measured} - COP_{predicted})}{(n-1)}}. \tag{17}$$

Results and Analysis

Classification of the Thermal Energy Consumption

Classification results of the tested SVM models are listed in Table 7 and evaluated based on the overall accuracy.

Table 7: Balanced accuracy for 15- and 30 minutes data points.

Case	Method	Balanced accuracy (15 min)	Balanced accuracy (30 min)
1	linear	0.53	0.44
	quadratic	0.48	0.50
	cubic	0.44	0.49
	RBF	0.25	0.41
2	RBF	0.57	0.51
3	RBF	0.56	0.55

Figure 8 presents a confusion matrix of the hierarchical SVM classifiers. The classification of the classes 0 and 1 is performed with a higher accuracy compared to the higher classes. Thus, since the points of the higher classes were mostly misclassified in neighboring classes, this does not have a strong influence once the thermal energy is integrated in the time domain.

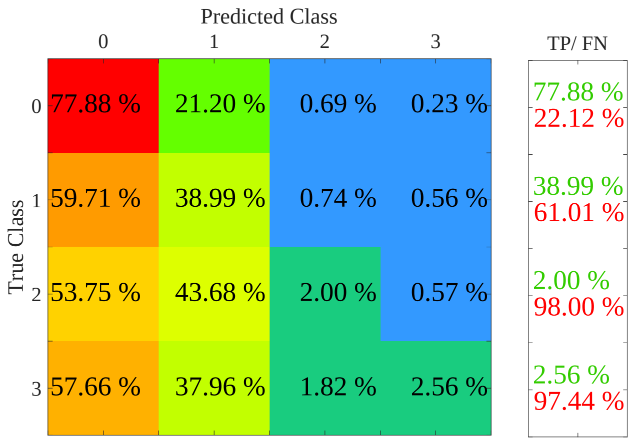

Figure 8: Confusion matrix of the SVM classification.

Prediction of the Coefficient of Performance

Figure 9 shows a comparison of the predicted and measured COP per operating cycle. Each data point in Figure 9 refers to a weekly system's COP. As presented in Figure 9, predictions are mostly inaccurate when the measured COP is zero, which is a result of no hot water consumption over a week. In this case, the model output failed to detect that there will occur no DHW consumption for a week. However, the developed model pointed out a lower COP, compared to cases where the occupant was present in the apartment during a 7 days time interval.

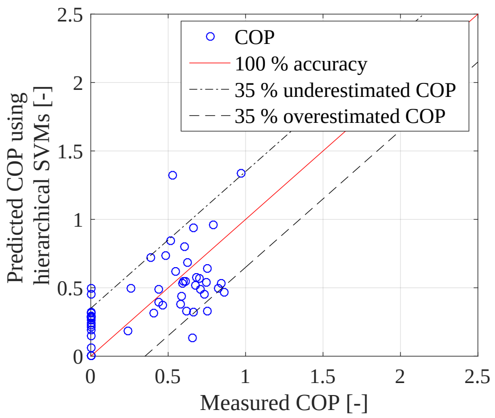

Figure 9: Comparison of the predicted and measured weekly performance.

The results are presented in Table 8, and compared to the COP predictions made using a detailed thermal simulation.

Table 8: SVMs classification results.

Method	MAE [-]	Standard dev. [-]	Comp. time
Hierarchical SVM (30 min)	0.238	0.492	4.11 sec
Applying thermal model	0.271	0.601	95.40 sec

Discussion and Conclusion

Since the training error converged at a mean average error of 18 %, the set of features is not powerful enough to fully represent the output. However, the final COP prediction is still more accurate, compared to the thermal simulation with a synthetic DHW consumption profile as input. Although the model showed good performance for detecting the DHW consumption events, it has poor accuracy for determinating the amount of consumed energy (classes 2-showering and 3-bathing). This is due to the under-representation of these data points in the available data set. Hence, model training on more representative data set is needed.

Although most DHW events have a duration of 1-7 minutes (Balke et al., 2016), optimal time discretization in achieved in case of 30 minutes steps. In addition, training in case of the 30-minutes time discretization required significantly less data points compared to a 15-minutes discretization. One of the possible reasons for such results is that a finer discretization is insufficient to describe the activities that usu-

ally occur prior to the water consumption. These may include apartment occupancy, or diverse activities in the kitchen and bathroom, which contain information needed for predicting DHW consumption event. These information are used in form of change in the indoor temperature by occupants presence, window opening, cooking and diverse source of electrical energy consumption.
An application of SVMs for thermal energy classification leads to comparable accuracy of the estimation of the COP compared to the detailed thermal building simulation, while reducing the computational time. Different modelling approaches pointed out that the hierarchical SVMs lead to significantly better performance, compared to the SVMs classifiers generated by a MATLAB classification toolbox. In addition, hierarchical SVMs outperformed the classifier with higher penalty factors for the under-represented classes.
This model may be coupled with a thermal building simulation for modelling DHW consumption events based on the further activities. In addition, this method is suitable for modelling the AWHP system's performance by using the occupant behavior data that are not in direct relationship with the DHW consumption. This is of a significant importance for the overall building simulation. In that case, an additional simulation input for the DHW consumption profile is not needed. One of the main contributions of this work is that it does not require any input information about the AWHPs technical details. As a result, it is applicable for a wide range of decentral DHW heat pumps.

Acknowledgements

We appreciate the financial support of this work by the German Federal Ministry of Economics and Energy (BMWi) as per resolution of the German Parliament under the funding code 03ET1289D.

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