# Forecasting Heat Demand with Complex Seasonal Pattern Using Sample Weighted SVM

Masoud Salehi Borujeni, Wanqing Zhao

***Abstract*— Short-term forecasting of heat demand is crucial for controlling district heating networks and integrated electricity and heat supply systems. The forecast specifies an estimate of the energy required in the coming hours which enables the controller to proactively manage the storage units and schedule the heat generation. Consequently, improving the accuracy of heat demand forecasting can lead to reduced operational cost and increased reliability of the energy supply. This paper presents the development of a sample weighted Support Vector Machine (SVM) to improve the accuracy of heating demand forecasting. As the dynamics of heat demand time series change over time, recurrence plot analysis is first used to investigate any seasonal behavior and its relationship to ambient temperature. Then, to capture this seasonal behavior, a membership-function-based method is presented to generate the weight of each sample in learning a SVM model. This method is evaluated using a dataset with half hourly resolution from an industrial case study in the UK. Compared to conventional forecasting methods, the proposed approach shows significantly better accuracy in 24 hours ahead forecasting of heat demand.**

**Keywords—heat demand, recurrence plot, seasonal behavior, online forecasting, district heating system.**

## I. Introduction

Due to the fast growth of microgrids and smart district heating systems, a wide range of controllers for optimal control of these systems have been developed aiming to improve operational efficiency and reduce energy costs and GHG emissions. Among these, the prediction-based method has been shown particularly efficient to optimize the operation of such systems [1]. As it uses predicted values of power generation and consumption in the coming hours, the controller can use those estimates to optimally schedule the generation and manage the storage units to handle future energy shortage/surplus [2]. One of the important variables that its accurate forecasting can significantly reduce the operating costs, is the heat demand [3]. It includes hot water consumption and space heating, accounts for a high percentage of total energy consumption. In the UK, the heat demand's share of total energy use in homes is about 68% [4]. The predicted heat load (usually for a short-term period e.g. 24 hours) can be used in the optimal control of combined heat and power (CHP) units, boilers, or heat pumps [5].

In previous studies, different methods were used to forecast the heat demand being a time series prediction problem. Fang and Lahdelma (2016) analyzed heat demand data and selected the influencing variables such as air temperature and wind speed as the inputs of a seasonal autoregressive integrated moving average (SARIMA) [6]. Ahmad and Chen (2018) have developed different machine learning models such as Gaussian process regression, multiple linear regression, and artificial neural network to predict heat demand. Their models have been made to consider many variables, including ambient temperature, wind speed and direction, and solar radiation [7]. Similarly, this was done by Idowu et al. (2014) using different machine learning approaches and they incorporated the ambient temperature, solar radiation, and humidity into the model [8]. Although these studies have attempted to develop a variety of methods for modeling heat demand, their common denominator is to highlight the seasonal behavior of heat demand.

Some other studies have mainly focused on addressing the seasonal behavior of heat demand. Bergshtinson et al. (2021) have shown the seasonal behavior of heat demand throughout the year and accordingly classified one year data into summer, winter and a transition period [3]. Potocnik et al (2021) in addition to seasonal behavior, provided a detailed description of the various linear dependence between ambient temperature and heat demand in different seasons [9]. This seasonal behavior, which is also observed in other variables such as solar radiation and wind speed [10], can be modeled by using a time parameter as an input in predictive models [6] or by classifying the dataset into different seasons [11]. However, the main challenge in both methods is recognition of different seasons and the transitions between them.

This paper presents a novel method for modeling such seasonal behavior based on the sample weighted training approach. Initially, linear and nonlinear methods are utilized to analyze heat demand data, and then the effect of ambient temperature on this variable is investigated. The Recurrence Plot (RP) is used as a nonlinear data analysis technique to recognize the different seasons based on the structural changes in the dynamical behavior of heat demand. Then, based on the results of the analysis, a new method for modeling heat demand is presented. The proposed approach incorporates the seasonal behavior of data into SVM model training by means of a weight coefficient. The results show that this technique increases the accuracy of heat demand forecasting compared to the conventional methods.

The paper is organized as follows. Section 2 introduces the data of a case study and describes the data analysis. Section 3 presents the proposed sample weighted model for forecasting the heat demand. Section 4 provides a comparison of the results between the proposed approach and other machine learning approaches. Finally, section 5 concludes the paper.

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## II. Data Description and Analysis

This section presents the dataset of heat demand and its dynamical and seasonal behavior analysis as follows:

### A. Site and Data

Half-hourly heat demand data and ambient temperature for one year from 01/01/2020 to 31/12/2020 are shown in Fig. 1. Heat demand data are provided for an initial phase of a development of 153 properties including 1-to-3-bedroom flats, 3-bedroom semi-detached houses, and 4-bedroom detached houses in the southeast of the UK. The energy system was modelled by SMS-PLC with contributions from Vital Energi Utilities Limited, taking into account the building archetypes, dimensions and constructions, as well as meteorological data of the region. It is considered that the daytime internal temperature set point is 21˚C until 10 pm and 16˚C overnight. Data reveal that the average heat demand is 39.3 kWth, while its minimum and maximum are 8.8 kWth and 172.9 kWth, respectively. In addition, the average temperature in this region is 11.4˚C, with the minimum being -3.2˚C and the maximum 30.7˚C.

### B. Time Series Analysis

In previous studies, the impact of various variables such as ambient temperature, wind speed and direction, humidity, and solar radiation on heat demand has been investigated, and it was found that ambient temperature is the most influential variable [12]. As mentioned by Nigitz and Golles (2019), given that the meteorological variables are related to each other, considering all of them would increase the complexity of the model without much potential to improve the prediction [13]. Therefore, here only the effect of ambient temperature on heat demand is considered to demonstrate the effectiveness of the proposed approach. Fig. 2 (a) illustrates the Auto-Correlation Function (ACF) of heat demand. The plot shows there is a high linear correlation between heat demand samples with a daily period (48 samples). In addition, the cross-correlation between heat demand and ambient temperature, shown in Fig. 2 (b), reveals these two variables have a meaningful negative linear relationship as a decrease in ambient temperature increases heat demand.

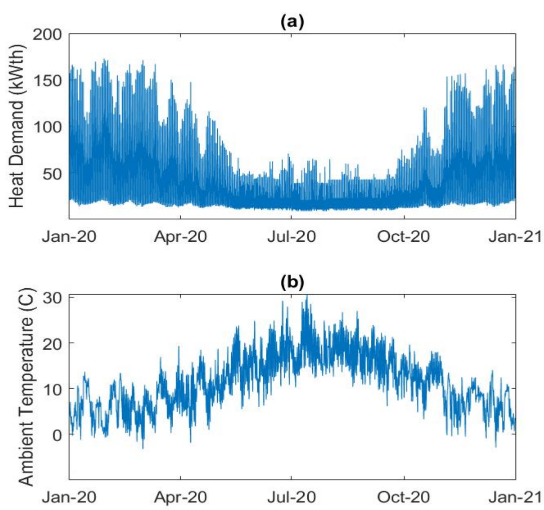


Figure 1. Half-hourly data for one year from 01/01/2020 to 31/12/2020 a) Heat demand b) Ambient temperature

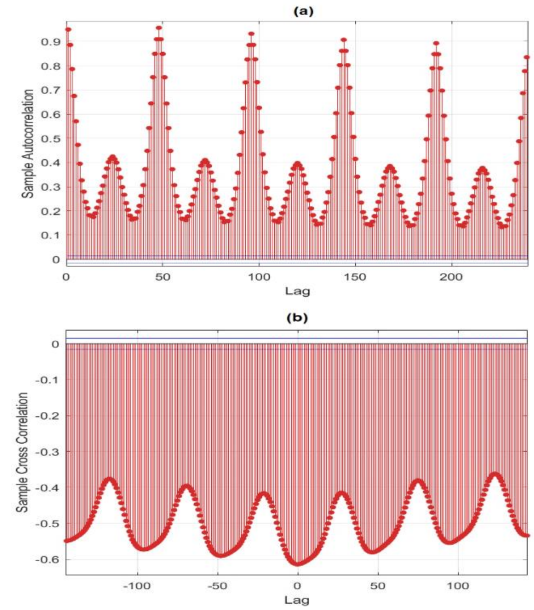


Figure 2. a) Auto-correlation function of heat demand data b) Cross correlation function of heat demand and ambient temperature

The next issue to consider is the analysis of the dynamical behavior of heat demand. Recurrence Plot (RP) is used here as an advanced technique to identify hidden patterns and structural changes in complicated data. Given a time series $A = \{a_1 \quad a_2 \quad \dots \quad a_n\}$, the RP matrix is calculated as follows:

$$R_{ij} = \left\| x_i - x_j \right\|. \tag{1}$$

where, $x_k$ is the kth phase space trajectory of the time series and is defined as:

$$x_k = \left\{a_k, a_{k+\tau}, a_{k+2\tau}, \dots, a_{k+(d-1)\tau}\right\}. \tag{2}$$

where d and $\tau$ represent dimension and delay, respectively [14]. Although a lot of information can be extracted from the RP, the important points can be summarized as follows [10]:

a) Dynamical behavior: RP can reveal that a time series is periodic, chaotic, or stochastic. Parallel diagonal lines in the RP show the system is periodic and the vertical distance between the lines specifies their oscillation period. If these diagonal lines occur beside single isolated points, the process could be chaotic and separate points represent a stochastic time series.

b) Seasonal behavior: disruptions in the pattern and separate blocks represent seasonal behavior.

Fig. 3 shows the RP of heat demand as the dimension and the delay of the data are 6 and 16, respectively. The false nearest neighbor is used for dimension calculation [15], and mutual information is used for delay calculation [16]. As shown in Fig. 3 (a), three separate patterns along the main diagonal are observed in the RP in which the dark block in the middle of the pattern represents summer (hot seasons) and the other two represent winter (cold seasons). On the other hand, parallel diagonal lines in Fig. 3 (b) represent heat demand data are periodic with an oscillation period of 48 samples (24 hours).

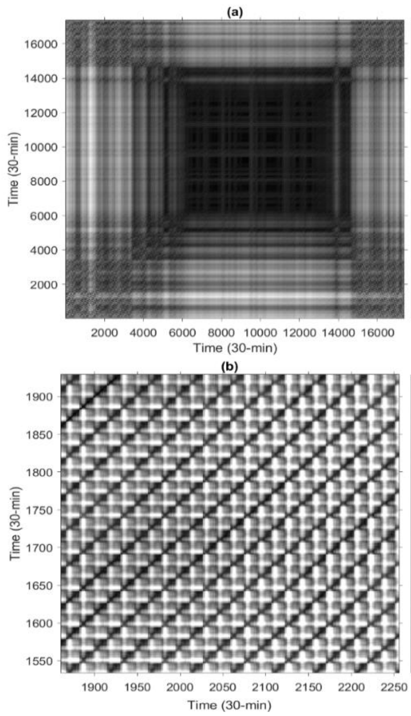

Figure 3. a) The RP of heat demand, (b) a zoomed in portion of RP

While RP is used to analyze a time series, Cross Recurrence Plot (CRP) can be used to investigate the nonlinear interrelationships between a pair of time series. CRP matrix is calculated as follows:

$$R_{ij} = \left\| x_{1,i} - x_{2,j} \right\|. \tag{3}$$

where $x_1$ and $x_2$ which are calculated by (2), represent the trajectory vectors of the first and the second time series, respectively [17]. Fig 4. shows the CRP of heat demand and ambient temperature. In CRP patterns, a small distance between the phase space trajectories of two time series, which is visualized by darker color spectrum, indicates greater nonlinear dependence. Fig. 4 shows that the interrelationships between heat demand and ambient temperature change over time. The disruption in the middle of the plot reveals that heat demand data and ambient temperature have a strong nonlinear relationship in winter, but it is weak in summer. So, it can be concluded that not only does the dynamical behavior of heat demand change over time, but the effects of ambient temperature on heat demand are also subject to seasonal variation.

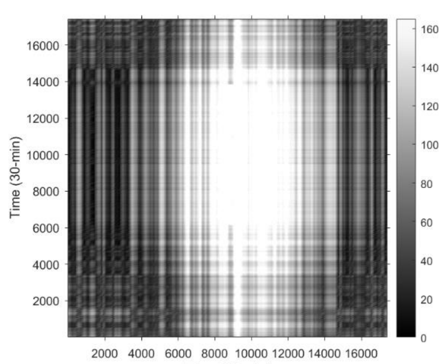

Figure 4. CRP of heat demand and ambient temperature

## III. Proposed Approach

According to the analysis described in the previous section, the dynamical behavior of the time series of heat demand and its relationship with ambient temperature change over time. Hence, a new method based on sample weighted SVM is presented to model this complex behavior by considering the transition between seasons. While standard SVM uses all samples equally in training the model, sample weighted SVM emphasizes some samples more than others. This technique is useful when there is more confidence on some training samples, the samples become less important over time, or some training samples are more relevant than others [18]. This method has been utilized for different applications. Wang et al. (2020) developed a sample weighted SVM to predict hypoglycemic drugs of type 2 diabetes by considering the relevant–irrelevant label pair as a metric to generate the samples' weights [19]. Yu et al. (2020) used this method to reduce the effects of outliers in the training datasets of a credit risk model [20] and Tang et al (2019) also implemented this method for forecasting stock turning points [21]. Here, this method is developed to predict heat demand with complex seasonal behavior which is outlined in this section.

### A. *Formulation of the Sample-weighted SVM*

Define Given a training dataset such as $\{x_i, y_i, SW_i\}$, for i = 1, 2, …, N, where $WS$ is the sample weight, the prediction function of a SVM is defined as follows [22]:

$$f(x) = w^T \Phi(x) + b. \tag{4}$$

where Φ(x) is a nonlinear function that maps the input variables $x_i$into a high dimensional space, w is the weight vector and b is bias. In order to calculate the model parameters, the following optimization problem is to be solved:

$$\mathrm{J}=\frac{1}{2}\|w\|^2 + \frac{1}{2}\mathrm{C}\sum_{i=1}^{N} SW_i . \varepsilon_i^{\,2}. \tag{5}$$

Subject to:

$$y_i = w^T \Phi(x_i) + b + \varepsilon_i. \tag{6}$$

where C is the regularization parameter and ε is the training error. The solution to (5) and (6) is derived by constructing the Lagrangian function:

$$\mathrm{L(w,b,}\varepsilon\mathrm{,a)} = \frac{1}{2}\|w\|^2 + \frac{1}{2}\mathrm{C}\sum_{i=1}^{N} SW_i . \varepsilon_i^{\,2} - \sum_{i=1}^{N} a_i \left[ w^T \Phi(x_i) + b + \varepsilon_i - y_i \right]. \tag{7}$$

where $a_i$ is the Lagrange multiplier and the final form of the prediction function can be obtained as follows:

$$y(x) = \sum_{i=1}^{N} a_i K(x, x_i) + b. \tag{8}$$

Here, $K(x, x_i)$ is the kernel function given as $\Phi^T(x)\,\Phi(x_i)$ so that the nonlinear mapping $\Phi(\cdot)$ needn't to be known explicitly. In this paper, RBF-Kernel is used:

$$K(x, x_i) = \exp\left(\frac{-0.5\|x - x_i\|^2}{\sigma^2}\right). \tag{9}$$

Where $\sigma$ represents the Kernel coefficient.

### B. *Construction of the Weight Vector*

In order to develop a sample weighted model, it is necessary to determine the weight assigned to each sample.

Fig. 5 illustrates a method to construct the weight vector taking into account both seasonal changes and daily temperature. According to Fig. 5, during each training process, the weight vector is updated by multiplying the seasonal coefficient (Ws) by the temperature coefficient (Wt).

To specify the Ws, the moving average of the ambient temperature (MA) is applied to the membership function shown in Fig. 6, where the values of Tw and Ts are specified by comparing the season blocks in Fig. 4 with the moving average curve (Fig. 7). According to the pattern shown in Fig. 4, the first dark block represents winter, approximately from 1 to about 6300, and the bright block represents summer, approximately from 7900 to 12300. As the MA values for the time of 6300 (the end of winter) and 7900 (the start of summer) are 14 and 16 ˚C, a sample with an associated moving average temperature lower than Tw (14˚C) belongs to winter, with an associated moving average temperature higher than Ts (16˚C) belongs to summer, and between these two values belongs to the transition period.

To calculate Wt for i[th] sample, (10) is used. It shows a sample whose associated daily temperature is close to the next day's temperature will weigh more in the training process.

$$W_t(i) = 1 - \frac{|T_d(k) - T_d(K+1)|}{D_T}. \quad (10)$$

$$D_T = \max(|T_d(k) - T_d(K+1)|) \qquad k = 1, 2, \dots, K \quad (11)$$

where $T_d(k)$ represents the associated daily temperature of the i[th] sample, $T_d$ is the predicted next day's temperature, k is the day index of the i[th] sample and K is the number of the training samples. As the weather forecasting services provide the accurate prediction of the next day's temperature, it is assumed that these values are used directly as input to our model.

### C. *Architecture of the Predictive Model*

This section presents the architecture of the predictive model. As shown in Fig. 8, after receiving the data, the moving average value is calculated. Using this value, the

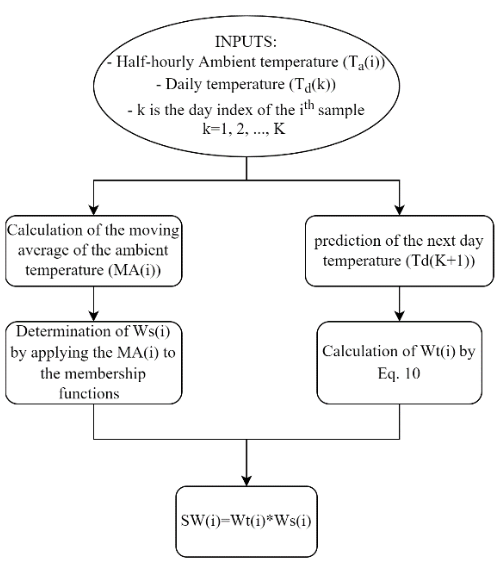


Figure 5. Flowchart of the weight vector construction

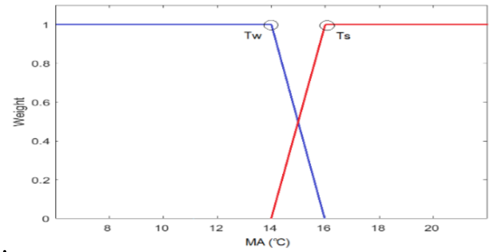


Figure 6. Membership function of season changes

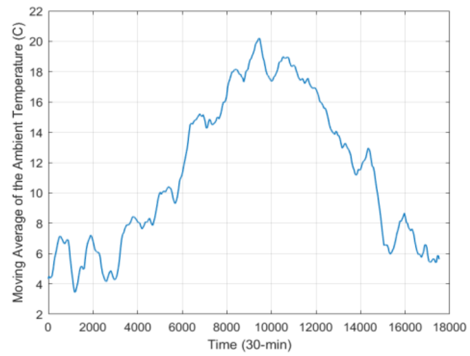


Figure 7. The moving average of the ambient temperature

sample's weight is determined based on the described method in Section 3.2. Then, the input vectors are normalized by the min-max method to lie between 0 and 1 [23].

$$x' = \frac{x - min\,(x)}{max(x) - min\,(x)}. \quad (13)$$

As The sample weight vector is constructed based on the daily ambient temperature and updated every 48 samples (24 hours), so the model will be retrained every 48 samples. In the case of model training, the expanding window technique is used to ensure all the available information is utilized in the training process [24]. Following the training of the model, the normalized amount of heat demand for the next 24 hours (48 samples ahead) is predicted and finally, the predicted value is denormalized.

Based on the results of the analysis, it was determined that heating demand and ambient temperature have a strong dependency during winter, but they are not dependent during summer. Following these results, the feature selection for winter and summer was conducted separately. While only historical data of heating demand are considered for summer, historical data of both heating demand and ambient temperature are used for winter. In the validation stage, by using the backward feature elimination [25], the following combinations of input vectors were selected for winter and summer, respectively:

$$\{H_d(\mathrm{t}-48), H_d(\mathrm{t}-49), \dots, H_d(\mathrm{t}-54)\,, \\ H_d(\mathrm{t}-96), H_d(\mathrm{t}-144), \mathrm{MA}(\mathrm{t}-48), MA(\mathrm{t}-96), \\ \mathrm{MA}(\mathrm{t}-144), T_d(\mathrm{t}-1), T_d(\mathrm{t}-2), T_d(\mathrm{t}-3)\}. \quad (14)$$

$$\{H_d(\mathrm{t}-48), H_d(\mathrm{t}-96), \dots, H_d(\mathrm{t}-240)\}. \quad (15)$$

where the numbers represent the lags of each vector.

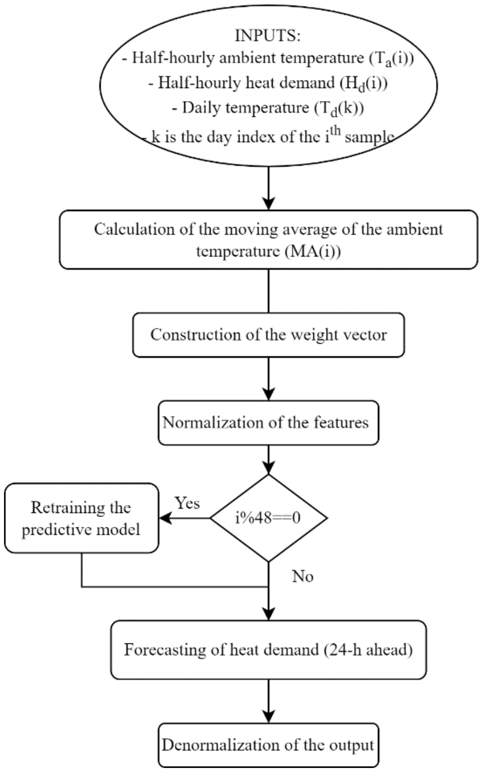


Figure 8. Architecture of the predictive model

## IV. Results and Discussion

In this section, the results of the heat demand forecasting (48 samples ahead) by the proposed approach are presented. In order to test it in both winter and summer, 9000 samples from the available database are considered for training and validation and 8520 samples for testing. Therefore, the test period runs from 07.07.2020 to 31.12.2020. Modified Mean Absolute Percentage Error (Mod-MAPE) and Mean Squared Error (MSE) are used to evaluate the accuracy of the proposed approach. These metrics are defined as follows [26]:

$$Mod\_MAPE\% = \frac{1}{N}\sum_{i=1}^{N}\frac{|HD_A(i)-HD_P(i)|}{\mathrm{Mean}(HD_A)} \times 100. \tag{16}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(HD_A(i) - HD_P(i))^2. \tag{17}$$

where $HD_A$ is actual heat demand, $HD_P$ is the predicted one, and $N$ is the number of test samples. According to Table I, the prediction results of the proposed approach with sample-weighted SVM are compared to those of several conventional linear and nonlinear forecasting methods. The input vectors of all conventional models are considered as (14), and their coefficients were determined by using the 5-fold cross-validation technique and grid search method [27]. Moreover, to make the comparison between the methods as fair as possible, all the conventional methods are retrained every 48 samples.

Table I shows that the linear model has the lowest accuracy in forecasting heat demand with a MAPE of 13.60% and a MSE of 55.28. In artificial neural network models, Radial Basis Function (RBF) has better accuracy compared to Multi-Layer Perceptron (MLP), which has a 4.9% reduction in MSE over linear regression.

Table I. Comparison results of heat demand prediction

| Method | Mod-MAPE% | MSE | Parameters |
|---|---|---|---|
| Linear regression | 13.60 | 55.28 | |
| MLP | 13.34 | 53.93 | No of neurons: [26, 28]<br>Activation: tanh<br>Regularization:4.7e-6 |
| RBF | 12.62 | 52.54 | No of neurons: 150<br>overlap coefficient: 3.7 |
| SVM | 12.32 | 51.63 | C=0.1998, $\sigma$= 0.0439 |
| Proposed approach | 11.64 | 46.52 | C=0.1998, $\sigma$= 0.0439 |

Table II. Prediction accuracy for different seasons

| Method | Summer | Transition period | Winter |
|---|---|---|---|
| SVM | 12.47% | 12.47% | 11.17% |
| Proposed approach | 11.52% | 11.69% | 10.42% |

The next method is the standard SVM, which has the best accuracy among the conventional methods with MSE 51.63 and MAPE 12.32%. Nevertheless, the proposed approach yielded the highest forecasting accuracy. Not only this method has the lowest MAPE value of 11.64%, but it also has a MSE value that is 9.9% below the best conventional method, i.e., standard SVM. The significant reduction in MSE indicates that the proposed approach has effectively reduced the forecasting errors.

In Table II, a comparison of prediction accuracy (MAPE) for different seasons is provided between the proposed approach and the standard SVM method (which has the highest accuracy among conventional methods).

The result indicates that the proposed approach has improved the accuracy of the prediction in both seasons and during the transition period. The improvement in summer is more than in other periods, which can be explained by the choice of the predictive model inputs for this season. While the ambient temperature is an input for the SVM model in this season, the proposed approach uses only historical data of heat demand to predict the future values.

Furthermore, Fig. 9 illustrates the half-hourly results of heat demand forecasting by the proposed approach. As it can be seen, not only the short-term forecasting was done with high accuracy, but the long-term trend was also captured appropriately.

## V. Conclusion

This paper presented a method for forecasting short-term heat demand with complex seasonal behavior by using sample weighted SVM. The data was first analyzed using linear and nonlinear analyses to investigate their dynamic and seasonal behaviors. Then, the effect of ambient temperature on heat demand was studied. Following the observed seasonality of

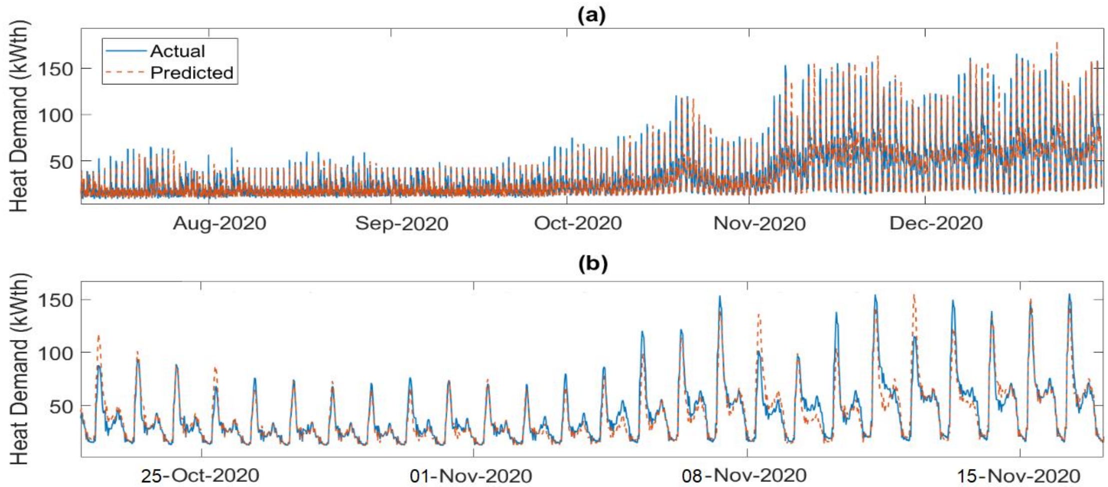


Figure 9. a) Results of heat demand forecasting by the proposed approach b) a zoomed in portion of (a)

heat demand, an approach based on the daily temperature and the seasonal change membership function was developed to construct the weight vector to be used in training SVM models. A comparison between the proposed approach and several conventional forecasting methods shows that our method can model the seasonal behavior effectively, resulting in a reduction of 9.9% in MSE and a higher accuracy for heat demand forecasting.

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