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Day-ahead Prediction of Building District Heat Demand for Smart Energy Management and Automation in Decentralized Energy Systems

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***Abstract*—This paper proposes an Artificial Intelligence (AI) based data-driven approach to forecast heat demand for various customer types in a District Heating System (DHS). The proposed day-ahead forecasting approach is based on a hybrid model consisting of Imperialistic Competitive Algorithm (ICA) and Support Vector Machine (SVM). The model is built using two years (2015 - 2016) of hourly data from various buildings in the Otaniemi area of Espoo, Finland. Day-ahead forecast models are also developed using Persistence and four other AI based techniques. Comparative forecasting performance analysis among these techniques was performed. The proposed ICA-SVM heat demand forecasting model is tested and validated using an out-of-sample one-year (2017) hourly data of the buildings' district heat consumption. The prediction results are presented for the out-of-sample testing days in a one-hour time interval. The validation results demonstrate that the devised model is able to predict the buildings' heat demand with an improved accuracy and short computation time. Moreover, the proposed model demonstrates outperformed prediction accuracy improvement, compared to the other five evaluated models.**

***Keywords*—SVM, ICA, district heating, prediction, energy efficiency, energy management, AI, machine learning, building, decentralized energy systems, smart cities, smart grid.**

I. Introduction

In the recent decentralized power system paradigm, a building can be considered as a prosumer having its own local energy supply with the assumption that power balancing can possibly be achieved locally. Buildings consume large quantity of energy. According to the Center for Clean Air Policy (CCAP), buildings share almost 40% of the global energy demand [1] and as Eurostat, buildings share 38.1% of the energy demand in the European Union (EU), much greater than any other area, comprising transport (33.3%) and industry/factory (25.9%) [2]. Specifically, heating demands (space heating, water heating and space cooling) shares about 55% of the world building energy demand [3]. The implementation of efficient and optimal building energy management systems (BEMS) is anticipated to produce a peak saving of 8% of the energy usage in the EU [4].

For reducing the power consumption and enhance compliance with the EU policies on buildings energy efficiency [5], it is necessary to regulate effectively the available Heating, Ventilation, and Air Conditioning (HVAC) systems.

Hence, heat demand (energy consumption of HVAC systems) forecasting is vital for optimal, efficient and smart energy management. This largely assists the control and management of BEMSs, in the contemporary smart grid context.

Previous works in the area of heat demand prediction for buildings can be classified as classical and data-driven techniques [6], [7]. The classical methods use equations that define the physical characteristics of a system to estimate the outcome while the data-driven techniques relate to artificial intelligence (AI), machine leaning and deep learning where observations of system inputs and outputs are gathered for model development. The observed data is then employed to describe mathematical model of the system [6]. Plenty of researches have recently taken into account the use of AI, machine learning and deep learning to build data-driven systems because of the recent fast deployment of smart meters and sensors to collect system data. Various data-driven AI based methods have been used for heat demand forecasting in different scenarios, support vector regression [8], multiple regression [9], artificial neural network (ANN) [10], [11]. Regarding heat demand forecasting, the AI based data-driven methods have shown a considerable accuracy improvements over the classical methods. The AI methods have the advantages of establishing models from big data sizes, easy adaptability and fast model parameter updating capability [12].

In district heating system (DHS), several progresses have been undertaken to achieve effective operational control from the economic and ecological viewpoints.

Nevertheless, most previous works are limited to the generation side [11], [13] and [14]. The focus of this paper is to assist smart building energy management from the demand control side based on a data-driven hybrid AI model to forecast building heat demand in district heating systems.

However, as reported above, most of the heat demand forecasting models developed so far are at national or regional levels. There have been only very few studies on heat demand forecasting at small-scale levels. Thus, this paper aims to contribute in addressing the problem of heat demand forecasting in buildings. Besides, most of the forecasting models by the prior researchers employed limited set of predictors, and hence, it has become a major problem to obtain a reliable forecasting performance and accuracy.

Moreover, most of the previous support vector machine (SVM) based heat demand forecasting approaches have employed a Back Propagation (BP) training technique to obtain the SVM model parameters. Although the BP training technique needs less computation time, it may be stuck by suboptimal (local) solutions.

This paper proposes a hybrid AI model combining the imperialistic competitive algorithm and support vector machine (ICA-SVM) for the day-ahead prediction of district heat demand in buildings. The paper uses the imperialistic competitive algorithm (ICA) optimization algorithm to search for the optimal values of the SVM model parameters. ICA, unlike BP algorithms, is capable to find global optimal solutions. Hence, optimal parameter sets of the SVM model and thus accurate forecasts can be obtained by the optimization process of the ICA algorithm. The hybrid ICA-SVM approach is chosen to develop building district heat demand forecast model mainly because of its improved training mechanism, higher accuracy and smaller learning time.

The proposed ICA-SVM based hybrid heat demand forecasting approach is compared with Persistence, ANN (back-propagation feedforward ANN), GA-ANN (GA combined with ANN), SVM (back-propagation SVM), and GA-SVM (GA combined with SVM), to demonstrate its robustness regarding prediction accuracy and other performance indexes.

The paper layout is presented below. Section II presents the devised prediction approach and model framework. Section III defines the data collection and preparation techniques. The ICA-SVM hybrid framework is given in Section IV. The various performance criteria used to estimate the prediction accuracy are given in Section V. The experimental findings and statistical analysis of the devised heat demand forecasting strategy are given in Sections VI. The paper is finally concluded in Section VII.

II. Proposed Heat Demand Prediction Strategy

This paper devises a novel building district heat demand prediction model based on the combination of ICA and SVM. The past values of the predictor variables and heat demand data are employed to train the SVM model using the ICA parameter optimization. The future values of the predictors are then employed to predict the future heat demand using the trained ICA-SVM model. The model is validated with actual district heat demand information of various buildings in the Otaniemi area of Espoo, Finland. The proposed model has the ability to relearn any time when there is new learning dataset. The model schematic is shown in Figure 1.

III. Data Collection and Preprocessing

The predictor dataset used to develop the proposed building district heat demand forecasting model, in this paper, are past values of district heat demand, meteorological data (ambient air temperature, dew-point temperature, ambient humidity, ambient air pressure, wind speed, wind direction, and solar irradiation), daily variations (hours in a day), weekly variations (days in a week), monthly variations (months in a year), seasonal variations (seasons in a year), building occupancy, previous 24h average heat demand, 24h lagged heat demand, and 168h lagged heat demand data. An actual heat demand data of different customer types are considered while developing the forecasting model.

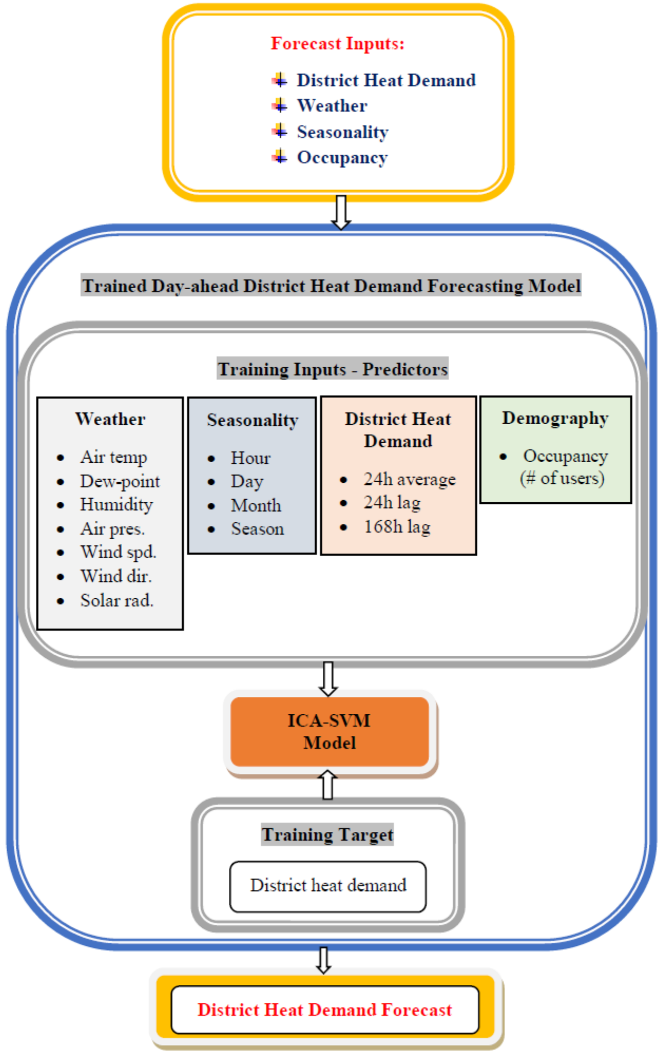

Figure 1. Proposed building district heat demand forecasting model.

The meteorological data is obtained from the nearest weather station of the Finnish Meteorological Institute (FMI) [15], while the calendar (seasonality) information is available in [16]. Due to limitation of direct measurement of building occupancy data, we use indirect representation of the occupancy with two additional variables – holiday/weekend indicator and period of the day variables.

Some of the predictor variables are processed to more simplified and matching representations ahead of the SVM learning. All the data values are converted into hourly (mean) values. The predictors and target data are finally arranged in one-hour resolution to fit the resolution differences of the different data sources. The weather forecast data record time zone (UTC) is converted to the local time to synchronize it with the time zone of the Espoo city where the buildings are located.

IV. Proposed Hybrid ICA-SVM Model

A. *Imperialist Competitive Algorithm (ICA)*

The ICA optimization technique is employed, in this study, in order to optimally adjust the SVM parameters, for achieving a possible maximum prediction accuracy of the proposed district heat demand forecasting model. ICA algorithm is a newly emerging optimization method in the class of evolutionary algorithms. It was inspired by the imperialistic competition which is the socio-political evolution of humans for developing a powerful imperialistic authority [17].

The algorithm begins with a starting (first) solution of population of $N_{country}$, which are classified into two distinct categories called imperialists and colonies based on the functional values of the solution that are indicated with (N_{imp}) and (N_{col}), respectively. In this algorithm terminology, the combination of imperialists and colonies is said to be empires. Each colony in the first population are proportionally distributed to the empires according to the powers of the imperialists. The power of empires is inversely proportional to their cost (functional value). The normalized cost of imperialists is given below:

$$C_n = c_n - max_i(c_i) \tag{1}$$

where c_n is the nth imperialist cost and C_n is the associated normalized cost of the imperialist. Assuming this normalized cost is computable for all the imperialists, the normalized power of each imperialist is given by:

$$P_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \tag{2}$$

At the assimilation stage, every empire's colonies start moving toward their target imperialist, right away the establishment of the initial empires. Figure 2 shows this movement of colony toward its relevant imperialist by x units and θ deviations; where, x and θ are random parameters that enjoy uniform distributions.

$$x \in U\ (0, \beta \times d) \tag{3}$$
$$\theta \in U\ (-\gamma, \gamma)$$

where β, called assimilation coefficient, is a number defined to be slightly bigger than 1; d is the straight distance from the imperialist to the colony; γ, called revolution rate, is a parameter that controls the angular rotation from the initial position.

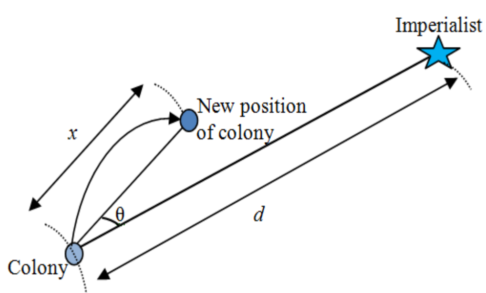

Figure 2. Colonies moving toward their pertinent imperialist.

The total cost of each empire is composed of the authority of the imperialist and the colonies, and defined by:

$$T.C._n = Cost(imperialist_n) + \xi.mean\{Cost(colonies\ of\ empire_n)\} \tag{4}$$

where $T.C._n$ is the nth empire absolute cost; ξ, called power coefficient, is positive number slightly less than 1.

The ICA optimization process converges when all the empires but the strongest one finally downfall. This sole empire will control all the colonies.

Mathematically speaking, this sole empire is the desired optimal solution of the optimization problem in question.

B. Support Vector Machine (SVM)

SVMs are non-parametric methods that essentially depend on kernel functions. Vapnik et al. [18] established the essentials of SVMs in 1995. SVMs are getting significant credits nowadays due to a number of noticeable characteristics and promising hands-on performances. SVM has been effectively implemented to prediction tasks and pattern classifications, mainly the clustering of two unlike pattern categories.

The SVM basic operational principle is mapping datasets to higher dimension representative hyperplanes using nonlinear mappings or approximations. Linear-regressions in the upper-dimension hyperplanes are associated with non-linear regressions in the lower-dimension plane, and articulated below [19], [20].

$$y(x) = w.\Phi(x) + b\ ;\ \ \Phi\colon R^n \rightarrow R^N \tag{5}$$

where, $y \in R^N$ is a training target; $x \in R^n$ is a training input (predictor); b is a bias parameter; $w \in R^N$ is weight/coefficient parameter; $\Phi(x)$ is a non-linear mapping-function; and Φ: $R^n \rightarrow R^N$ is a non-linear mapping that converts the initial training inputs to the upper-dimension characteristic hyperspace.

Figure 3 illustrates the configuration of an SVM, where input x is transformed into output y via the mapping-function $\Phi(\cdot)$. The yield of the regression y is the linear integration of scaled $\Phi(x)$.

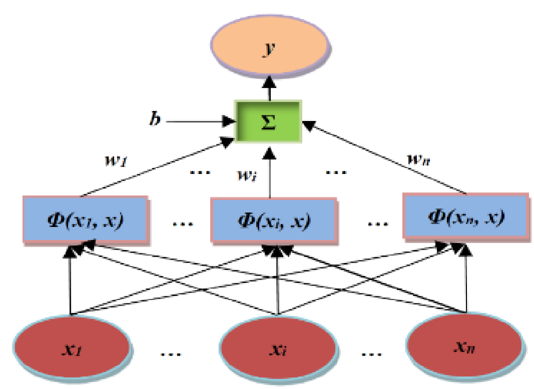

Figure 3. Structure of SVM

A special SVM known as *linear-epsilon-insensitive SVM (ε-SVM)* is used in this study due to its scarceness representation capacity. The ε-SVM objective function is described based on the ε-insensitive loss-function. The SVM model parameters, w and b, can be obtained optimally by solving the constrained fitness function formulated below.

$$min\ \left\{\tfrac{1}{2} w^T w + \gamma \textstyle\sum_{i=1}^{N} (\xi_i + \xi_i^*)\right\} \tag{6}$$
$$subject\ to\colon y_i - w.\Phi(x_i) - b \le \varepsilon + \xi_i$$
$$w.\Phi(x_i) + b - y_i \le \varepsilon + \xi_i^*$$
$$\xi_i, \xi_i^* \ge 0$$

where, ξ_i and ξ_i^* are auxiliary parameters; γ is a normalization parameter; N is a training window length; and ε is a loss parameter.

The optimization problem expressed in (6) is a quadratic programming type, and generally solved by solving its equivalent dual-problem defined below.

$$min\left\{\begin{array}{c}\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i-\alpha_i^*).\Phi(x_i,x_j).(\alpha_j-\alpha_j^*)- \\ \sum_{i=1}^{N}(\alpha_i+\alpha_i^*).\varepsilon+\sum_{i=1}^{N}(\alpha_i-\alpha_i^*).y_i\end{array}\right\} \quad (7)$$

$$subject\ to\text{: }\sum_{i=1}^{N}(\alpha_i-\alpha_i^*)=0\ ;\ \alpha_i,\alpha_i^*\geq 0$$

Solving for the positive Lagrange-multipliers ($\alpha_i - \alpha_i$*), the final formulation of the SVM regression output y is described by:

$$\hat{y}(x)=\sum_{i=1}^{N}(\alpha_i-\alpha_i^*).K(x,x_i)+b \quad (8)$$

where, $K(x_i, x_j) = \Phi(x_i).\Phi(x_j)$ is known as kernel-function of the SVM model.

From the Karush-Kuhn-Tucker (KKT) optimality condition [19] for quadratic-programming type objective functions, all the terms ($\alpha_i - \alpha_i$*) cannot have non-zero values. The SVM model training samples related to the non-zero terms with regression errors equal to or greater than ε are called *support vectors*. For given n training window length, the ε-SVM calculates a $2n\times2n$ kernel-matrix. The RBF kernel is used in this study, and expressed below.

$$K(x_i,x_j)=exp\left(-\frac{\|x_i-x_j\|^2}{\sigma^2}\right) \quad (9)$$

where, σ is a Gauss parameter (width of RBF kernel) and defines the impact area of the support-vectors in the training window domain. As described above, the *ε-SVM* model in this study employs the ICA to effectively search its parameters for improved prediction accuracy.

V. Prediction Accuracy Evaluation

To evaluate the accuracy of the devised hybrid ICA-SVM heat demand forecasting strategy, the MAPE (mean absolute percent error), RMSE (root mean squared error) and NMAE (normalized mean absolute error criteria are utilized. They are defined as follows.

$$MAPE=\frac{100}{N}\sum_{h=1}^{N}\left|\frac{H_h^a-H_h^f}{H_h^a}\right| \quad (10)$$

where, H_h^a and H_h^f are the actual and forecasted values of the heat demand at hour h, respectively, and N is the forecasting horizon and its value is 24 for day-ahead forecast.

$$RMSE=\sqrt{\frac{1}{N}\sum_{h=1}^{N}\left(H_h^a-H_h^f\right)^2} \quad (11)$$

$$NMAE=\frac{1}{N}\sum_{h=1}^{N}\frac{\left|H_h^a-H_h^f\right|}{H_{peak}} \quad (12)$$

where, H_{peak} is the building peak aggregate district heat demand.

VI. Case Study and Experimental Results

In this paper, the hybrid ICA-SVM model is developed for 24h-ahead building district heat demand forecasting. District heat demand data of four building types (customer classes) in the Otaniemi area of Espoo, Finland have been used to construct and validate the forecasting model. The buildings are Building A (residential building type), Building B (educational building type, contains classrooms and laboratories), Building C (office building type), and Building D (mixed use building, contains computer laboratories and health care center).

The buildings have a peak (in the three years period: 2015 - 2017) aggregate district heat demand of 720 kW, 25,210 kW, 710 kW, and 7,740kW, respectively.

The prediction performance of the devised forecast model is verified with a one-year (2017) window length testing data. However, to illustrate the testing results here, the model testing result is given for randomly chosen four weekdays and four weekends/holidays representing the weekdays and weekends of the four seasons of the year: summer weekday (Wednesday - July 26, 2017), summer weekend (Sunday - July 16, 2017), fall weekday (Thursday - Oct 12, 2017), fall weekend (Saturday - Oct 28, 2017), winter weekday (Monday - January 9, 2017), winter holiday (Sunday - January 1, 2017), spring weekday (Tuesday – April 18, 2017), and spring weekend (Saturday – April 8, 2017). Hence, particular days with better heat demand profiles are not chosen deliberately. This demonstrates an irregular forecast accuracy distribution in the testing year that reveals the actual heat consumption in the buildings.

The forecast results are presented for the random testing days with one-hour time resolution. The heat demand forecasts by the proposed hybrid ICA-SVM method are depicted in Figures 4 - 5, for weekdays and weekends/holidays, respectively. The forecast plots are shown for the residential building only, due to limitation of space.

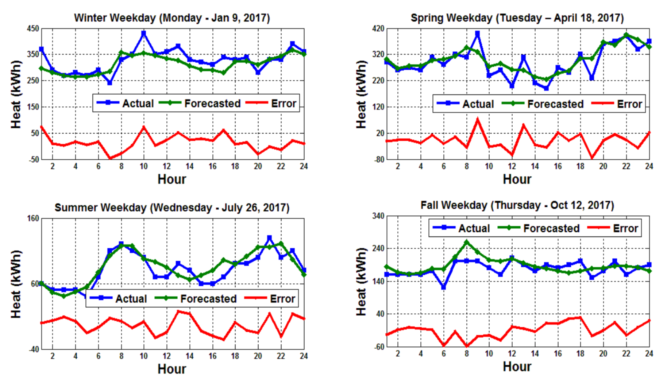

Figure 4. Real vs. forecasted district heat demand in weekdays for Building A – residential building

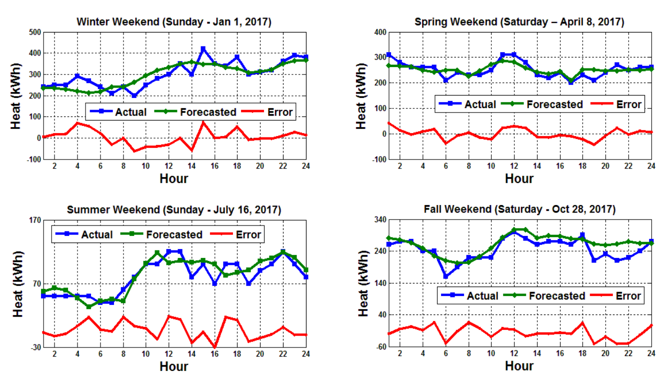

Figure 5. Real vs. forecasted district heat demand in weekends for Building A – residential building

As it can be observed in Figures 4 - 5, the forecasts by the devised hybrid ICA-SVM model follow the actual heat demand trends with smaller gaps (errors).

Tables I provides the values of the criteria employed to estimate the forecasting error of the proposed hybrid ICA-SVM model for 24h-ahead forecasting of building district heat demand.

As given in Table I, the proposed building heat demand forecasting model has effectively achieved very accurate values in all the evaluated accuracy criteria. The model has given accurate and acceptable forecasting accuracy for all building types. Specifically, the model has achieved an excellent performance (MAPE of 8.08%) for the residential building type and relatively lowest accuracy (MAPE of 16.12%) for the educational building type.

Table II presents a performance comparison between the devised hybrid ICA-SVM based building district heat demand forecasting strategy and other five strategies (Persistence, ANN, GA-ANN, SVM, and GA-SVM), based on the MAPE criteria.

TABLE I
ERROR ANALYSIS OF THE PROPOSED MODEL FOR BUILDING A – RESIDENTIAL BUILDING

Day Type		MAPE (%)	RMSE (kW)	NMAE (%)
Winter	Weekday	5.91	25.76	2.73
	Holiday	7.14	28.32	3.02
Spring	Weekday	7.08	26.02	2.91
	Weekend	5.59	17.10	1.98
Summer	Weekday	10.60	10.31	1.21
	Weekend	12.54	11.81	1.41
Fall	Weekday	8.79	19.85	2.19
	Weekend	6.94	21.30	2.39
Average	Weekday	8.10	20.49	2.26
	Weekend	8.05	19.63	2.20
Total Average		**8.08**	**20.06**	**2.23**

TABLE II
COMPARATIVE MAPE (%) FOR BUILDING A – RESIDENTIAL BUILDING

Day Type		Persistence	ANN	GA-ANN	SVM	GA-SVM	ICA-SVM
Winter	Wd[1]	12.70	7.39	6.55	6.11	6.03	5.91
	Hd[2]	21.60	9.04	7.54	7.41	7.32	7.14
Spring	Wd	13.83	8.97	7.98	7.44	7.26	7.08
	We[3]	15.06	6.68	5.99	5.86	5.72	5.59
Summer	Wd	11.22	13.59	11.96	11.14	10.87	10.60
	We	19.27	14.92	13.59	13.29	12.99	12.54
Fall	Wd	16.23	10.99	9.74	9.08	8.97	8.79
	We	16.32	8.50	7.54	7.37	7.28	6.94
Average	Wd	13.50	10.24	9.06	8.44	8.28	8.10
	We	18.06	9.78	8.67	8.48	8.33	8.05
Total Average		**15.78**	**10.01**	**8.86**	**8.46**	**8.31**	**8.08**

[1]Wd = Weekday, [2]Hd = Holiday, [3]We = Weekend

The devised hybrid model provides the lowest forecast error; the total mean MAPE obtained, respectively for the residential type, educational type, office type and mixed-use type buildings, is 8.08%, 19.3%, 13.71% and 11.04%.

The devised model total mean MAPE increment compared to the other five models is 48.79%, 19.3%, 8.80%, 4.49 and 2.77%, respectively, for the residential building type, 42.22%, 18.99%, 9.8%, 4.84% and 2.89%, respectively, for the educational building type, 48.34%, 35.72%, 23.74%, 15.21% and 9.26%, respectively, for the office building type, and 56.50%, 34.08%, 21.42%, 13.14% and 9.36%, respectively, for the mixed-use building type. The same training dataset were used for each of the presented models and each model was implemented with its optimal parameters and setups.

VII. CONCLUSIONS

This paper developed a new and effective hybrid model for 24h-ahead forecasting of district heat demand of buildings using a predictor dataset that consists of district heat consumption history, meteorological parameters, seasonal variations, and building occupancy. The devised hybrid model is based on the hybridization of the ICA and SVM. A two-year (2015 - 2016) window length training data of predictor variables is utilized to develop the forecast model of the devised model. The forecasting accuracy of the devised model is tested with a one-year (2017) window length testing data. The modeling approach has the ability to learn any time when there is a new training dataset. The application of the devised model for 24h-ahead building heat demand forecasting is novel and effectively successful. The total mean values of MAPE, NMAE and FS, obtained for randomly chosen four weekdays and four weekends/holidays in the testing year, are 8.08%, 2.23% and 54.23%, respectively, for the residential type building, 16.12%, 2.63% and 17.80%, respectively, for the educational type building, 13.71%, 3.96% and 61.17%, respectively, for the office type building, and 11.04%, 3.59% and 50.62%, respectively, for the mixed-use type building. The devised model outperforms other five evaluated heat demand forecasting models, regarding forecasting accuracy measures for all the building types. Therefore, the presented numerical results and performance comparisons verify the capability and suitability of the devised hybrid model for a day-ahead (short-term) heat demand forecasting in building energy systems.

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