Deep Learning and IoT Based Load/Demand Forecasting for District Heating

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Abstract — **In large cities, district heating system is a network of pipelines where heating is delivered to a number of customers from a centralized heating station, central plant. Ideal operational strategy is to deliver enough heat in order to satisfy heating demands of each customer with a minimum cost. Nevertheless, nowadays many district heating systems in Serbia are operated largely based on operational experience, without any available tools for predicting future states or demands. Due to the interactive, adaptive, and interconnected nature of the district heating systems, their components and outside environment, they must be capable of negotiating constantly changing scenarios. Being among large energy consumers, district heating systems, could be optimized with help of deep learning methodologies and extend capabilities of artificial neural networks (ANNs), such as convolutional neural networks (CNN) and long short-term memory (LSTM). In this paper control system of a district heating plant is empowered with a model that predicts the future heat demand – heat load forecast. Based on this model, controller generates values that meet the predicted heat demand without violating the system constraints. In addition to that, IoT devices that are part of the district heating system provide quantitative measurements of the processes they are involved in, which in turn generate data streams that have not existed before and provide for improvements of modelling and control of the system.**

Keywords: **Deep learning, artificial neural networks, IoT, load forecasting, distribute heating systems**

I. INTRODUCTION

Heat load prediction and gas consumption forecast in district heating systems (DHS) are important technologies for economical and safe operations of such systems. Improvement of district heating systems operation can be founded of control enhancement, based on reliable prediction of consumers' heat consumption and gas usage since production could be efficiently altered to match the real demands.

Heating systems in large cities are organized trough the district heating companies, which are responsible for the delivery of heating energy produced in the central plants trough the heating network. At the same time, they are expected to keep the cost of produced and delivered heat as low as possible. Namely, urban areas in big cities with high density of demand for heat are mostly using district heating system which is most beneficial in economic and environmental aspects. District heating systems produce hot water, steam and/or chilled water at a central plant and then distribute the energy through underground pipes to buildings connected to the system. Individual buildings connected to district heating no longer need boilers and customers use the hot water provided by DHS to meet their space heating, water heating and other needs. Once used in customer buildings, the water is returned to the central plant for reheating then recirculated through the closed-loop piping system.

Analysis of heat load for district systems was provided in [1], offering study of factors influencing the value and character of heat load, where linear regression models for heat load in DHS have been developed. In [2] to predict heat load in buildings data driven supervised machine learning models were used, three machine learning algorithms have been compared, while Support Vector Regression (SVR) has been marked as the most efficient model. Similar research was made in [3], where the short-term forecast models are generated using four supervised machine learning techniques with conclusion that SVR was also the most efficient model for heat load forecast. In [4] convolutional neural networks have been used for energy forecasting, with promising results. A review of parametric, non-, and semi-parametric methods and models for heat load was presented in [5], where methods for online prediction of heat load with available meteorological forecasts have been developed. In [6] computational intelligence i.e soft computing techniques were considered, combining support vector regression to build predictive models of heat load in DHS. Two support vector regression schemes with a radial basis function and a polynomial function have been used as the kernel functions. Experimentally obtained data from one heating substation have been used for creating and testing the developed predictive models. Similar research was made in [7] where authors showed that prediction of customer heat needs by using adaptive neuro-fuzzy method could improve production and adjust it to real customer's needs.

Furthermore, in [8] it is demonstrated that proposed Artificial Neural Networks empowered with Numerical Weather Prediction variables can predict the heat load precisely. Proposed method has been declared as capable to directly improve the forecasting accuracy as well. In [9] an artificial neural network (ANN) model for short term natural gas consumption forecast in DHS has been presented, using a Levenberg-Marquardt training algorithm. Research reported in [10] claims improvement of the heat load prediction through the introduction of a recurrent neural network for adapting the dynamical variation of heat load together with a new kind of input data in consideration of the characteristics of heat load data. In [11] main idea was to achieve quality prediction for a short period in order to reduce the fuel consumption for heat energy production and improve exploitation of equipment. Improved neural network model has been proposed for 1 to 7 days ahead prediction of heat consumption of energy produced in small district heating system, showing improved accuracy. Finally, our results from [12] demonstrated efficiency of ANN and neuro-fuzzy models for heat load and gas consumption forecast in DHS system.

Following previous research, in this paper efficacy of computationally intelligent models for gas consumption and heat load forecast in DHS has been tested extending previous ideas by using deep machine learning, convolutional networks [13] and Internet of Things (IoT) paradigms. An attempt has been made to increase accuracy by providing additional data for prediction and more complex models.

II. Data from District Heating System of a Large City in Serbia

Situated in southern Serbia, the City of Niš is the third largest city of Serbia, covers around 600 km^2 of land and has approximately 255 000 inhabitants. District heating company of the City of Niš has two main separate networks and several minor grids. There are also some other entities that have smaller district heating systems. District heating is primarily produced with natural gas and the heat is used exclusively for covering space heating demand.

Two large district heating networks are Krivi vir and Jug. PUC City Heating Plant is a public municipal company, which was founded by the Niš city assembly. Figure 1 shows total heat delivered to consumers by DHS Niš for the several recent heating seasons, while Figure 2 shows its gas consumption for the several recent heating seasons.

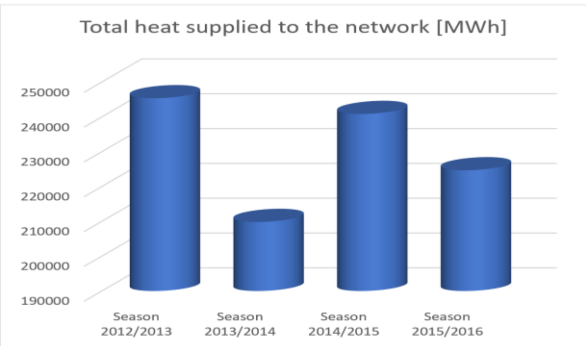

Figure 1: Total heat delivered to consumers by DHS Niš

The heating season commences on October 15th and ends on April 15th. In the period as of October 1st to 14th and April 16th to May 3rd, buildings are exceptionally heated if in the latest Republic Hydro-meteorological Institute weather forecast of the previous day, or the first weather forecast on that day, it is anticipated that an average daily temperature will be below +12^{0}C. The suppliers of heat energy are responsible to achieve and maintain the foreseen temperatures in beneficiaries' quarters even if the outdoor temperature drops to -15^{0}C.

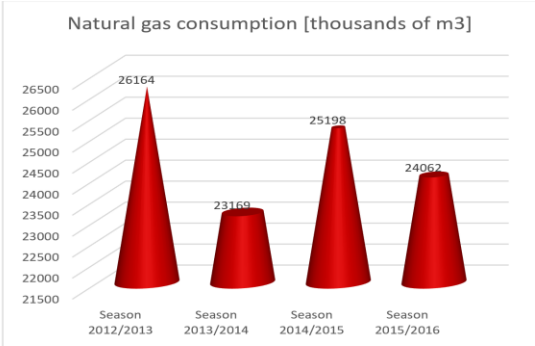

Figure 2: Total gas consumption of DHS Niš

Supervisory Control and Data Acquisition (SCADA) system of local heat sources of the Jug heating network encompasses control of the functional blocks within the plant itself. Monitored data for the heating source plant Jug for the heating season 2016/2017 has been used in this study. Observed values included but were not limited to gas consumption, outer temperature, total plant power, water and gas flows, primary and secondary water temperatures, etc. All variables were monitored with one-minute interval to provide detailed analysis, with time interval increased and data averaged to 15 minutes, 30 minutes, one hour and to daily values to provide for generalization. Change of total heating power (ranging from 0 to total power of above 60MW) and change of outer temperature for January 2017 are shown in Figure 3 and Figure 4 respectively.

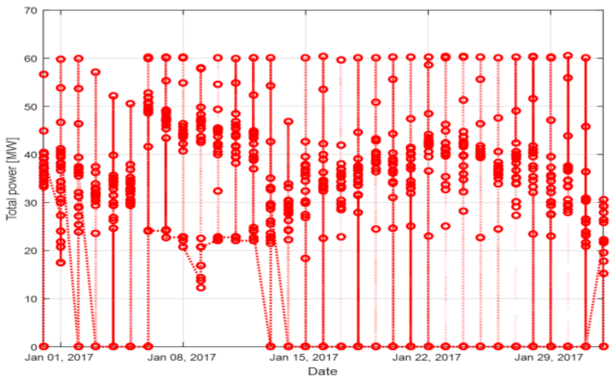

Figure 3: Total power of Jug power plant change in January 2017

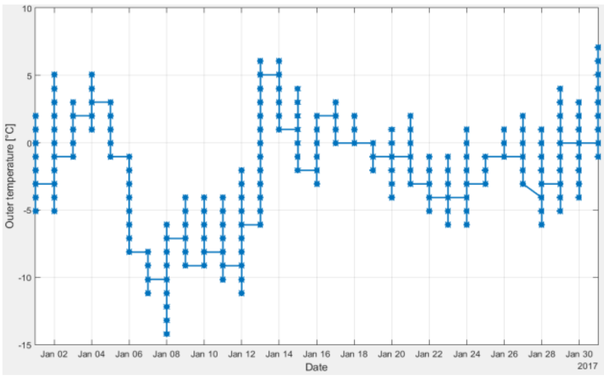

Figure 4: Outer temperature change in Niš during January 2017

District heating is not operating in summer and it is not used for preparation of sanitary (domestic) hot water. Almost all hot tap water is instead heated by electricity.

III. Heat load and gas consumption prediction by machine learning

It is important that DHS forecasts are available and accurate, since they are needed for the production planning and control. When the district heating load is fluctuating a lot, decision is needed when to start a new boiler, in order to avoid unnecessary start and stop costs on the boilers. Also, natural gas consumption prediction is of the interest to organize supply efficiently and economically.

Machine learning as a field of computer science that gives computers the ability to learn without being explicitly programmed as an application of artificial intelligence (AI). As elaborated in introduction, machine learning has been proven to be an efficient method used to devise complex models and algorithms that lend themselves to DHS prediction and could be used in DHS predictive analytics.

A. *Multilayer perceptron neural networks (FNN) and ANFIS networks*

Idea of using feedforward networks, specifically multilayer perceptron networks and adaptive neuro-fuzzy inference systems (ANFIS) for heat load and gas consumption forecasting has been explored in our paper [12]. Here, updated deep learning-oriented and convolutional network solutions have been considered. Deep learning network proposed for gas consumption forecasting has been shown in Figure 5.

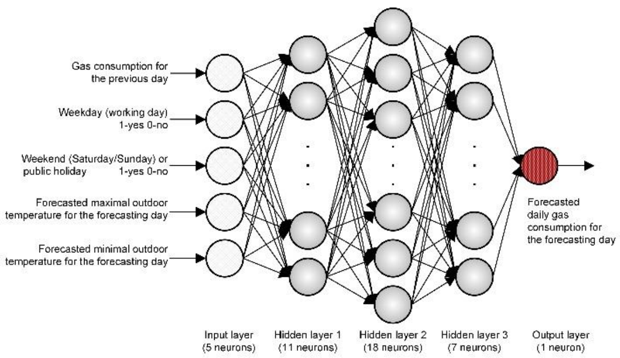

Figure 5: Deep learning MLP network for gas consumption prediction

B. *Convolutional neural networks (CNN)*

In machine learning, a convolutional neural network (CNN) is a class of deep, feed-forward artificial neural networks that has successfully been applied to analysing visual imagery. CNNs use a variation of multilayer perceptron's designed to require minimal pre-processing. They are also known as space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics.

Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field.

CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage.

Convolutional layers apply a convolution operation to the input, passing the result to the next layer. The convolution emulates the response of an individual neuron to visual stimuli. Each convolutional neuron processes data only for its receptive field, as illustrated in Figure 6.

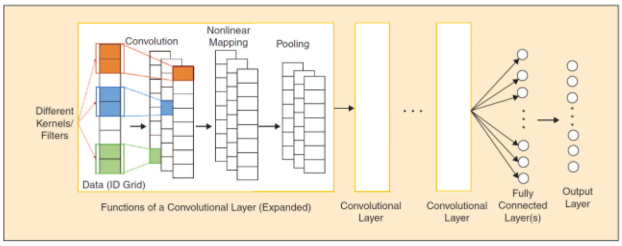

Figure 6: A CNN architecture [14]

Although fully connected feedforward neural networks can be used to learn features as well as classify data, it is not practical to apply this architecture to images.

C. *Long short-term memory (LSTM)*

Long short-term memory (LSTM) units (or blocks) are a building unit for layers of a recurrent neural network (RNN). A RNN composed of LSTM units is often called an LSTM network. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell is responsible for "remembering" values over arbitrary time intervals hence the word "memory" in LSTM. Each of the three gates can be thought of as a "conventional" artificial neuron, as in a multi-layer (or feedforward) neural network: that is, they compute an activation (using an activation function) of a weighted sum. Intuitively, they can be thought as regulators of the flow of values that goes through the connections of the LSTM hence the denotation "gate". There are connections between these gates and the cell.

The expression long short-term refers to the fact that LSTM is a model for the short-term memory which can last for a long period of time. An LSTM is well-suited to classify, process and predict time series given time lags of unknown size and duration between events. LSTMs were developed to deal with the exploding and vanishing gradient problem when training traditional RNNs. Relative insensitivity to gap length gives an advantage to LSTM over alternative RNNs, hidden Markov models and other sequence learning methods in numerous applications.

There are several architectures of LSTM units. An LSTM (memory) cell stores a state, for either long or short time periods. This is achieved by using an identity activation function for the memory cell. In this way, when an LSTM network is trained with backpropagation through time, the gradient does not tend to vanish, Figure 7.

The LSTM gates compute an activation, often using the logistic function. Intuitively, the input gate controls the extent to which a new value flows into the cell, the forget gate controls the extent to which a value remains in the cell and the output gate controls the extent to which the value in the cell is used to compute the output activation.

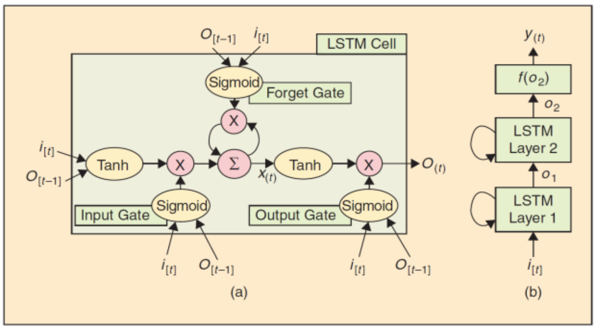

Figure 7: (a) An LSTM cell and (b) a multilayer LSTM network [15]

There are connections into and out of these gates. A few connections are recurrent. The weights of these connections, which need to be learned during training, of an LSTM unit are used to direct the operation of the gates. Each of the gates has its own parameters that is weights and biases, from possibly other units outside the LSTM unit.

D. IoT platform

The Internet of things (IoT) is the network of physical devices, vehicles, home appliances and other items embedded with electronics, software, sensors, actuators, and connectivity which enables these objects to connect and exchange data. Each thing is uniquely identifiable through its embedded computing system.

The IoT allows objects to be sensed or controlled remotely across existing network infrastructure, creating opportunities for more direct integration of the physical world into computer-based systems, and resulting in improved efficiency, accuracy and economic benefit in addition to reduced human intervention. When IoT is augmented with sensors and actuators, the technology becomes an instance of the more general class of cyber-physical systems, which also encompasses technologies such as smart grids, virtual power plants, smart homes, intelligent transportation and smart cities. The applications for internet connected devices are extensive, and their application in DHS systems allows for data streams that have not existed before.

IV. Results and Conclusions

As elaborated in introduction, different types of machine learning approaches have been developed to forecast gas consumption and heat load/demand in district heating. Since evidences indicate that the external factors strongly influence the heat load, in order to make the prediction results more accurately, the weather factors should be taken into consideration when making machine learning models. Here, these weather parameters and other IoT enabled data are considered as the important inputs of machine learning models. Outputs of the considered models are gas consumption forecast and heat load forecasting.

Short-term heat load prediction on and gas consumption prediction is realized using real measured data for the whole representative winter heating season, from the heat source of the large Serbian city district heating network. Prediction is performed using several deep machine learning techniques, such as MLP neural networks, ANFIS networks, CNN networks and LSTM networks.

Results obtained by prediction models have been compared with real gas consumption and heat load on the heat source, leading to a conclusion that satisfactory results could be obtained with moderate prediction errors.

It is important that DHS of the City of Niš does not provide uninterrupted 24h heating service, while instead the heating period is mainly from 5 a. m. to 9 p. m. Also, high ambient temperatures lead to the turning off heating in certain daily intervals, which makes modelling of the heat load forecast more complicated but also more significant. Encouraging preliminary results with deep learning and convolutional networks and with IoT approach open prospective for further research that could include more weather related and other variables.

Acknowledgment

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