Intelligent Heat Demand prediction for Advanced District Heat Plant Control

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***Abstract*— In urban areas the most efficient, environment friendly and cost-effective method for supplying heat to buildings is by district heating systems (DHS). However, by optimizing the production of heating energy in DHS further improvement of the efficiency, operation cost reduction and raise of the profitability can be achieved. This goal cannot be met without a detailed analysis and adjustment of the heat supply according to the user demands. Accurate heat demand (especially peak load) is very hard to predict and Artificial Intelligence techniques like LSTM neural networks and DNN are most commonly used for development of Data Driven Models (DDM) for this prediction. In this paper various methods for heat load prediction applicable in District Heating System of Faculty of Mechanical Engineering in Nis (FMEDH) will be considered where Knowledge Based Models (KBM) and DDM for heat demand prediction will be analyzed while the goal that goes beyond State of the Art is development of Hybrid KBM/DDM model. Prediction models can further be used by the operators as a support for District Heat Plant Control as well as by the consumers as a decision making support for heat cost reduction if several heating sources are available (e.g. DHS, Solar energy, Heat pump, Air conditioning system etc.)**

I. Introduction

Additional increase of energy efficiency in district heating system can be achieved by accurate heat demand prediction and as a consequence there can be decreased fuel consumption and decreased emission of combustion products into the atmosphere. Heat production efficiency can be optimized through the use of appropriate procedures for running heat sources alongside short-term heat demand prediction combined with preparation for adjusting heat source work parameters to the predicted heat load for a few hours in advance [1]. The simple diagram of the DHS is presented in figure 1. [1]

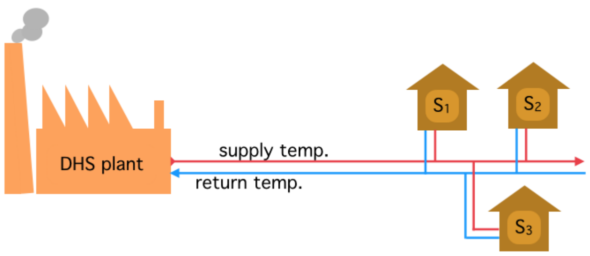

Figure 1. Simple diagram of the DHS

II. State of the Art

Related work in the area of energy (e.g. thermal, electric, cooling) demand estimation in buildings as well as in the area of heat demand prediction in DHS is categorized into two approaches, namely Knowledge Based (also known as forward, classical [2] or expert rules) approach and data-driven (inverse) approach [1].

In the Knowledge Based approach, equations describing the physical behavior of a system are used to predict the output. Today, most sophisticated numerical methods for predicting building energy consumption (building heat demand) are implemented in building energy performance simulation tools. One of the possible ways to improve balance between building energy consumption and occupant thermal comfort in existing buildings is to use simulation-assisted operation of HVAC systems. Simulation-assisted operation can be formulated as a type of operation that implements knowledge of future disturbance acting on the building and that enables operating the systems in such a way to fulfill given goals, which in nature can often be contradictory. The most important future conditions on building energy consumption are weather parameters and occupant behavior and expectations of thermal environment. In order to achieve this type of operation, optimization methods must be applied, i.e. optimal daily operation strategies must be defined for HVAC systems. Methodology used in [3] is namely based on using building energy performance simulation software EnergyPlus (either directly for predicting heating demand or for training NN), data available in short-term weather forecasts and developed software.. Objective of the research is to reduce building energy consumption while satisfying thermal comfort and reducing environmental impact DHS Plant produces.

The output of the data-driven methods on the other hand is based on data of the historical behavior of the system. The data-driven methods, which use regression models to find the most accurate function to map the input parameters to the observed output, can be further divided in statistical and machine learning methods. In statistics, the complexity of these functions is often predetermined by the regression model whereas in machine learning this complexity is learned by the method itself [4].

In paper [2] the authors performed heat demand prediction with Elman Neural Networks based on past demand and temperature combined wind speed and direct solar radiance. They concluded that while wind speed increases prediction accuracy by itself, combining it with solar radiance has the opposite effect. In paper [4] Particle Swarm Optimization (PSO) of feedforward neural network weights is used in order to improve short-term heat demand prediction in transient heating. Of account of time, previous consumption data and ambient temperature two neural network were trained, one with PSO and the other one without it. The optimized neural network outperformed the traditional feedforward neural network in the whole test dataset. Using data from a district heating system, the research [5] focuses on identifying consumer groups with similar behavior by self-organizing maps (SOMs) and predicting detailed heat demand for identified groups with multilayer perceptrons (MLPs) to which evolutionary algorithm has been applied. Results suggest that a valid representation of consumers can be formed using a limited number of typical demand profiles. Production planning is an essential tool in keeping the cost of supplied heat as low as possible, minimizing fuel usage and avoiding wasteful use of available resources [1]. The author engaged in forecasting demand with neural networks based on power output and measured temperature from two plants collected during a multiple year period. A software application was developed, enabling the user to alter the neural network setup, in terms of the number of cells in the hidden layer and activation function.

HeatFor [6] is a software solution for heat demand forecasting in district heating systems based on heating system measurements, historical data, and current and predicted weather conditions using machine learning techniques. Predictions from the system can be used for production planning and optimization as well as providing a more secure supply for consumers. This system has the ability to adapt to changes in heating network and consumer behavior and learn over time making its predictions more reliable the longer it is used.

For estimating energy demand at the consumption environment commonly used data-driven methods are SVR [7], Multiple Regression [8], and Neural Networks based methods [9.]. Other methods have included a grey-box model [10], a physical-based dynamic system model [11] and a simple piecewise linear model [12]. Ma et al. [13.] utilized a Gaussian mixture model for heat demand forecast in nine different buildings. Bacher et al. [14] used a grey-box model to forecast heat demand in 16 detached houses. Machine learning techniques were applied by Idowu et al. [15] to forecast heat demand in 10 residential and commercial buildings. Lausteretal. [16] applied a low order thermal network model to simulate the heat load of a research campus with 200 buildings, but considered only the office buildings. Various approaches of heat demand forecasting have been studied. For instance, in [17] a simple model is offered where heat consumption is divided in a component dependent on the ambient temperature and a second part that characterizes consumer behavior. The former is defined as a piecewise linear function obtained by solving a linear least squares problem, but the latter is derived from weekly patterns in heat consumption. The authors of [17.] found that their results are of comparable accuracy to those obtained by more sophisticated commercial forecasting tools that relay on ARMA models. Similarly, in [18], the authors also used two components. The social component assumed a daily character and it was found by means of BoxJenkins methodology. A recent study based on the demand profile of Espoo in Finland found a linear regression model with a two-week social component to be the most useful in practice [19]. The authors of [20] compared ARIMA, EWMA (exponentially weighted moving average), linear regression and artificial neural network (ANN) models for thermal load forecasting. They concluded that of the models contrasted the ANN produced the most accurate results. A number of different studies have confirmed the applicability of ANN in heat demand forecasting at both, domestic level [21] and the whole district heating (DH) network [22], [23]. The authors of the current paper have previously analyzed ANN use in predicting electricity market prices and water inflow in reservoirs [24]. The goal now is to test an ANN based thermal load prediction model and compare it to one built on polynomial regression. The secondary objective is to evaluate the benefits that might arise if these models are combined. Predicted thermal load inaccuracy cost minimization is the final goal of this research. The case studies are based on the district heating network in Riga, Latvia, particularly, the zone supplied by cogeneration plants. The work investigates yearly heat demand profiles and continues previous research on power demand prediction [25,26].

III. CASE STUDY AN D DISCUSSION

The research elaborated in this paper focuses on Faculty of Mechanical Engineering in Nis District Heating System (FMEDH), that produces, distributes and delivers energy for space heating in one part of City of Nis to various consumers: several technical faculties which are part of University of Nis [3,4] (Faculty of Mechanical Engineering, Faculty of Civil Engineering and Architecture, Faculty of Electronic Engineering), three secondary technical schools (schools for mechanics, electrics and construction), Technical Higher School in Nis, Student dormitory, Student restaurant and central kitchen, and a residential settlement build in early 2000s located in Nikola Tesla Boulevard in Nis. Total heating area served by FMEDH is nearly 90.000m2. In addition to existing consumers, several new ones are expected in the next period: Science and Technology Park Nis, Annex of Faculty of Electrical Engineering, new Student Dormitory, and two more residential building blocks. With connection of these new consumers, total heating area will be more than 120.000m^2.

Heating energy is produced in boiler plant consisting of two hot water boilers with nominal capacities of 8.3MW and 8.7MW. Boilers are equipped with combined natural gas/heavy fuel oil burners, but for the last several years only natural gas is used as a primary fuel. Fans on both boilers are equipped with frequency drives enabling good adjustment of boiler capacity to real heat demand. Several more auxiliary systems are in boiler plant: pumping system, pressure maintaining system, system for preparing (softening) water refill water and control system.

Produced energy is distributed to consumers through four different branches by circulating water of required temperature (controlled variable). Each branch delivers heating energy to consumers of the same type, i.e. technical schools, residential buildings, faculties, student dormitory and restaurant. Nominal operating temperature regime for primary side is 120/75ºC.

Heating energy is delivered to consumers through indirect type heating substation. Currently there are 12 heating substations, equipped mainly with plate heat exchangers although there are shell and tube heat exchangers in several substations. Besides heat exchanger, heating substations have control valves on the primary side enabling control of heat delivered to each consumer, as well as ultrasonic heat flow meters for measuring delivered heating energy. Secondary supply water temperature (water entering heat emitters in heated areas) is control variable. Nominal operating temperature regime for secondary side is 90/70ºC.

FMEDH over the years invested in various parts of the whole system leading to fully automated system in production, distribution and delivery of heating energy. SCADA system is installed and running for more than 10 years, so the operators can react remotely (overpassing local PLC logic), in every moment, to changing conditions.

Figure 2. Building, boiler room and dispatcher centre in FMEDH

Three levels of control are implemented in FMEDH. The first one, protects the boilers from low-temperature corrosion, by constraining, from the bottom side, return boiler water temperature. Only when this condition is satisfied can heating energy by delivered to consumers. Primary supply water temperature is controlled in boiler plant by PLC offsetting it against outside temperature (two-point heating curve control). In heating substations, secondary supply water temperature is controlled by PLC controlling water flow through the control valve on the primary side, but also offsetting this temperature against outside temperature (two-point heating curve and four-point heating curve). By implementing these two control loops, qualitative-quantitative control is achieved throughout the system. Control equipment in heating substations and boiler plant is from different periods (generations). Most of the heating substations and boiler plant are equipped with PLCs of older generation (two-point heating curve), but several are equipped with PLCs of new generation (four-point heating curve), representing good starting point for comparing consumers of the same type (e.g. residential buildings) with different operation strategies which can be implemented as a result of heat demand prediction patterns. Heat production, with all technical parameters in all parts of energy-chain (fluid flow, temperatures, pressures) is monitored and all acquired data are stored in SCADA databases, on regular intervals.

The main goal of the solution proposed in this paper is the design and development of the prediction models that can assist in decision making of the FMEDH operators as well as consumers that are using various heat sources. The proposed architecture of the proposed hybrid solution is presented in Figure 3.

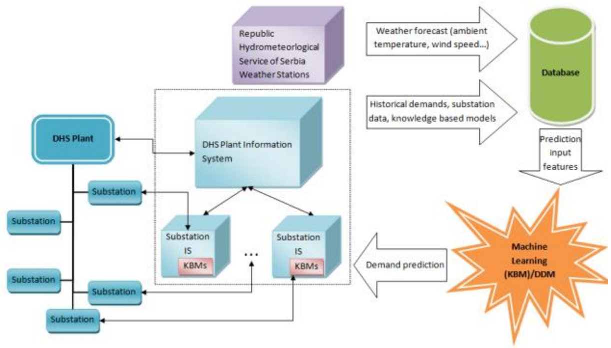

Figure 3. Proposed architecture of Decision Support System

The Intelligent Prediction based Decision Support System uses input data from a dedicated database in which acquired data from DHS Plant, Substations and Weather Forecast is stored, while hybrid Machine learning based prediction model delivers short term heat demand predictions that are then used as a decision making support.

Data that is collected in DHS Plant and Substations is stored in DHS Information System as well as individual Substation information systems. This data includes, among other things, historical heat demand data and heat demand Knowledge Based Models (KBMs) for individual buildings (which are not developed for each building connected to DHS). An additional external data source is the weather forecast, acquired from Republic Hydrometeorological Service of Serbia weather stations. All acquired data is stored in the database from where it is fed to the Hybrid Machine Learning KBM/DDM prediction model. This prediction model is a Data Driven Model (DDM) at its basis, relying on acquired data input features (historical heat demand, weather forecast…). However, it can also be extended with developed KBMs, especially when there is no training data, making it a Hybrid DDM/KBM prediction model. Predictions generated by the model are sent back to the DHS Plant Information System to be used in decision making and production planning and optimization.

IV. CONCLUSION

An accurate heat demand prediction enables efficient planning and operation of both production and distribution of district heating. Accurate demand prediction is essential in order to optimize and plan production and utilize heat storage units, while district heating network operators can also operate their network more efficiently and reliably by having an accurate heat demand forecast. The results are that security of supply is increased and costs are reduced at the same time.

The advance beyond State of the Art is the development of the gray box prediction model that uses both KBM and DDM. Using a hybrid predictive model will provide predictions even in situations when one of the KBM and DDM lacks sufficient data, by relying more heavily on the other approach or approximating the model using existing known models. In the case of a lack of training data, the Hybrid KBM/DDM prediction model would form its prediction based on Expert knowledge and physical model. On the other hand, for buildings without developed KBM, an intelligent system will determine an appropriate candidate KBM based on building feature similarity and adapt it according to feature distinctions.

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