A Decision Support System for Monitoring and Control of Thermal Substations in District Heating Networks

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***Abstract*—A remote control and monitoring system of thermal request profiles in buildings is crucial for the effective operation of thermal substations connected to a district heating network. The acquired data can be used to develop a dynamic thermal model describing the operation of a thermal substation coupled to a reference building using different surrogate approaches. This work presents a decision support system for predicting the thermal request profile at a building level and optimizing the substation operation. The equipment needed and the development of the remote control monitoring system is initially described. Then, the utilization of surrogate models for generating a dynamic thermal model is presented. Finally, we validate the proposed decision support system through the experimental analysis of an actual unit, serving a building of 6,000m^2 in the district heating network of Kozani, Greece. Surrogate models are generated capable of preducting both the primary and the secondary source temperature. The presented methodology could be utilized in the context of a building model, incorporating the local thermal substation model. Results can be useful towards the optimization of the district heating operation, as well as towards the integration of alternative primary energy sources, potential renewable based ones, which is the case through the on-going decarbonization of the Greek electrical system.**

***Index Terms*—Decision support, optimization, simulation, real-time and embedded systems.**

I. Introduction

District heating is a technology that is commonly used for house heating and producing domestic hot water. Various works (e.g., [1] [2]) highlight the benefits of district heating networks to provide thermal loads to buildings-consumers in terms of flexibility and efficiency of operation. However, a major issue is the management of thermal inertia phenomena and therefore the backlog of the network itself, or its subsystems. The utilization of the flexibility benefits offered by these structures, managing the above phenomenon, presupposes a sufficient understanding of it; within this context, physical models are hard to be implemented [3]. At the same time, the control systems and the operating strategies that govern them are important.

The intelligent management of district heating networks requires the monitoring and acquisition of thermal demand at various levels: thermal plant, distribution network, and building levels. The building-level thermal request profile is of great importance since operating actions can be applied for control and automation purposes [4]. This can be predicted either through white-box models (for a thorough review, see [5]) or through black-box models (or a thorough review, see [6]). White-box models include advanced tools for building analysis, e.g., EnergyPlus [7] or TRNSYS [8], while black-box models include neural networks and machine learning methods. White-box models are more complex because they require a thorough understanding of all related factors that affect the load at the building level. On the other hand, black-box models do not require physical principles to calculate thermal dynamics but are purely based on data that can be trained to infer relationships between inputs and outputs.

In this work, we utilize black-box models to predict the thermal request profiles. The vast majority of similar models in the literature include neural networks (e.g., [9] [10] [11]), deep learning methods (e.g., [12] [13] [14]), support vector machines (e.g., [15] [16] [17]), and tree-based methods (e.g., [18] [19] [20]). This work presents a decision support system for predicting the thermal request profile at a building level and optimizing the substation operation. The proposed DSS incorporates seven surrogate approaches to generate the thermal request profile, namely ALAMO, Artificial Neural Networks, Support Vector Regression, Radial Basis Functions networks, Gaussian Process Regression, Random Forests, and

Kriging. The inclusion of several surrogate models allow us to experiment and find the most suitable one for each scenario.

In order to use black-box models for the prediction of thermal request profiles, a remote control and monitoring system, based on smart heat meters, needs to be used in the thermal substations. Section II presents the remote control monitoring system for thermal substations, which can be used for receiving measurements and transmitting data from smart heat meters to the DSS. Section III presents the DSS that generates dynamic thermal models describing the operation of a typical substation coupled to a reference building. Finally, in Section IV, the DSS is validated through the experimental analysis of an actual unit, serving a building of 6,000m^2 in the district heating network of Kozani, Greece.

II. Development of a Remote Control and Monitoring System for Thermal Substations

This section presents the remote control and monitoring system for thermal substations, which can be used for receiving measurements and transmitting data from smart heat meters to the DSS (Fig. 1). A low-cost (approximately 100 Euros) and efficient system was developed. This system has two main modules: the hardware interface module and the software communication module. The hardware interface module enables the system to interface with hardware devices, while the software communication module allows the system to communicate with software modules. At the heart of this system is an Arduino MKR WiFi 1010 microcontroller [21] coupled with an Arduino MKR 485 shield [22]. The microcontroller is responsible for all communication and controls in this system. The specific selection of the microcontroller was made based on its ease of use, cost, and reliability.

The smart heat meters used in the examined thermal substations of the district heating network of Kozani, Greece, are Kamstrup MULTICAL 602 [23] and Kamstrup MULTICAL 603 [24]. In order to acquire the data from these smart heat meters, we utilized the Modbus RTU communication protocol. The Modbus RTU module was installed in the smart heat meters. In addition, two temperature sensors Maxim Integrated DS18B20 [25] are used to also measure the temperature of the secondary supply and return flow pipe.

In Fig. 2 a sample substation unit is presented, so that the measurement sensor positions are clarified (parameters colored in red). There are also some calculated parameters that will be explained in Section IV (parameters colored in blue). The developed monitoring and control system measures and transmits every hour the following data:

- E_1 [MWh]: the energy consumed from the primary source in the form of transferred heat,
- V_1 [m^3]: the hourly water volume of the primary source,
- T_1 [^oC]: the temperature of the primary source supply pipe,
- T_2 [^oC]: the temperature of the primary source return pipe,
- T_3 [^oC]: the temperature of the secondary source supply pipe,
- T_4 [^oC]: the temperature of the secondary source return pipe.

III. Design and Development of the Decision Support System

There are three primary components that constitute the decision support system (Fig. 3): i) the database - knowledge base of the system, ii) the optimization module, and iii) the user interface. The Arduino microcontroller collects input from the smart heat meter, through the Modbus RTU protocol and the sensors, and send them, through WiFi, to the database - knowledge base every hour. Users select the reference building and trigger the optimization module to generate a new dynamic thermal model. This model describes the operation of the substation coupled to the building.

The thermal models are generated using different surrogate approaches. The DSS currently utilizes the following surrogate techniques:

- ALAMO [26] utilizes machine learning techniques for generating accurate and interpretable models of a simulation or an experimental black-box system,
- Artificial Neural Networks (ANNs) can be used to develop surrogate models without having to finely tune the degree of complexity of the surrogate models,
- Support Vector Regression (SVR) aims to interpret the data and their relationships into the best fit line,
- Radial Basis Functions networks (RBFs) are similar to ANNs but differ due to their reliance on the radial spread of each RBF function in each dimension,
- Gaussian Process Regression (GPR) is a probabilistic machine learning technique that can be used to build surrogate constitutive models,
- Random Forests (RFs) use multiple decision trees as a prediction method,
- Kriging can generate generalized linear regression models that account for the correlation in the residuals between the regression model and the observation.

IV. Experimental study

In this section, we validate the proposed decision support system through the experimental analysis of an actual unit, serving a building of 6,000m^2 in the district heating network of Kozani, Greece. By using measured data of the actual site heat exchanger, a surrogate model of the heat exchanger is developed.

The methodology for the development of the heat exchanger surrogate model can be viewed in Fig. 4. The data acquired from the site amounts to three weeks of hourly measurements (from January 25^{th} to February 17^{th}). By using measurements from two selected days of operation, the following parameters are calculated (see Fig. 2):

- $\dot{m}_1$ [kg/s]: the primary loop mass supply,
- $\dot{m}_2$ [kg/s]: the secondary loop mass supply,
- ε [-]: the heat exchanger effectiveness.

The equations that were used are presented in Equations 1–3:

Fig. 1. The developed remote monitoring and control system.

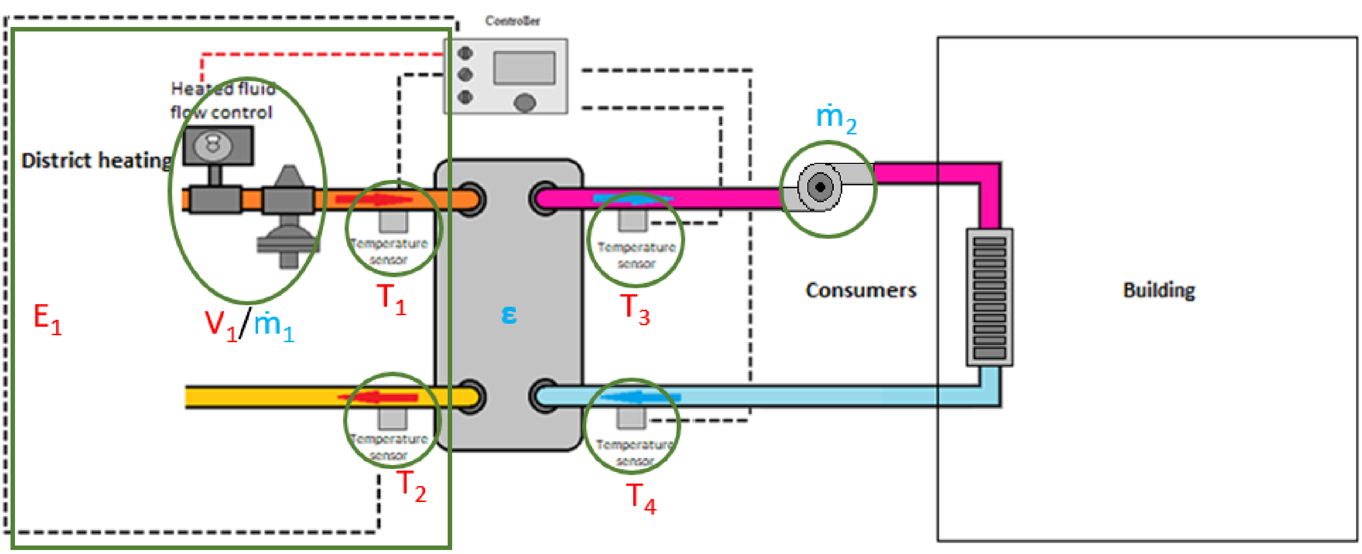

Fig. 2. A substation unit is shown schematically along with the locations of the measuring sensors and the derived terms.

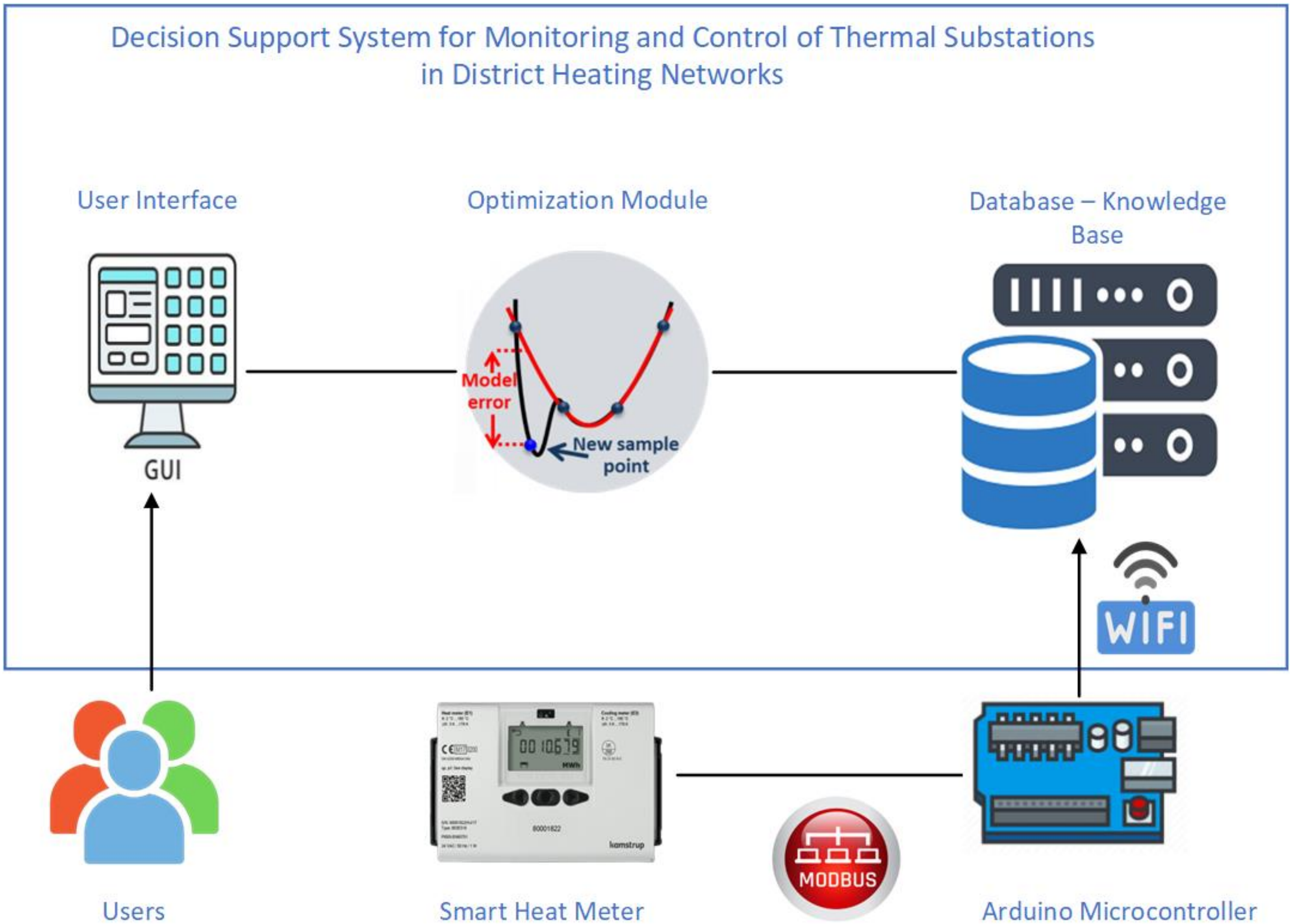

Fig. 3. Decision Support System's architecture.

$$\dot{m}_1 = d_w \frac{V_1}{3600} \quad (1)$$

where d_w is the density of the water.

$$\dot{m}_2 = \frac{\dot{m}_1 C_p (T_1 - T_2)}{C_p (T_3 - T_4)} \quad (2)$$

where C_p denotes the thermal capacity of the water flowing in each source.

$$\varepsilon = \frac{\dot{m}_1 C_p (T_1 - T_2)}{\dot{m}_{min} C_p (T_1 - T_4)} \quad (3)$$

where $\dot{m}_{min}$ corresponds to the lowest of the flow mass supplies (in primary and secondary source) for each time instance.

This way, a data batch is created that consists of the following measured and calculated data, from those two selected days of operation:

- Primary source supply pipe temperature [^oC],
- Primary source mass supply [kg/s],
- Secondary source return pipe temperature [^oC],
- Secondary source mass supply [kg/s],
- Heat exchanger effectiveness [-].

For the purposes of this experimental study, data fitting took place with the use of ALAMO, using the above data batch. The fitting phase splits into three separate scenarios, where each one has different input parameters. The fitting scenarios are explained below:

- Scenario 1: Correlate primary-side and secondary-side temperatures and mass supplies to the heat exchanger effectiveness,
- Scenario 2: Correlate only primary-side and secondary-side temperatures to the heat exchanger effectiveness,
- Scenario 3: Correlate only primary-side and secondary-side mass supplies to the heat exchanger effectiveness.

Each scenario provides a different surrogate model as a result. For validation purposes, the surrogate models, originated from the three scenarios, will be tested in a different day of substation operation.

The results of the fitting performance are presented in Fig. 5. First of all, the surrogate model of scenario 1 comes with an adequate accuracy, when compared to the values that come

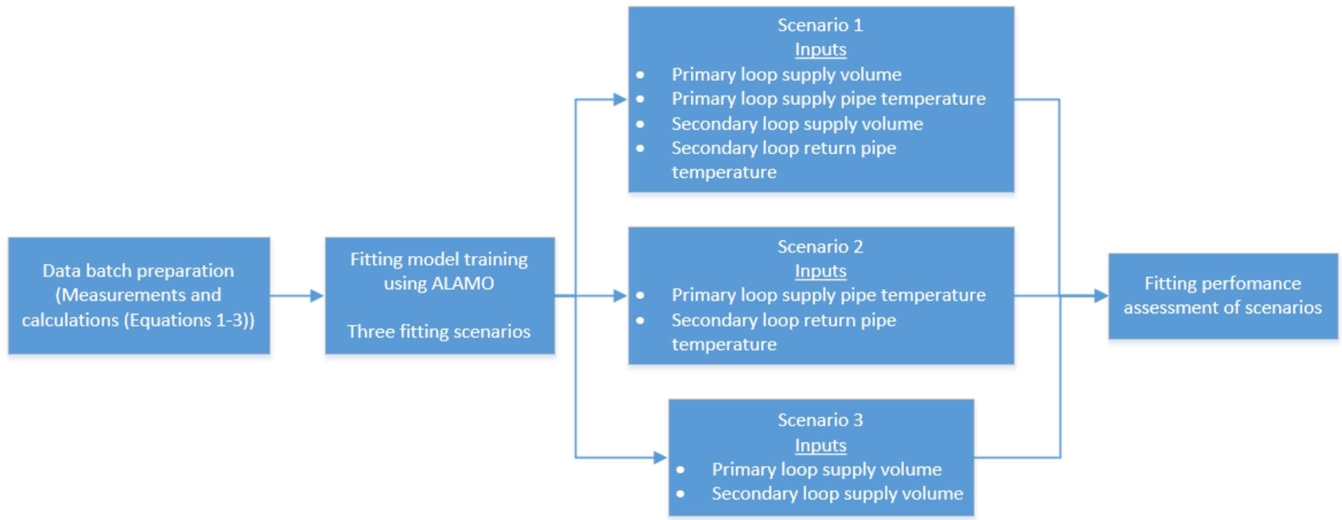

Fig. 4. Experimental study methodology.

from the thermal balance equation. Moreover, the surrogate models of scenarios 2 and 3 have less accuracy than the surrogate model in scenario 1 due to the fact that they are trained using partial information of the actual system. It is noted that scenario 2, which is trained using the temperatures of the water flows coming in the heat exchanger, performs slightly better against the model created in scenario 3, which was trained by the mass supplies. While this might imply that temperature data has more value than mass flow data, it is reminded that the measurement step was hourly. The temperature changes in the systems are much slower than pressure and flow changes [27]. That means temperature behaviours are more likely to be captured than those of the mass supplies, and that may affect the model training performance. Furthermore, this also means that the specific measurement time step might hinder scenarios 2 and 3 surrogate models' performance. It is therefore recommended that model training using data with a briefer measurement time step be examined in the future. Lastly, as stated in [28], the heat transfer coefficient per unit of surface area of a heat exchanger is mostly affected by fluid velocity. Thus, the mass supplies data of the fluids should have more impact than the respective temperature data. Therefore, in case of having partial data from the heat exchanger operation, it is indicated that the mass supplies have a more significant impact on the training of the surrogate model. Despite that, the inclusion of both temperatures and mass supplies of the flows can still provide the best surrogate model training performance, as more information about the heat exchanger is included.

V. Conclusions

The building industry is responsible for roughly 40% of the world's energy use. Innovative digital tools and appliances like smart heat meters improve building energy efficiency while also enabling consumers to better manage their energy costs. In that regard, we present a decision support system for predicting the thermal request profile of a building and optimizing the substation operation. A remote control and monitoring system of thermal request profiles in buildings is incorporated in this decision support system for the effective operation of thermal substations. The acquired data are used to develop a dynamic thermal model using different surrogate approaches.

We validated the proposed decision support system through the experimental analysis of an actual unit, serving a building of 6,000m^2 in the district heating network of Kozani, Greece. The generated surrogate model enables the prediction of both the primary and secondary source temperatures. With this feature, a simulation of the daily operation of the substation can be conducted. The presented methodology could be utilized in the context of a building model, that is able to help develop and validate optimal control strategies. Those strategies can be used for the enhanced utilization of the district heating network flexibility.

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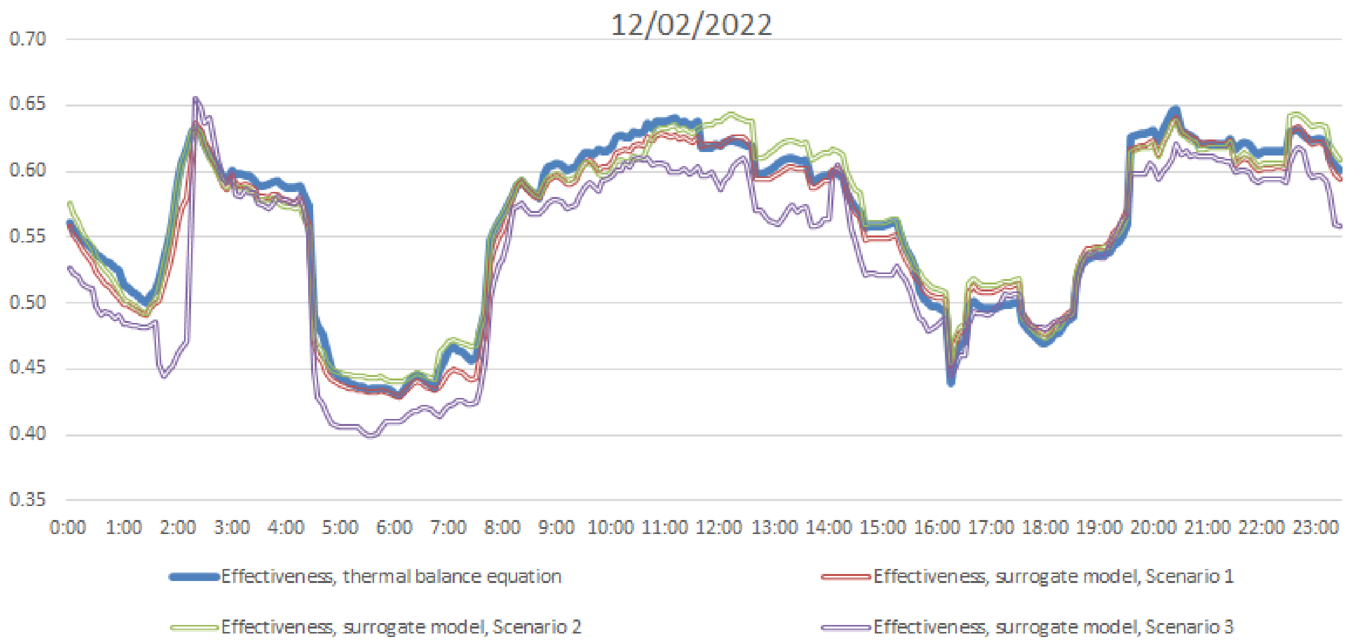

Fig. 5. Performance results of the surrogate models, compared to the calculated heat exchanger effectiveness.

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