Applied Thermal Engineering 196 (2021) 117233

Contents lists available at ScienceDirect

Applied Thermal Engineering

journal homepage: www.elsevier.com/locate/apthermeng

Integrated model concept for district energy management optimisation platforms

Víctor F. Sánchez *, Antonio Garrido Marijuan

TECNALIA, Basque Research and Technology Alliance (BRTA), Bizkaia Science and Technology Park, Astondo bidea 700, Derio, Spain

ARTICLE INFO

Keywords:
District Heating
District Modelling
Model Predictive Control
Co-simulation
Modelica
Supervised Machine Learning

ABSTRACT

District heating systems play a key role in reducing the aggregated heating and domestic hot water production energy consumption of European building stock. However, the operational strategies of these systems present further optimisation potential, as most of them are still operated according to reactive control strategies. To fully exploit the optimisation potential of these systems, their operations should instead be based on model predictive control strategies implemented through dedicated district energy management platforms. This paper describes a multiscale and multidomain integrated district model concept conceived to serve as the basis of an energy prediction engine for the district energy management platform developed in the framework of the MOEEBIUS project. The integrated district model is produced by taking advantage of co-simulation techniques to couple building (EnergyPlus) and district heating system (Modelica) physics-based models, while exploiting the potential provided by the functional mock-up interface standard. The district demand side is modelled through the combined use of physical building models and data-driven models developed through supervised machine learning techniques. Additionally, district production-side infrastructure modelling is simplified through a new Modelica library designed to allow a subsystem-based district model composition, reducing the time required for model development. The integrated district model and new Modelica library are successfully tested in the Stepa Stepanovic subnetwork of the city of Belgrade, demonstrating their capacity for evaluating the energy savings potential available in existing district heating systems, with a reduction of up to 21% of the aggregated subnetwork energy input and peak load reduction of 24.6%.

1. Introduction

District heating (DH) systems play a key role in reducing the aggregated thermal energy consumption of European building stock. However, the operational strategies of these systems present further optimisation potential, as most of them are still operated according to reactive control strategies [1,2]. Typically, the building-level heating system service temperatures and DH production and distribution temperatures are set according to static heating curves, allowing for adjustment of these settings to the evolution of weather conditions. Additionally, most existing DH system distribution networks operate according to variable flow rate strategies. This combined use of heating curves and variable flow rate strategies contributes to reductions in return temperatures, building-and district-level distribution thermal losses, and pumping energy consumption. However, the definitions of the heating curves and pressure settings for the pumping groups are performed according to historical data based on previous operational strategies that were typically defined to minimise service deficiency risks. Similarly, building energy management systems operate local systems according to reactive control strategies, e.g. by adjusting the energy requested from the thermal network to the evolution of the local demand and, if available, to the production of locally deployed distributed energy resources. Therefore, it can be concluded that these strategies are still of a reactive nature [3]. Thus, they do not fully capture the existing optimisation potential allowed by predictive strategies, e.g. those based on the holistic forecasting of weather and boundary conditions, and on control-setting definitions according to real-time evaluations of alternative control strategies [4].

Ideally, as shown in the existing literature, districts should be operated as integrated systems (buildings and thermal network infrastructure) to minimise the aggregated district energy demand and peak loads through the implementation of model predictive control (MPC) strategies. In this regard, [5] presented the development, implementation, commissioning, and results of an online system based on machine learning (ML) algorithms (e.g. decision trees) for real-time demand

* Corresponding author.
E-mail address: vfrancisco.sanchez@tecnalia.com (V.F. Sánchez).

https://doi.org/10.1016/j.applthermaleng.2021.117233
Received 24 November 2020; Received in revised form 21 May 2021; Accepted 8 June 2021
Available online 16 June 2021

Nomenclature

ANNs	Artificial Neural Networks
DDM	Data Driven Model
DH	District Heating
DHW	Domestic Hot Water
DR	Demand Response
DSM	Demand-side Management
FMI	Functional Mock-up Interface Standard
FMU	Functional Mock-up Unit
HVAC	Heating, Ventilation, and Air Conditioning
IDM	Integrated District Model
ML	Machine Learning
MLP	Multi Layer Perceptron
MPC	Model Predictive Control
R^2	Coefficient of determination
SVM	Support Vector Machine
SVR	Support Vector Regression
ω	Weigh vector of the support vector machine method
b	Bias component of the support vector machine method
ϕ	kernel function of the support vector machine method
ϵ	Error range of the predictions of the support vector machine method
C	Penalty term of the support vector machine method
ξ_i, ξ_i^*	Slack variables of the support vector machine method
X	Feature vector
Y	Target

forecasting and optimisation of the operation of a district heating system. Another study ([6]) concerned the development of an intelligent, context-aware, and adaptive energy management platform for optimising the operation of a district energy system, by taking advantage of the predictions produced by several artificial neural network (ANN) models utilised within a genetic algorithm. This system produced significant cost savings compared to reactive control strategies. In [7], a model predictive control system based on simplified physical models (for the buildings and thermal network) was developed and applied to a virtual use case comprising three office buildings and two energy supply sources. According to the obtained results, the peak loads were significantly decreased and the supply temperature was minimised, thereby reducing the distribution heat loss in the network. In [8], a DH system MPC controller was developed based on the DH infrastructure modelling language Modelica [9], focusing on the aggregated district energy demand/production balance. Finally, [10] provided a review of MPC works based on data-driven models (DDMs) focused on demand response applications, and showed the opportunities created by MPC systems based on data models in buildings connected to smart networks.

To enable the transition to MPC systems, the development of district energy management optimisation platforms (such as the solution developed in the framework of the MOEEBIUS project [11]) is required. These platforms incorporate prediction engines for providing the capacity to evaluate alternative energy management strategies, such as those exploiting predictive models. Owing to the complex and multiscale nature of districts, the scope of these models must include demand-side dynamics (buildings), the interface between the buildings and DH system (thermal substations), and the infrastructures of the DH systems, including the distribution network and heating plants. The traditional simplistic modelling approaches are based on building demand aggregation, and are not adequate for addressing the dynamics present in thermal networks (e.g. temperature distributions over the thermal network, or distribution thermal losses), or for providing accurate predictions for DH system operational management optimisation. Additionally, to generate reliable performance predictions, an accurate calculation of the return temperatures, i.e. from the buildings to the thermal network, is necessary. This is only possible if the dynamics present in the interface between the buildings and thermal network are evaluated by exploiting a multiscale, multidomain, and fully integrated district model. These statements have been confirmed by previous research activities documented in the literature. The work described in [12] consisted of the development of the 'OpenIDEAS' framework, based on the Integrated District Energy Assessment by Simulation (IDEAS) Modelica library [13], which was designed for integrated district energy modelling and simulation. The work in [14] described an integrated Modelica model to evaluate the district-level energy savings produced by the retrofitting of buildings connected to a network branch. In [15], a Modelica-based framework for DH/cooling system modelling and operational optimisation was described, including the application of the framework to two virtual DH systems, thereby revealing the importance of a detailed evaluation of district-level dynamics. Similarly, the work described in [16] focused on the optimisation of the network supply temperatures of DH systems, and stressed the need for an accurate modelling and evaluation of the district infrastructure-level dynamics.

Physics-based models and DDMs are the most generalised energy behaviour modelling approaches used in the building and district domains. Each of them presents specific advantages and limitations in relation to their use in MPC implementations. Several works and abundant literature can be found related to the modelling approaches existing in this domain. In [17], an analysis and comparison of physics-based and data-driven building energy modelling approaches was provided, whereas [18] gathered a case study focused on building temperature prediction through physics-based and DDMs; in regards to the latter, it evaluated the low prediction accuracy loss and suitability for real-time use. In [19], a detailed review and comparison between the physics-based and DDMs as evaluated through simulations was presented, and hybrid models were identified as the most promising building energy consumption modelling approaches.

Owing to their nature, physics-based models are very suitable for generating accurate predictions of the energy behaviours of buildings and DH infrastructure even when operating under different climatic conditions, user behaviour patterns, and system operational settings, provided that they are physically compatible with the technical characteristics of the system, and that all the input data related to the physical parameters are available. According to the literature, these models are particularly suitable for MPC approaches. The work described in [20] consisted of the development of an MPC system based on an EnergyPlus/MATLAB prediction engine for a building equipped with an underfloor air distribution system; it achieved significant energy savings. In [21], an MPC system based on an EnergyPlus energy prediction engine was used to optimise the control rules of an administrative building and to minimise its energy consumption. In [22], an advanced MPC system based on a control-oriented dynamic thermal model was developed for radiant floor systems, and was tested in a TRNSYS-MATLAB co-simulation testbed. The test results showed that, compared to a conventional on–off controller, the MPC controller could use building thermal mass to optimally shift energy consumption to low-price periods. Similarly, [23] focused on an MPC energy management system based on a resistance–capacitance model for optimising the operation of a residential building equipped with air-sourced heat pumps for heating and domestic hot water (DHW) production, and a floor heating system. The results showed that an optimal control aimed at minimising energy costs while limiting peak power could lead to savings of up to 25% compared to a rule-based control.

However, owing to the multidomain and multiscale nature of DH systems, the development of physical models is a very challenging task; it requires deep knowledge, and sufficient experience with building and DH system physics. Additionally, detailed information related to buildings and/or DH system infrastructures is not always available; moreover, owing to the detailed definitions of these models, the required computational times are significantly higher than for DDMs. In addition, none of the existing procedural legacy building simulation programs such as EnergyPlus [24], eQUEST [25], and TRNSYS [26] provide the modelling capabilities required for integrated district model composition, as they were conceived for building architectonic and building technical system design. The implementation of these tools is based on large monolithic blocks consisting of programming procedures composed of causal assignments for defining model equations, numerical solution algorithms, and data input/output routines. As a consequence, the addition of new modelling capabilities to legacy building simulation programs becomes technically complex and inefficient, as has been documented in the existing literature. In [27], a comparison between legacy building simulation programs and equation-based modelling languages was described, including two MPC use cases that displayed the advantages of the latter. Similarly, [28] provided a comparison of a multizone building energy model developed in an equation-based modelling language with the TRNSYS building model, and concluded that the development time was five to ten times faster. In [29], a review of the limitations of legacy building simulation engines and tools (e.g. EnergyPlus, DOE2 [30], eQUEST, and Riuska [31]) was provided.

Equation-based modelling languages such as Modelica provide a powerful and promising alternative to legacy simulation programs. Specifically, Modelica is an object-oriented acausal modelling language designed for the multidomain modelling of dynamic systems. Through this modelling language, physical modelling and executable simulation program development are decoupled, as the latter is solved by dedicated modelling and simulation environments such as OpenModelica [32] or Dymola [33]. In Modelica, the mathematical equations for describing the physical behaviours of systems are encapsulated within components, and the relationships among the interface variables are captured by standardised interfaces. This allows for component connection, and for reproducing the modularisation and connectivity rules of real equipment to form subsystems, systems, or complete architectures. In the last decade, several specific libraries such as the Modelica Buildings library [34], Modelica Building Systems library [35], AixLib library [36], and IDEAS library have been developed with dynamic models for building and DH system modelling, and several initiatives such as the International Energy Agency- Energy in Buildings and Communities Annex 60 [37,38] and International Building Performance Simulation Association Project 1 [39] have increased the availability of libraries for building and district modelling. The literature related to Modelica works in this domain is diverse and abundant. In [40], the development of a new mathematical model for pipes optimised for DH systems managed according to variable supply temperature and flow rate strategies was reported, along with its Modelica implementation. Similarly, the work compiled in [41] discussed the development of a mathematical model for a twin pipe incorporating the heat transfer from the supply pipe to the return pipe, including its Modelica implementation. In [42], a description of the development, implementation, and validation of a dedicated Modelica library for DH system modelling was provided. In [43], an innovative heating and cooling thermal network concept was designed (with waste heat recovery and bidirectional heat exchange between prosumers and the network), and its potential was compared to traditional solutions using Modelica models. Another study ([44]) provided an analysis of the capacity of Modelica and the Modelica environments for modelling and simulating electromechanical power systems. The work compiled in [45] described the development of a Modelica-based MPC controller for DH system infrastructures aiming to optimise the generator status, supply temperature, and pumping system differential pressure settings. In spite of all of the above, the capacities given by these Modelica libraries are not comparable to those provided by legacy building simulation programs, thereby reducing the possibility of a prompt transition to the use of Modelica in this domain. Furthermore, a physical component-oriented system composition architecture is not compatible with an efficient definition of complex DH systems, owing to the scalability limitations created by the cost associated with the connection and instantiation of a large number of component models involved in DH system modelling.

DDMs are generally developed using different techniques (e.g. ML, statistical methods) and historical data series, including the input and output parameters of the target dynamic system (the district); they allow for the definition of numerical algorithms without any explicit modelling of the physical behaviours of the system. These algorithms are able to capture the existing behavioural patterns and to provide predictions for the energy behaviours of buildings and DH system infrastructures, starting from the input parameter sets that define their statuses and boundary conditions. Owing to their nature, detailed information regarding the physical parameters is not necessary, and a deep understanding of the district technical domain, although highly advisable, is less critical. Additionally, the required calculation times are shorter than those for physical models, making them suitable for real-time applications in building and district management systems. A rich and varied literature is available on the use of data models in this domain. In [46], a review was provided on recent applications of DDMs for building energy behaviour forecasting. Similarly, in [47], a review of building DDM applications is described, including the prevalent ML methods, relevant parameters, forecasting horizons, and prediction accuracy. The work described in [48] concerned the development, implementation, and operational service of real time demand forecasting systems through ML algorithms and in [49], ANNs were used to predict heat demand and return water temperatures based on outdoor temperature forecasting and historical data series. In [50], a new method for district heat demand prediction based on ANNs and duplicated feature elimination was described. The method was successfully applied to a district heating network containing tens of buildings at a university campus, and reduced the training time by 20% from traditional methods while maintaining the prediction accuracy. In [51] a Chebyshev distance-based agglomerative hierarchical clustering approach was proposed for gathering historical prediction residuals of similar operating conditions into the same cluster. A quantile-based approach was proposed to estimate the prediction interval of a predicted cooling load by using a cluster of the most similar operating conditions. The method was successfully tested using an ANN-based building cooling load prediction model. In [52], an MPC system based on an ANN building cooling energy consumption prediction model was developed and exploited to optimise the setpoints of air handling units. The system was tested in a three-story office building using an EnergyPlus-MATLAB test bed, and showed a reduction in cooling energy consumption of 10% compared to a conventional control strategy. In [53], a bidirectional long short-term memory neural network-based approach was proposed for detecting and classifying substations that use night setbacks regularly. The proposed approach was evaluated using data from 10 anonymous substations in Sweden, and the results showed that the proposed approach outperformed conventional detection methods. In [54], a novel technique for estimating commercial building energy consumption from a small number of building features and gradient boosting regression models was presented. The models were validated using the New York City Local Law 84 energy consumption dataset, and were applied to the city of Atlanta to successfully create aggregated energy consumption estimates. Similarly, in [55], a rough set theory was used to find the critical factors involved in building energy consumption to facilitate the development of a deep neural network for predicting building energy consumption. The data from 100 civil public buildings were used for a rough set reduction, and the proposed method was tested in a laboratory building at a university in Dalian. The results were compared with those of several ML methods, and demonstrated the superior accuracy of the proposed method. Notwithstanding the above, the main limitation of DDMs regarding their use in energy management systems based on MPC approaches is their lack of capacity to generalise the behaviours of districts operating under new strategies, i.e. for which no dataset is available.

In summary, it can be concluded that district modelling remains a complex technical field, and several limitations remain unsolved, including the following.

- The limitations of building simulation programs for providing complete physical demand-side modelling efficiently.
- The insufficient maturity level of the multiscale and multidomain modelling tools for the building and district domains.
- The existing limitations for complex DH infrastructures include detailed physical modelling, owing to scalability issues.
- The limited capacity of DDMs to generate predictions for districts operating under unseen strategies.

The aim of the work described herein is the development of an integrated district model (IDM) concept for overcoming the limitations of legacy building simulation programs and Modelica for district modelling. It takes advantage of co-simulation techniques to enable integration of the building and DH system physical models, by exploiting the potential of the functional mock-up interface standard (FMI) [56]. From the perspective of demand-side modelling, the main contribution of the developed IDM consists of a new procedure based on the combined use of physical models and DDMs that allows for complete demand-side modelling, without the need for developing detailed physical models for each building in the district. This is a significant barrier to the implementation of MPC approaches, owing to significant high resources required for the development of building models. Instead, the proposed method takes advantage of the structures of urban DH systems, as these are typically formed by an arbitrary number of building groups built according to designs similar from architectonic and functional system perspectives. The method is based on (1) the development of a building energy demand prediction model for the buildings of a district through supervised ML regression techniques and (2) on the definition of a detailed physical model (EnergyPlus) for a single building of each type. The data-driven building demand forecasting model is exploited to generate a demand correction function for each of the buildings in the district. These correction functions, combined with detailed physical building models, can produce energy demand predictions for all buildings operating according to alternative demand-side management (DSM) strategies.

In relation to DH system infrastructure physical modelling, the main contribution of the developed IDM is the development of a new Modelica DH library with specific models for enabling DH system model composition according to a subsystem-oriented architecture. These subsystem models are conceived so as to encapsulate the equipment components existing in the actual subsystems, i.e. by reproducing their modularity and connectivity rules. Additionally, the flexibility and scalability required to adapt the models to any specific DH project are added through dedicated algorithms, and the modelling capacities are optimised to evaluate all of the relevant dynamics. Ultimately, the developed Modelica library allows for the optimisation of the resources required for the detailed definition of complex DH system models, significantly reducing the risk of modelling errors. The developed IDM is tested on the Stepa Stepanovic subnetwork (Serbia) to evaluate its capabilities.

Regarding the structure of the rest of this paper, Section 2 provides a description of the methods defined to develop the IDM, and Section 3 describes the testing process of the developed models in the Stepa Stepanovic subnetwork, including the production process of the IDM for the demo district and the evaluated optimisation scenarios. The results from the testing processes of the defined models and the impacts of the optimisation scenarios are discussed in Section 4. Finally, Section 5 concludes the paper.

2. Methods

2.1. Integrated district model through co-simulation

Co-simulation is an innovative simulation technique that allows for data exchange during time integration between two or more simulation tools, so as to solve coupled systems of equations [57]. These techniques can be applied in the district modelling domain to overcome the limitations existing in this specific field in regards to both building simulation tools and Modelica, as described in [58,59]. More specifically, from the development of the first version of the FMI in 2010, designed to standardise the procedure for coupling simulation tools, the potential of these techniques has been constantly increasing, as illustrated by the existing literature. In this regard, [60] described the extension of a building management system with an interface based on the FMI that allowed the implementation of fault detection algorithms. Similarly, [61] illustrated the applicability of co-simulation concepts based on the FMI for the simulation of buildings and community energy systems by comparing several state-of-the-art approaches. Finally, [62] described four completely different applications of the FMI in the building simulation domain.

The procedure designed in this study to generate the IDM took advantage of the possibilities provided by co-simulation techniques and the FMI standard to couple a Modelica model for a DH system (heating plant, solar plants, distribution network, and thermal substations) with the EnergyPlus models of the buildings (including building-level heating, ventilation, and air conditioning (HVAC) systems) connected to the DH system, after being encapsulated into functional mock-up units (FMUs) [63]. With this approach, it was possible to split the physical system of the district into several parts that were homogeneous from the perspective of the physical domain and the scale (building and district) they belonged to, without losing actual integration among the different models. This allowed for the development of specific models for each part of the physical system using suitable modelling and simulation tools with the capacity to accurately capture all the dynamics present in each specific model. In the case of the IDM herein, the building thermal substations were established as the most suitable interface between the building models and network infrastructure model.

2.2. Combined use of physical and data driven models for district demand-side modelling

The created IDM acted as the base of the energy prediction engine for the developed district management system. The functionalities provided by this platform were based on the capacity of the IDM to evaluate alternative operational strategies on the demand side and DH system side, owing to the physical modelling approach. However, the traditional procedures for district demand-side physical modelling, as pure aggregations of the physical models of each and every district building, were unfeasible from the perspective of the required resources. This barrier was overcome by exploiting the synergies obtained from the combined use of physical models and building energy demand models, as obtained through ML techniques. More specifically, the sequential procedure displayed in Fig. 1 was defined to allow complete demand-side modelling, and included the following aspects.

- Building typologies existing within the district were defined according to their use and architectonic/system design.
- A representative building was selected for each of the defined building typologies.
- Physical models (EnergyPlus) were developed for the representative buildings (including their HVAC systems).

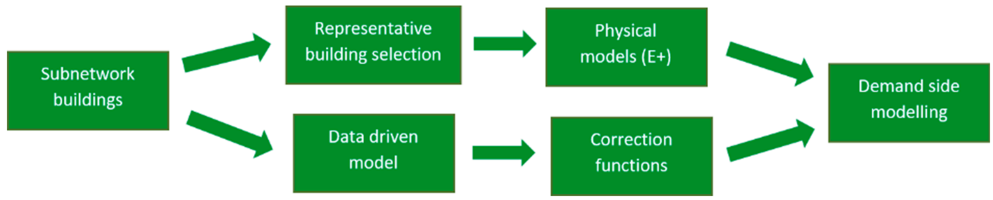

Fig. 1. Demand-side modelling through the combined use of physical and data driven models.

- A building demand forecasting model was developed through supervised ML regression techniques, taking advantage of the historical data of the heating demands of the buildings.
- A specific building demand correction function was defined for each building by taking advantage of the predictions provided by the data model.
- Hourly/sub-hourly demand predictions were generated for all the buildings of each type by taking advantage of the demand correction functions, and of the predictions produced by the physical models developed in EnergyPlus for the representative buildings.

As described in the available literature, support vector machine regression (SVR) and ANNs are the most commonly employed supervised ML methods in the building and district domains. In this regard, [64] proposed a detailed review of ML based building energy performance prediction methods (e.g. ANNs, SVR) and presented the principles, applications, advantages, and limitations of these ML algorithms. Similarly, [65] reviewed recently developed building energy performance models, including engineering, statistical and ML methods and described relevant applications of ANNs and SVR. Finally, another study [66] proposed a detailed review of buildings energy performance modelling (physical, ML and hybrid models) and identified ANNs and support vector machines as the predominant ML methods. Thereby, SVR and ANNs were selected for the development of the proposed method.

2.2.1. Support vector regression

SVR is a supervised ML method which aims to find a decision function or model for representing the relationships between features (x1, x2, x3,……. xi) and a target (y). It is based on the principle of structural risk minimisation, and takes advantage of the definition of one or more hyperplanes in a high-dimensional space that can be mapped through a kernel function ϕ, weight vector ω, and bias component b to the original feature space, as follows [67]:

$$Y = \omega\phi(X) + b \tag{1}$$

The goal of the SVR method is to minimise the probability that the model will make an error on an unseen data instance. This is achieved by finding the solution which best generalises the training dataset, by minimising a convex criterion function as follows:

$$Minimize : \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l} \xi_i + \xi_i^* \tag{2}$$

This calculation is subject to certain constraints, as follows:

$$y_i - \omega^T\phi(\overline{x_i}) - b \leq \epsilon + \xi_i \tag{3}$$

$$\omega^T\phi(\overline{x_i}) + b - y_i \leq \epsilon + \xi_i^* \tag{4}$$

In the above, ϵ denotes the prediction error range, ξ_i and ξ_i^* are the slack variables which ensure the existence of a solution for any ϵ, and C is a penalty term used to optimise the balance between data fitting and prediction smoothness. In this domain, the SVR method can provide better accuracy than most of the existing classical ML methods, and through the use of the regularisation parameter C, is not prone to overfitting problems. Its main limitation is the lack of a universal procedure for selecting the appropriate kernel function and its slow learning speed, making it a computationally less efficient method during the model training stage.

2.2.2. Artificial neural networks

Supervised ANNs are trained using historical data that describe the energy behaviours of buildings, for creating a model with the capacity to reproduce the relationships between the features and target. Owing to their accuracy and ability to represent non-linear processes, the use of supervised ANN models in this domain has been intense [67]. The main advantage of ANNs is their high prediction accuracy when large datasets free from fuzzy, noisy, or incomplete data, are available. However, their main limitations are the high computational resources required, slow learning process, and risk of overfitting.

The architecture of an ANN consists of an input layer, an arbitrary number of hidden layers, and an output layer. The input dataset (features) flows from the input layer through the hidden layers to the output layer, where the target value is obtained. In the case of the hidden layers, the output of each neuron is delivered to each neuron of the subsequent hidden layer after being multiplied by its corresponding neuron weight. The total output of any of the neurons of a specific hidden layer is calculated by summing all the inlets, including a bias contribution. Finally, an activation function is applied to the latter to define the output of each neuron. During the training stage, through a back-propagation process, different optimisation algorithms can be used to identify the weight and bias contributions to minimise the loss function value and correctly map outputs with inputs. Fig. 2 displays the architecture of an ANN consisting of a single hidden layer with three neurons.

2.3. New Modelica district heating (DH) modelling library

In the Modelica libraries available at the time of completion of this work, the district modelling was based on a physical equipment-oriented architecture, which is far from ideal for providing detailed definitions of complex DH systems in an efficient way. District modelling should instead be based on a subsystem-oriented modelling architecture, so as optimise the effort required for model development. To overcome this limitation, a new Modelica library was developed, including subsystem models specifically conceived for that purpose, according to a flexible and scalable approach required to allow modelling of DH systems of any size and complexity. Therefore, it was possible to maximise the capability to define typical existing DH system typologies.

The library models were developed using the physical component models available in the Modelica Standard Library (version 3.2.2), Modelica Buildings Library (version 4.0.0), and ThermoPower Library (version 3.1) [68]. These models were adjusted to align them with the implemented subsystem-oriented architecture approach. The code of the models was defined with specific algorithms to provide the flexibility and scalability required to adapt the models to any specific DH project.

Fig. 3 displays a very simple example of a DH system modelled using the subsystem models available in the developed Modelica library. In this specific case, the DH system is configured through an instance of the DH plant model, an instance of the pumping station model, and a distribution network consisting of two instances of the loop/branch subsystem model (as required to represent a network topology with a two-level hydraulic circuit hierarchy). Finally, the model of the DH infrastructure is completed by using several instances of the building

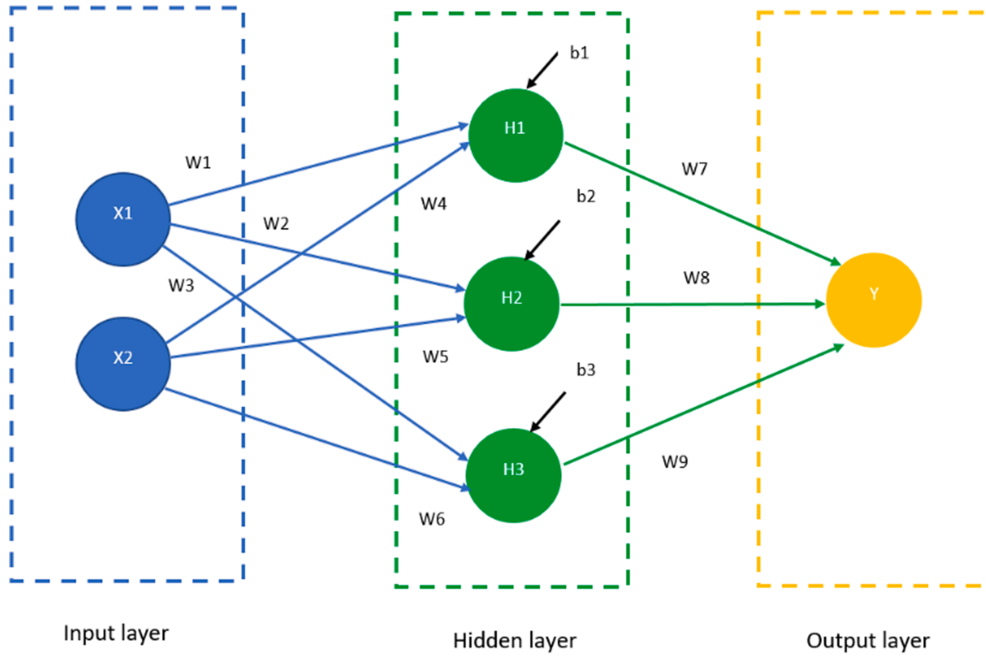

Fig. 2. Artificial neural network (ANN) architecture consisting of a single hidden layer with three neurons.

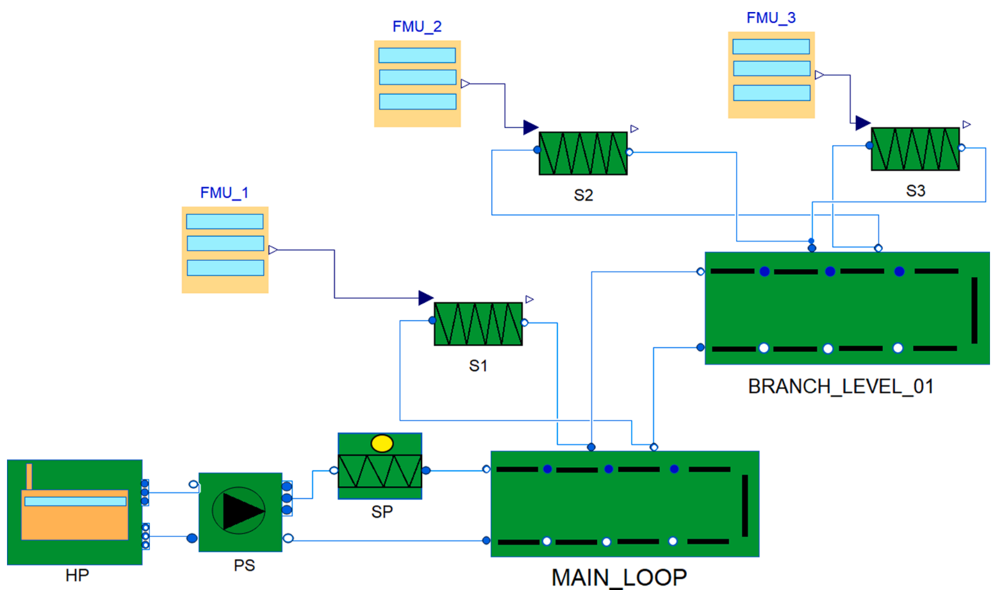

Fig. 3. District model defined through the subsystem architecture using the developed Modelica Library.

substation model deployed all over the branch hierarchy of the network, so as to integrate the impact of the energy requested by the buildings on the DH system. Additionally, as displayed in Fig. 3, the solar plant subsystem model incorporated into the developed Modelica library allows for the integration of solar production into the DH system. In the following sections, an overview of the different subsystem models is provided. A more comprehensive description of the technical features of the subsystem models can be found in [69].

2.3.1. DH plant model

The DH heating plants formed by water boilers and steam production plants are a very common plant typology in existing European DH systems. Considering this, the developed subsystem model was specifically designed to address this plant typology. All of the equipment existing in this type of plant was encapsulated within the designed model, and during model instantiation, it supported a flexible and scalable configuration regarding:

- the number of existing hot water generation groups and the specific component configuration within each generation group (heat generators, pumps, pipes, vertical stratified storage tanks, energy delivery heat exchangers, valves, and control components); and
- the configuration of the steam production plant in terms of steam generator and water heating line numbers.

Fig. 4 displays a simplified version of the component models encapsulated within a hot water production plant subsystem model as formed by a single water production group with thermal storage.

The steam production plant supported by the DH plant subsystem model consisted of an arbitrary number of steam generators coupled to

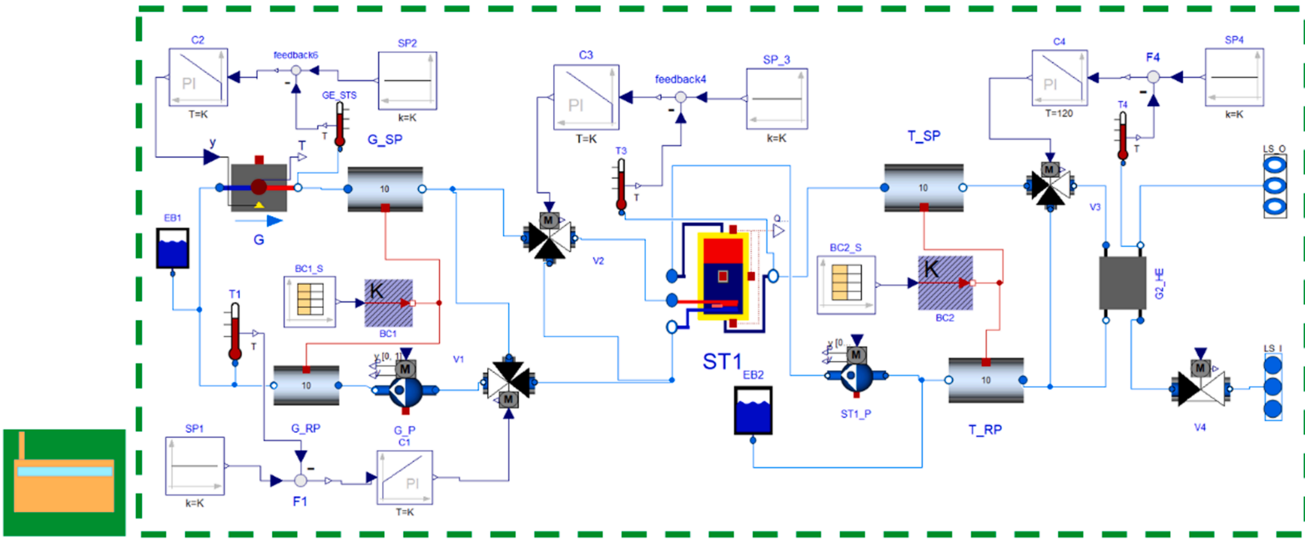

Fig. 4. Simplified version of the component models encapsulated within the district heating (DH) plant model for a DH plant with a single hot water generation group.

an arbitrary number of heating lines (condensers and subcoolers connected in series). Fig. 5 displays a simplified version of the component models encapsulated within the steam production plant of a generic DH plant with a single steam boiler and single water heating line.

2.3.2. Pumping station model

The pumping station model was conceived to encapsulate the physical components required to configure any DH system pumping station, including the pumps, pipes, pipe thermal boundary conditions, valves, and control components. It allowed for the flexibility and automatic scalability of the model, e.g. to adjust the number of existing pumping groups and number of pumps within each pumping group. In its simplest configuration, any DH model defined through the developed Modelica library would necessarily include a pumping station subsystem model connecting the demand side of the DH plant to the source side of all of the existing main distribution loops of the network. Depending on the specific topology of the modelled network, additional pumping station models could be integrated at any loop or branch hierarchy level. Fig. 6 depicts the component models encapsulated within the subsystem model of a specific pumping station formed by a single pumping group with two pumps.

2.3.3. Loop/branch model

The loop/branch model was conceived to encapsulate all of the hydraulic components required to configure any distribution of a thermal network of a DH system including pipes, connection ports, and pipe thermal boundary conditions. It could be used to model typical thermal network topologies (e.g. ring, radial, branched, meshed), and allowed for the evaluation of the impacts of the distribution of thermal losses and pressure drops over the network. Regarding connectivity, on the load side, the model allowed for the connection of an arbitrary number of branch models of a lower level in the branch hierarchy, or a direct connection to building thermal substations.

Similarly, on the source side, the model could be directly connected to the load side connections of a DH plant subsystem model, or alternatively, to the load side connection ports of one of the branches of a higher level in the branch hierarchy. Additionally, the model could be configured during instantiation to define the main loops (including a

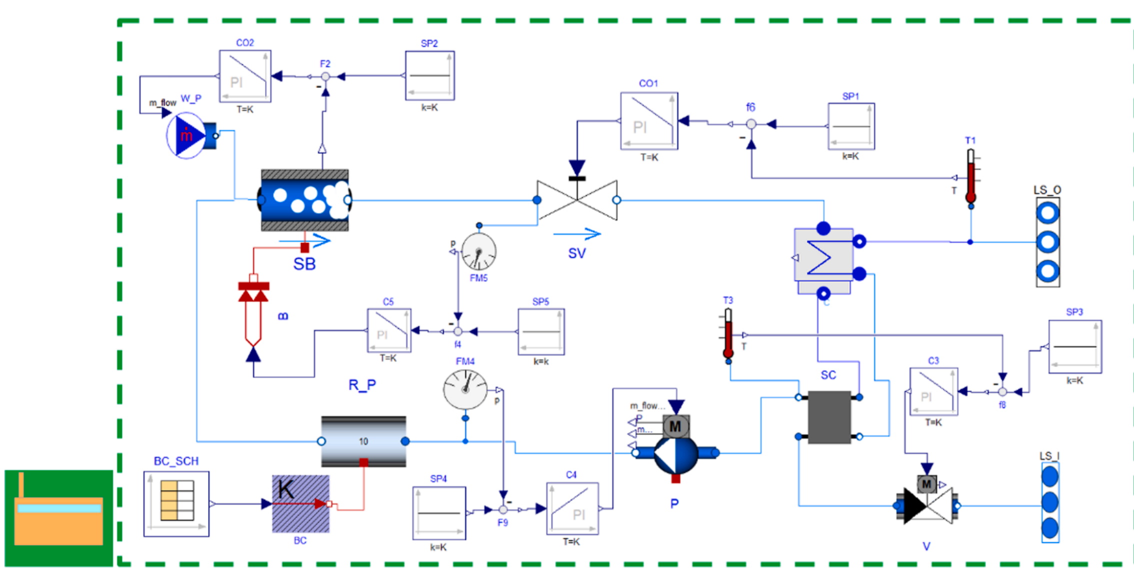

Fig. 5. Simplified version of the component models encapsulated within the heating plant model for a heating plant equipped with a single steam production boiler and a single heating line.

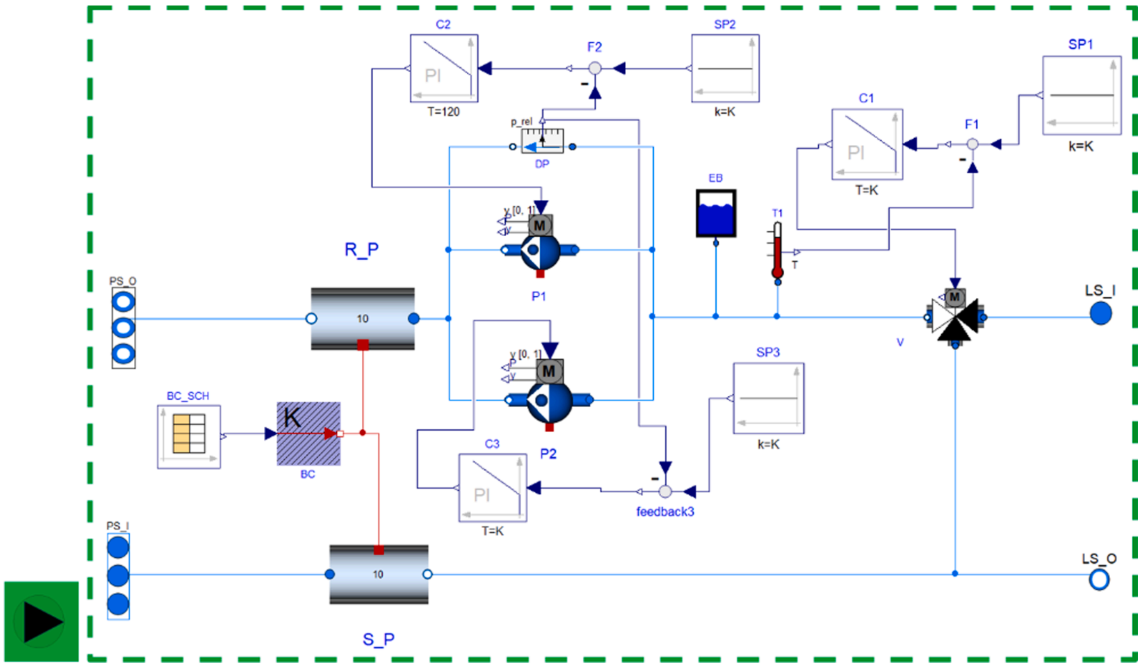

Fig. 6. Component models encapsulated within the pumping station subsystem model for a pumping station equipped with a single pumping group with two pumps.

bypass at the end of the loop) or branches of a lower level in the branch hierarchy (without a bypass). Fig. 7 depicts the physical component models encapsulated inside a loop/branch model for the specific case of a loop with four pairs of load-side connection ports.

2.3.4. Thermal substation model

The thermal substation model encapsulated all of the physical components forming a typical parallel-type thermal substation, including the DHW production heat exchangers, valves, control equipment, and components required to integrate the energy requested by the connected buildings. The model could be adjusted to set the presence/absence of a dedicated DHW production heat exchanger. Fig. 8 displays the connections of the physical component models encapsulated inside the thermal substation model of a parallel-type substation with dedicated heating and DHW production heat exchangers.

2.3.5. Solar collector plant model

This subsystem model was conceived to encapsulate all of the physical components required to configure a solar thermal collector plant, including collectors, pumps, pipes, storage tanks, valves, control equipment, and pipe and tank thermal boundary conditions. During the instantiation of the model, flexibility and scalability were available when configuring the solar field, in relation to the number of collector arrays connected in parallel and number of collectors connected in series in each array. Fig. 9 shows the component models encapsulated within the thermal collector plant model for a specific plant with a single collector array.

2.3.6. Auxiliary record classes

To allow for a simple and systematic introduction of the specifications of the physical components encapsulated within the defined models, several auxiliary record classes were defined and used as

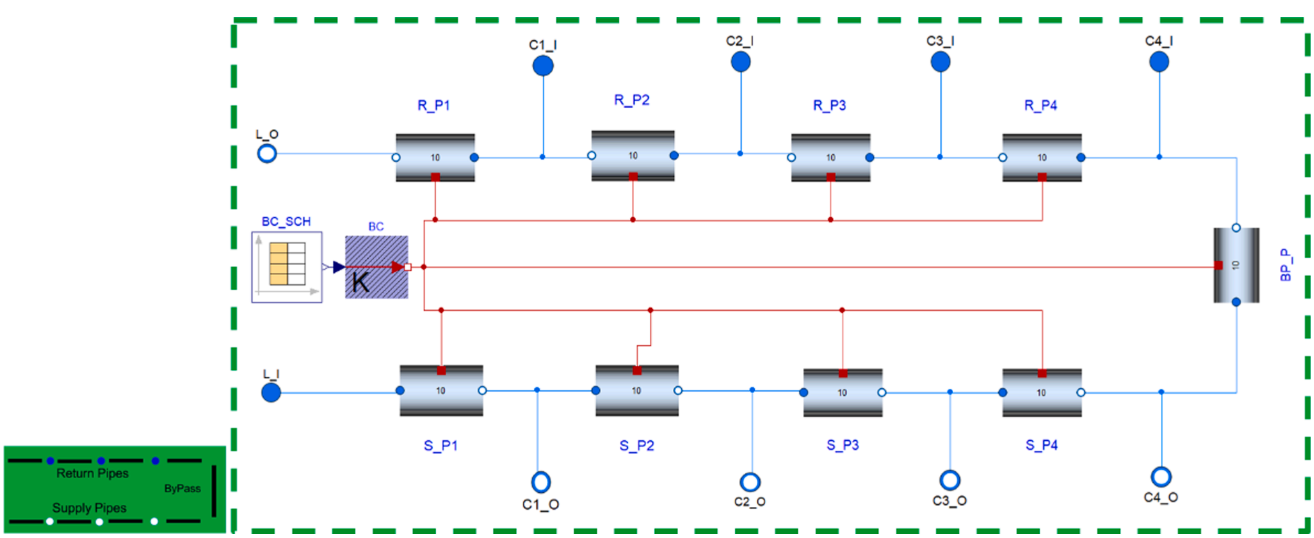

Fig. 7. Component models encapsulated within the loop/branch subsystem model for a loop with four connections, including the supply and return pipes, the inlet and outlet connection ports, and the bypass deployed at the end of the hydraulic circuit.

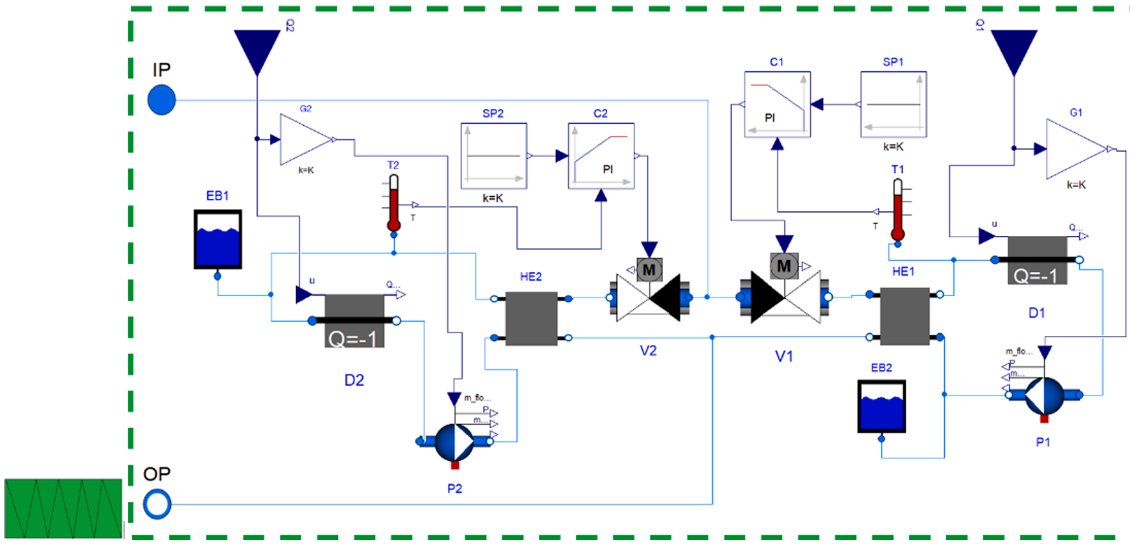

Fig. 8. Component models encapsulated within the parallel substation model including the heating heat exchanger (HE1), the DHW production heat exchanger (HE2), and the energy delivery control valves for heating (V1) and for DHW production (V2).

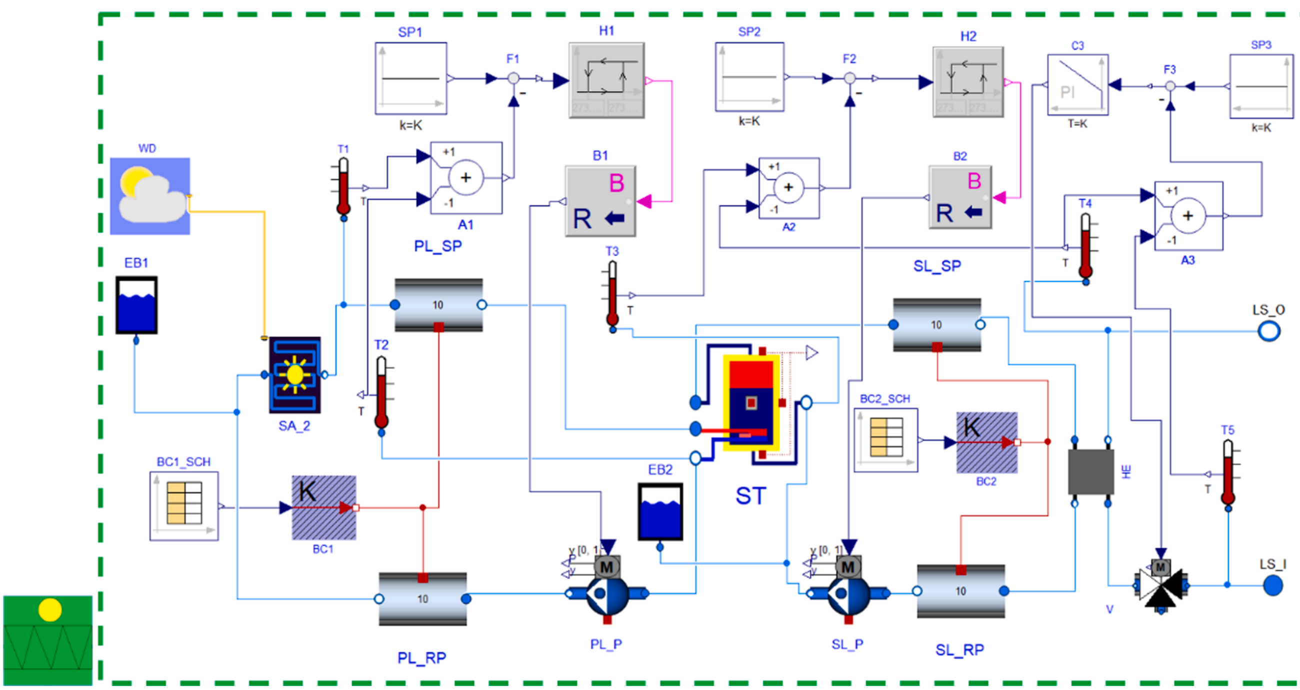

Fig. 9. Component models encapsulated within the solar collector plant subsystem model for a solar plant with a solar field formed by a single collector array, solar tank, solar energy delivery plate heat exchanger, mixing valve to adjust production temperature, and the two pumps required to produce water circulation.

necessary in the subsystem models (e.g. pipe specification, pump specification, plate heat exchanger specification, condenser specification, hot water boiler specification and hot water boiler performance specification, storage tank specification, two-way valve and three-way valve specifications, solar collector specification, and steam boiler specification).

3. Stepa Stepanovic use case

3.1. Vozdovac DH system and Stepa Stepanovic subnetwork

The Vozdovac system is one of the several heating networks that form the DH system of the city of Belgrade. It comprises of a DH plant and a two-pipe distribution network based on a branched topology. It meets the energy demand (heating and DHW production) associated with different areas of the city, including the Stepa Stepanovic neighbourhood. Three hot water boilers (total capacity of 241 MW) and two steam boilers (total production capacity of 22 t/h), all of which run on natural gas, produc the energy distributed to the mentioned areas from the Vozdovac heating plant.

The evaluation of the potential of the proposed IDM concept and of the developed Modelica library was performed based on the subnetwork of the Stepa Stepanovic neighbourhood. This subnetwork provides the energy required to cover the heat demand of 52 residential buildings, a kindergarten, and a primary school. Table 1 provides a summary of the specific HVAC systems existing in the residential buildings and educational buildings connected to the subnetwork. A more detailed description of the technical features of the Vozdovac system and of the

Table 1
Technical features of heating, ventilation, and air conditioning (HVAC) systems of the buildings connected to the subnetwork.

Buildings	Connection	Building level distribution	Emission subsystem	Ventilation
Residential	Indirect heating substation	Dedicated distribution circuits for different building orientations, equipped with variable flow pumps	Conventional hot water radiators with thermostatic valves	Mechanical exhaust systems in apartment kitchens and toilets Natural ventilation in the rest of the rooms
Kindergarten	Indirect heating substation	Common centralised distribution circuit equipped with variable flow pumps	Conventional hot water radiators	Several air handling units of different types operating according to constant air flow strategies
	Indirect ventilation substation		Several split and multi split units	Exhaust air systems for some specific zones (e.g. food preparation rooms)
Primary school	Indirect heating substation	Dedicated distribution circuits for the radiator and the radiant floor system equipped with variable flow pumps	Conventional hot water radiators Radiant floor system (multi-sports court)	Several air handling units of different types operating according to constant air flow strategies
	Indirect ventilation substation		Dedicated all air systems for some specific zones Several split and multi split units	Exhaust air systems for some specific zones (e.g. food preparation rooms, toilets, locker rooms, technical rooms)

buildings of the Stepa Stepanovic neighbourhood can be found in [70].

3.2. Integrated district model of the Stepa Stepanovic subnetwork

3.2.1. Co-simulation procedure

The IDM was developed to serve as the prediction engine for the district energy management platform developed in the framework of the MOEEBIUS project, according to a service-based distributed architecture. In the case of the Stepa Stepanovic subnetwork, owing to certain platform implementation limitations, it was necessary to modify the FMI/FMU-based co-simulation procedure, and to instead adopt a sequential co-simulation procedure [71]. The steps were as follows.

- For the complete prediction period (one day), simulation of the EnergyPlus models of the representative buildings was conducted to calculate the evolution of building-side variables at the boundary between the building models and subnetwork Modelica model (substation secondary side inlet temperature and water flow rate). According to the operator, hot water delivery at nominal temperature conditions was always guaranteed for all buildings. Therefore, the EnergyPlus building models were simulated assuming a nominal district supply temperature and capacity.
- A simulation of the infrastructure of the subnetwork's Modelica model was conducted for the complete prediction period to evaluate the aggregated impacts of the evolution over time of the energy requested by the buildings to the subnetwork, including the effects of infrastructure dynamics (e.g. distribution of thermal losses).
- The prediction process was launched several times during the day, allowing for the evaluation of alternative demand-side and district-side management strategies for optimising the implemented operational strategies in real time.

3.2.2. Physical models of the representative buildings

According to the procedure defined in Section 2.2, the district buildings were grouped into homogenous building typologies from the perspectives of their architectonic (e.g. envelope, compactness, solar access, orientation), user behaviour, and technical system features. For each of the defined building types, a representative building was selected, and its detailed EnergyPlus model was developed. In total, eight residential buildings and two educational buildings were modelled in EnergyPlus, including building-level HVAC systems. Fig. 10 displays the locations of the selected representative buildings within the neighbourhood, whereas Figs. 11 and 12 depict some of the eight developed EnergyPlus models.

Table 2 depicts the detailed modelling specifications applied in the development of the EnergyPlus models for the buildings connected to the Stepa Stepanovic subnetwork. A more comprehensive description of the modelling specifications can be found in [70].

Regarding the followed criteria in relation to the thermal zone definition, in the case of the residential buildings, each apartment was considered a single thermal zone with residential activity, so as to optimise the calculation speed for the models. Common and non-residential spaces were grouped into unconditioned thermal zones. In the case of the two educational buildings, the definition process followed to configure the thermal zones as integrated into the models required a more elaborate sequence, as follows:

- Analysis of the activities in the different spaces of the buildings.
- Identification of the different zone types according to the developed activities.
- Classification of the zones of the buildings according to the defined types.
- Aggregation of the zones of the same type located in adjacent positions and served by the same HVAC system.

3.2.3. Demand correction functions

The definitions of the correction functions required to produce the hourly heat request predictions (building demand) for all of the buildings were provided according to the procedure described in Section 2.1, through the following two-stage sequence.

- Development of the energy demand prediction model for the buildings of the Stepa Stepanovic neighbourhood through supervised ML regression techniques, starting from the energy demand data available for each building from September 2017 to May 2018.
- Definition of the specific correction functions for each of the buildings, by exploiting the predictions provided by the data model for each building of the neighbourhood.

As described in Section 2.1., by taking advantage of the hourly predictions provided by the EnergyPlus models for the representative buildings and of the developed correction functions, it became possible to provide hourly predictions of the energy requested by each building to the subnetwork.

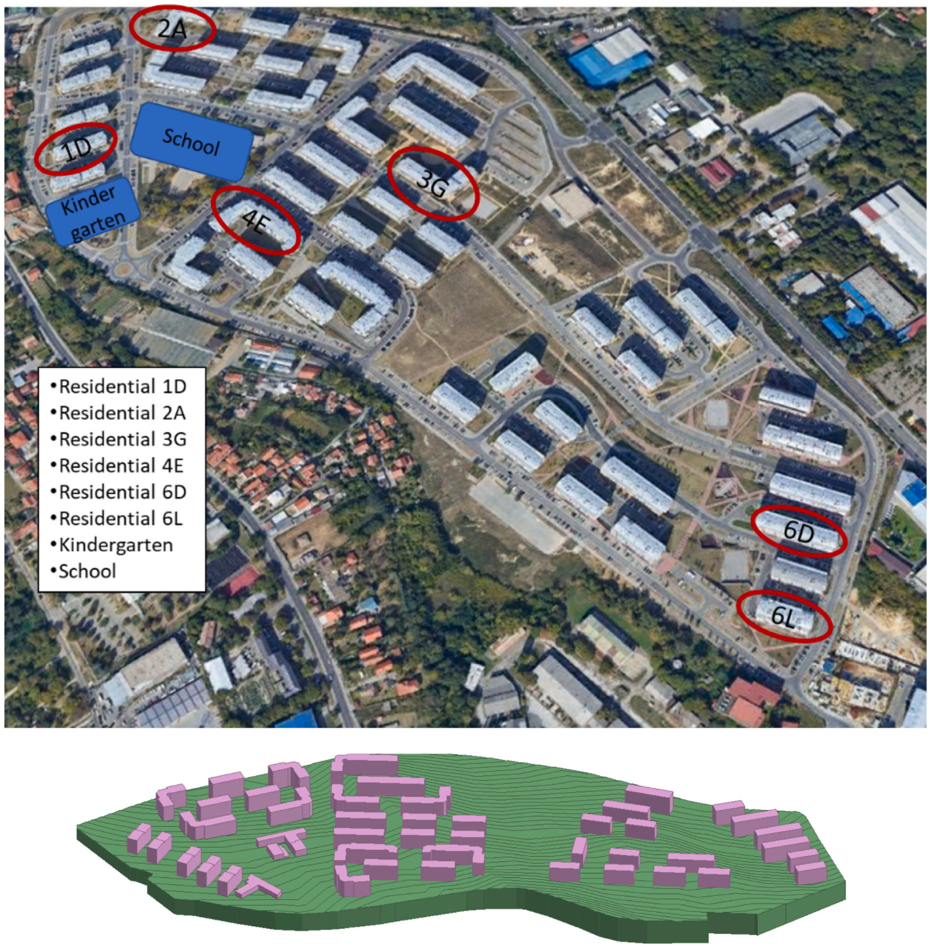

Fig. 10. Location of the representative buildings defined for the Stepa Stepanovic subnetwork.

Fig. 11. Residential representative building of group 2A. The rest of the residential models are omitted for the sake of brevity.

To produce the building heating demand model, SVR and ANNs with a multi-layer perceptron architecture (MLP) were used. As displayed in Table 3, the initially considered feature set included features related to climatic conditions, architectonic design, and user behaviour.

The available data set consisted of the monthly values of the energy requested by each of the buildings from September 2017 to May 2018. Owing to the lack of data with an hourly/sub-hourly resolution, it was necessary to base the procedure on a monthly building energy demand prediction model. In addition, in the cases of residential buildings, the availability of data for some of the architectonic features (e.g. infiltration rates) and many of the user behaviour related features (e.g. thermal comfort settings, ventilation rates, occupancy profiles) were only available for certain representative buildings. Therefore, the feature set to be used to produce the building energy demand prediction model was reduced, as displayed in Table 4.

The unavailability of data regarding the infiltration levels, ventilation rates, occupancy patterns, and thermal comfort preferences in the final feature set was expected to have a moderate impact on the accuracy of the predictions provided by the model, since according to the information provided by district operators, very similar values could be expected for all residential buildings in the district. The available dataset was split into three datasets: 75% of the data (corresponding to 43 of the buildings) were allocated to model training, 25% of the data were used for the testing dataset, and finally, all of the available data from nine of the 52 buildings in the district were used to generate the building demand prediction model validation dataset.

The values of the hyperparameters of the SVR model were optimised through a grid search process with cross-validation that allowed for obtaining an R^2 value of 0.96 for the monthly energy demand predictions provided by the model for the validation dataset. Similarly, the architecture of the ANN model (number of layers and number of neurons per layer), as well as the most relevant hyperparameters, were

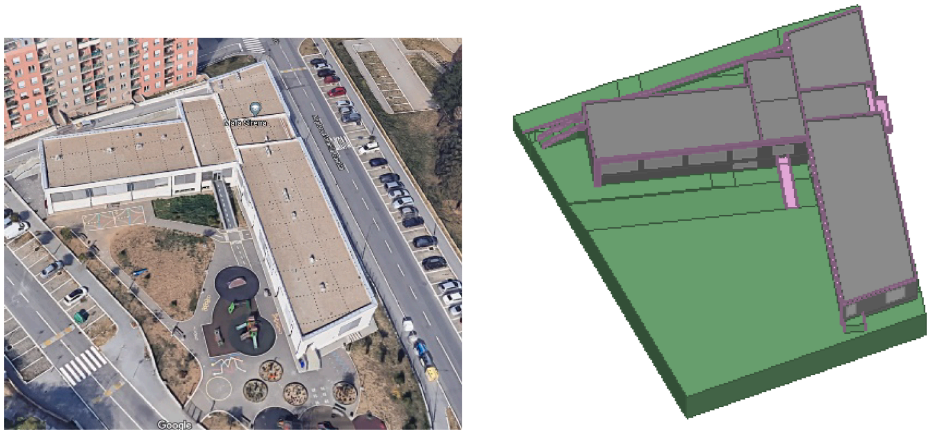

Fig. 12. Primary school model. For the sake of brevity the kindergarten model is omitted.

Table 2
Modelling specification of the EnergyPlus buildings connected to the subnetwork.

Modelling domain	Modelling specification
Architectonic	Detailed geometrical definition of the buildings and of the surrounding objects. Detailed definition of all the solutions of the thermal envelope (e.g. façade, roof, glazing)
User behaviour	Detailed occupancy schedule and density profiles Detailed definition of metabolic rates according to developed activities Detailed definition of the internal load profiles (lighting and electric equipment) User type specific definition of the thermal comfort, visual comfort and internal air quality settings
HVAC and domestic hot water (DHW) production systems	Detailed building substation modelling (inlet temperature, outlet temperature, inlet water flow rate) Detailed modelling of the topology of the building level distribution subsystem including distribution of thermal losses and the energy consumption of pumps Detailed modelling of the emission subsystem (hot water radiators, radiant floors, etc) Detailed modelling of the ventilation systems to evaluate the behaviour of air handling units (fans, heating coils, dampers, heat recovery heat exchangers) and exhaust mechanical ventilation systems Detailed modelling of the DHW production and storage system to evaluate the impact of stratification and thermal losses on the DHW storage tanks

Table 3
Preliminary feature set.

Initial Feature Set		
Climatic	**Architectonic**	**User behaviour**
Air dry bulb temperature	Orientation of each façade	Heating setpoint temperature
Solar irradiation	Length and surface of each façade	Ventilation rates
Wind speed	Window area of each façade	Occupancy patterns
Wind direction	Shading coefficient of each façade	Day of the week
Absolute humidity	Infiltration rate	Month of the year
	Thermal transmittance of façade, roof and glazing	Hour of the day
	Solar gain coefficient of glazing	
	Building heated area	

Table 4
Final feature set.

Final Feature Set	
Climatic	**Architectonic**
Air dry bulb monthly mean temperature	Orientation of each façade
Monthly mean solar irradiation	Length of each façade
Monthly mean wind speed	Surface of each façade
Monthly mean wind direction	Window area of each façade
Monthly mean absolute humidity	Shading coefficient of each façade
	Thermal transmittance of façade, roof and glazing
	Solar gain coefficient of glazing
	Building heated area

iteratively optimised (e.g. learning rate) allowing for an R^2 of 0.94 for the monthly building energy demand for the buildings of the validation dataset. The lower accuracy of the MLP model was a consequence of the insufficient number of available samples, which made it unsuitable for fully exploiting the potential of the ANN algorithm. Fig. 13 shows a comparison between the energy requested by each of the buildings of the validation set to the thermal network from September 2017 to April 2018, and the monthly predictions provided by the SVR and ANN models. The capacity of both ML models to provide moderately accurate predictions for all the months of the 2017–2018 heating season for all the buildings in the validation dataset is depicted. As expected, according to the R^2 values obtained for the ANN and SVR models, in general, the predictions provided by the latter are closer to the actual measured values.

Owing to the scope (time granularity and features) and quality limitations of the available dataset, the accuracy of the predictions provided by the model was moderate in comparison with the levels typically achievable within this domain through ML techniques. However, it was considered acceptable for the final goal of this procedure, i.e. the definition of the correction functions required to allow demand-side modelling. Fig. 14 displays the correction functions produced for the building groups of the neighbourhood using the described method. According to the values obtained for the correction functions, the buildings that are part of the same group display very similar patterns, thereby confirming the consistency of the performed building classification, and the technical robustness of the method proposed for demand-side modelling.

3.2.4. DH infrastructure Modelica model

The composition of the IDM was completed by using the Modelica model of the Stepa Stepanovic distribution subnetwork produced by exploiting the defined new DH system modelling approach and

Fig. 13. Energy requested by the buildings of the validation dataset from September 2017 to April 2018 vs support vector machine regression (SVR) and ANN predictions.

subsystem models of the developed Modelica library. Through the reduction of the effort required for model instantiation and connection, it was possible to provide the same level of modelling detail and to simultaneously enable an approximate reduction of 40% of the time required for model development, in comparison to the traditional equipment-based modelling architecture approaches (an approximate time saving of 15 h for a standard modeller).

The distribution loop/branch hierarchy consisted of 21 loops, sub-loops, and branches, and 56 substations connected to the loops/branches of the subnetwork. The considered level of detail in the modelling was able to accurately capture the topology of the distribution network and the locations within the Stepa Stepanovic neighbourhood of the buildings connected to the subnetwork.

3.2.5. Integrated district model calibration

The calibration process of the IDM consisted of the sequential calibration of the EnergyPlus models and the Modelica model of the district infrastructure. This process was based on the historical data available for

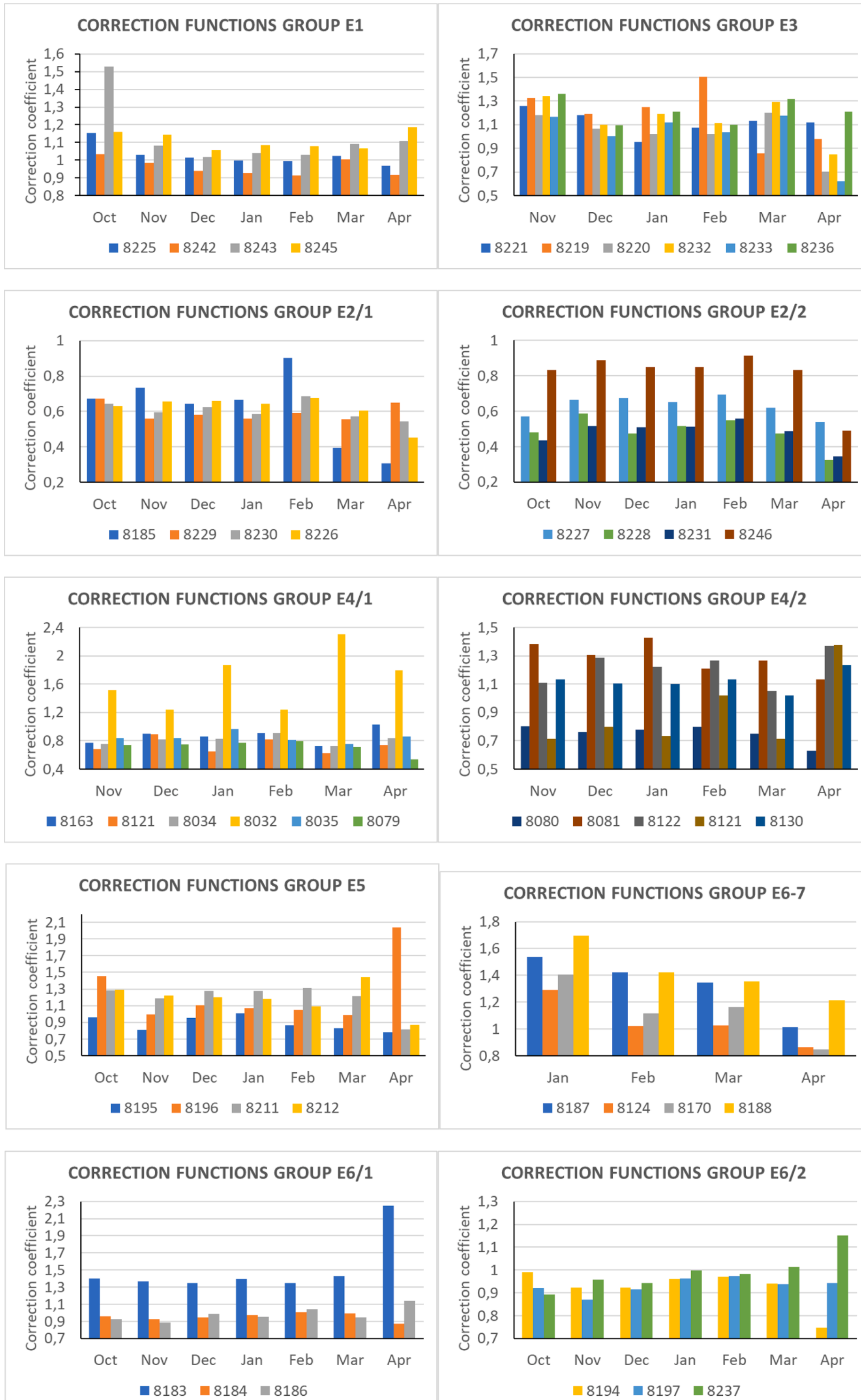

Fig. 14. Correction functions for the buildings included in the different building types connected to the subnetwork.

the 2017–2018 heating season (September 2017 to May 2018). The calibration and validation parameters are listed in Table 5.

Through the described procedure, the capacity of the IDM to reproduce the energy behaviour of the district was maximised, thereby reducing the difference between the predictions provided by the models and the actual figures to values below 10% for the building models and infrastructure model.

3.3. *Optimisation scenarios*

At the time of completion of this work, the priority for the operator of the Stepa Stepanovic subnetwork was to use the developed district management platform to exploit the existing demand-side flexibility, and to generate accurate aggregated district energy demand forecasts, so as to enable an optimised operation of the different heat generation technologies of the DH plant. Based on these preferences, and starting from the evaluation of the existing demand-side flexibility and user

Table 5
Validation and calibration parameters of the calibration procedure.

Parameters	EnergyPlus models (buildings)	Modelica model (subnetwork)
Validation	Energy requested by each building to the subnetwork (monthly building demand)	Vozdovac heating plant production temperature Vozdovac heating plant distribution temperature Substation primary side inlet temperature Subnetwork distribution of thermal losses
Calibration	Envelope thermal properties	Pipe insulation layer thickness
	Envelope optical properties	Conductivity of pipe insulation material
	Infiltration rates	Pipe length
	Internal gains (occupancy and equipment)	Monthly ground temperature
	Thermal comfort settings	
	Ventilation rates	
Initial gap (%)	25 – 40	20
Final gap (%)	10 – 5	< 5

constraints in residential and educational buildings, different DSM scenarios were defined with the support of subnetwork operators. After analysing the HVAC systems and actuators available in the buildings of the district, the defined DSM scenarios were focused on residential building comfort setting optimisation. Educational buildings were excluded from the scenarios owing to their reduced flexibility in terms of comfort settings (thermal and internal air quality), which was a consequence of the relative vulnerability of the users. In any case, the defined DSM scenarios addressed more than 90% of the aggregated subnetwork energy demand. The features of the DSM scenarios defined according to these criteria are summarised in Table 6.

Regarding DH system infrastructure management optimisation strategies, according to the performed conceptual analysis, it was concluded that, in the short term, the available potential was limited, owing to the existing constraints and the operational strategies already implemented in the reference scenario.

- The production and distribution temperature of the subnetwork were already adjusted according to weather compensation strategies (outdoor dry bulb air temperature and wind speed), exploiting a static heating curve which settled the subnetwork supply temperature setpoint in the range from 105 °C to 85 °C.
- The subnetwork pumping station was operated according to variable water flow rate strategies.
- The heating systems of the residential buildings consisted of conventional hot water radiators designed for a supply water temperature of 80 °C, which set a minimum subnetwork supply temperature of 85 °C.

Table 6
Description of the demand-side management scenarios defined for residential buildings.

Scenario 1	Scenario 2
Reduction of the heating Setpoint temperature to 20 °C (from the original value of 22 °C) Maximum acceptable discomfort period of one hour in setback to comfort settings transitions	Reduction of the heating Setpoint temperature to 20 °C (from the original value of 22 °C) Maximum acceptable discomfort period of one hour in setback to comfort settings transitions Free floating period for 50% of the apartments (from Monday to Friday) while apartments remain with no occupancy (central hours of the day)

- Distributed energy resources were not available in the Stepa Stepanovic neighbourhood.

However, in the medium term, the district operator is planning to gradually transform the DH system into a low-temperature DH system, including the deployment of renewable energy systems (e.g. solar thermal collectors), the reduction of the operational temperatures of the heating systems of the residential buildings, and the reduction of the production/distribution temperature of the DH system. Such a transition will provide the ideal frame to fully exploit the potential of the developed district management platform and IDM. Although a comprehensive analysis of all of the technical building and district level modifications involved in that transition is beyond the scope of the work described herein, to provide an initial evaluation of some of the optimisation options that would become available and to further test the prediction capabilities provided by the IDM, two additional scenarios were evaluated.

- Scenario 3: Starting from Scenario 2, this scenario was completed with the addition of subnetwork supply production/distribution temperature optimisation. The goal was to explore the additional energy savings and peak load reduction possibilities through a decrease in the distribution of thermal losses, with the currently existing minimum subnetwork distribution temperature value of 85 °C. Owing to the existing high minimum subnetwork supply temperature value, no major impact was expected for this scenario.
- Scenario 4: To obtain a more realistic estimate of the potential benefits through the optimisation of the subnetwork distribution temperature after the transition to a low-temperature distribution approach, the following modifications were assumed in this scenario.
  - o The emission system of the residential buildings was modified to operate at a service temperature of 60 °C.
  - o The Kv value of the control valves of the substations of the buildings connected to the subnetwork was increased, as necessary, to meet the existing heat demands while operating with significantly lower subnetwork distribution temperatures (higher water flow rate values).

The impacts in terms of energy consumption and peak load reduction were evaluated for the third week of January 2018 for each of the defined scenarios. Additionally, to ensure that stable network conditions had already been reached at the beginning of the target period, the simulation also included the second week of January. The month of January was selected as the most severe weather conditions of the 2017–2018 heating season took place in January. The computation time required for the simulation of each of the scenarios in a laptop workstation equipped with an Intel Core i7 9750H preprocessor (2.60 GHz and 6 cores) and 32 GB of RAM memory was in the range of 10–15 min.

4. Results and discussion

The impacts in terms of the energy consumption and peak load reduction of the proposed scenarios, according to the results provided by the IDM developed for the Stepa Stepanovic subnetwork, are discussed in this section. Table 7 displays the energy demand and peak loads of the residential buildings for the baseline scenario, and Fig. 15 summarises the impacts of the DSM scenarios (1 and 2) on each of the representative buildings.

After the implementation of the DSM optimisation measures considered for Scenario 1, the reduction in the energy requested by all of the representative residential buildings is in the range of 10%–20%. Similarly, the peak load reduction obtained for the residential buildings is in the range of 10%–25%. Scenario 2 provides an additional reduction of the energy requested by the residential buildings to the subnetwork that lies in the range of 4– 6%, leaving the absolute building demand reduction in the range from 17% to 24%. The impact of Scenario 2 in

Table 7
Energy demand and peak loads for the residential buildings (baseline scenario).

Building (Substation)	Baseline energy request (kWh)	Baseline peak load (kW)
Building 1D (8244 substation)	14100.53	255.26
Building 2A (8252 substation)	19544.40	351.97
Building 3G (8234 substation)	10588.53	223.21
Building 3G (8235 substation)	11827.80	200.06
Building 4E (8028 substation)	17624.61	229.32
Building 4E (8036 substation)	11997.63	334.42
Building 6D (8238 substation)	12246.03	252.85
Building 6L (8123 substation)	10000.56	206.28

terms of the peak load reduction is similar to that observed for Scenario 1, and for some buildings, it is moderately lower. This was a consequence of the free-floating period introduced in Scenario 2 for the central hours of the day, which generates relevant loads at the end of that period. Fig. 16 depicts the hourly evolution of the heat requested by residential building 1B for the third week of January. The rest of the buildings are omitted here for brevity.

As shown in Fig. 16, in general, the instantaneous value of the energy requested by building 1B to the subnetwork for Scenario 1 for all days in the week is reduced to within the range between 20 and 30 kW. The reduction in the setpoint from 22 °C to 20 °C has a beneficial effect for every hour at which the setpoint applies. The impact of Scenario 2 increases the savings by an additional 30–50 kW during workdays for the free-floating period included in this scenario. As can be observed, Scenario 2 creates a local demand peak on evenings when the free-floating period ends, and the savings in this period are less significant than those during mornings. Fig. 17 shows the impact at the subnetwork level of the DSM strategies (Scenario 1 and Scenario 2) and of the optimisation of the distribution water temperature (Scenarios 3 and 4), in relation to the subnetwork energy input (818.78 MWh) and peak load (13.73 MW) associated with the baseline scenario.

The aggregated heat load reduction obtained for the considered DSM scenarios is within the range of 13.8%–18%. The impact of the DSM scenarios in terms of the peak load reduction is moderately higher, and lies within the range of 10.85%–23.45%. Fig. 18 displays the impact of the considered DSM scenarios (1 and 2) on the subnetwork inlet energies.

The relevant but only moderate reduction of the distribution of thermal losses provided by Scenario 4 can be explained by the limited capacity of the substations of the buildings (designed to operate with a network supply temperature of 105 °C) to efficiently adapt their operation to the reduced network supply temperature (in the range between 75 °C and 65 °C). Owing to this limited capacity, Scenario 4 allows for a reduction in the mean subnetwork distribution temperature of 27% in relation to Scenario 2, but at the expense of an increase in the mean aggregated subnetwork water flow rate of 50%, which has a negative impact on the reduction of the distribution thermal losses. Fig. 19 depicts the evolution of the subnetwork distribution water temperature setpoint for the baseline scenario, and for Scenarios 3 and 4. In Scenario 3, the available unexploited potential to reduce the subnetwork distribution water temperature is such that the obtained reduction is always

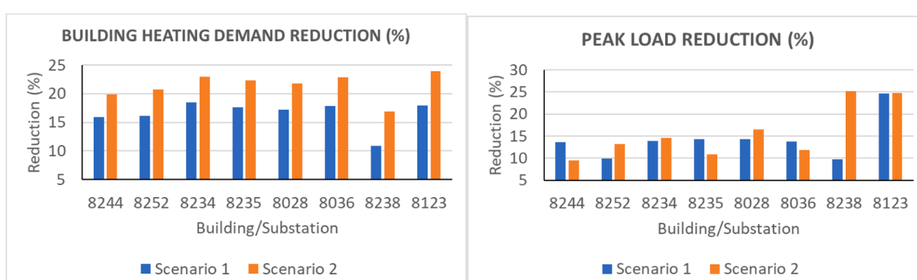

Fig. 15. Building demand and peak load reduction for the demand-side management (DSM) scenarios (1 and 2).

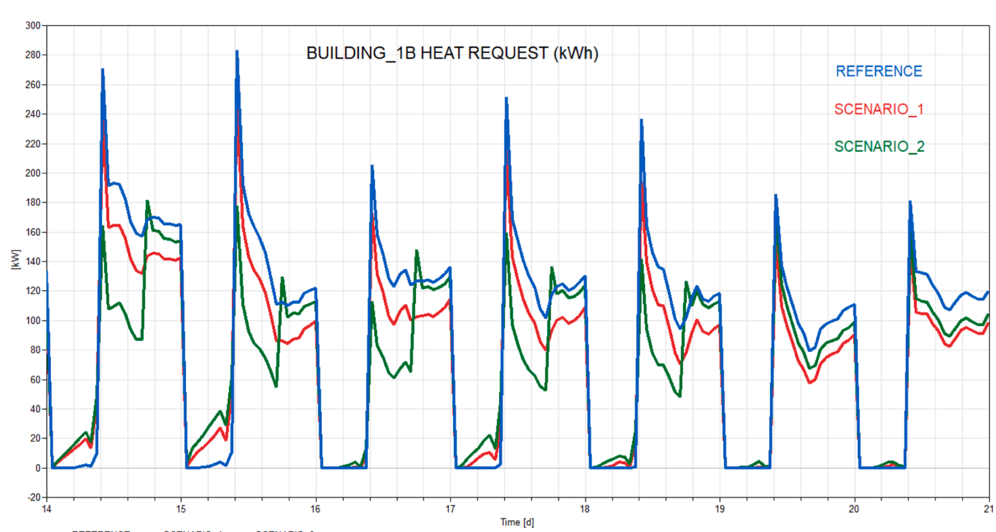

Fig. 16. Energy requested to the subnetwork by Building 1B. Third week of January 2018.

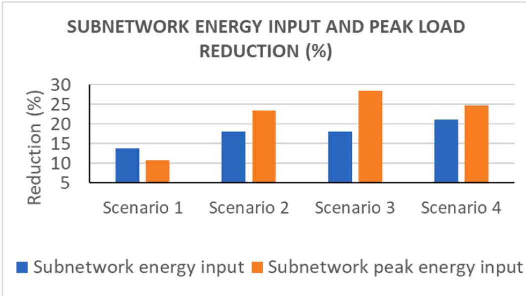

Fig. 17. DSM and district infrastructure management optimisation impact at subnetwork level.

below 10 °C. Fig. 20 displays the evolution of the aggregated subnetwork inlet water flow rate for Scenarios 2 and 4, where a strong increase associated with Scenario 4 can be observed. More specifically, the subnetwork inlet water flow rate for Scenario 2 falls in the range between 35 kg/s and 80 kg/s, and this range increases with the strategies followed in Scenario 4 to between 45 kg/s and 120 kg/s.

As part of Scenario 4, the substation control valves were resized. However, according to the obtained results, to fully exploit the existing distribution of thermal loss reduction potential, a complete redesign of the substations would be required (heat exchangers specifically designed for the proposed network supply temperatures), which is beyond the scope of the work described herein.

5. Conclusions

This paper presents a new IDM concept conceived to serve as the core of the energy prediction engine of a district energy management optimisation platform, as developed in the framework of the MOEEBIUS project. The physical, multiscale, multidomain, and integrated nature of the model enables the platform to evaluate the impacts of alternative district operational strategies, while analysing the dynamics existing in all of the involved time and space scales with the required accuracy.

The method, based on co-simulation, shows the potential to model, in a detailed way, the demand side of districts through the combined use of physical building models (EnergyPlus) and a building demand

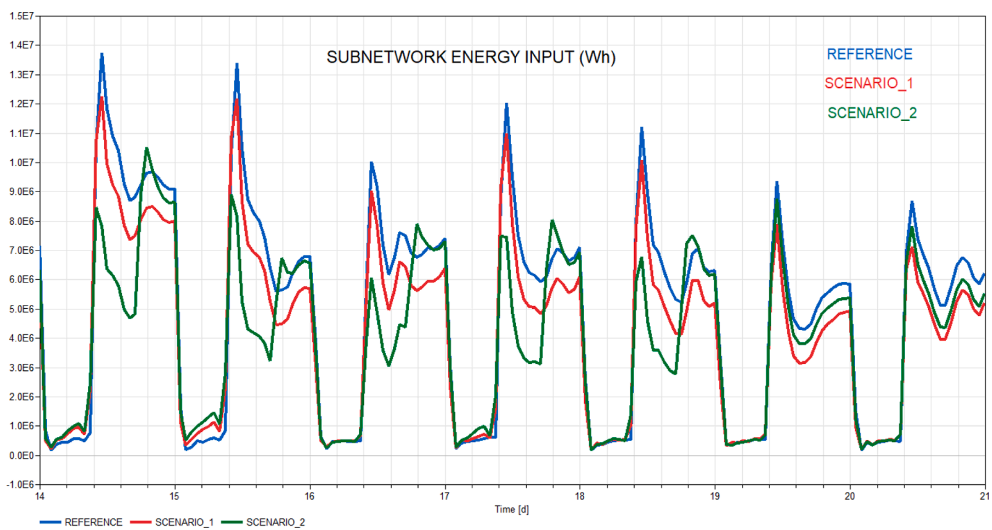

Fig. 18. Subnetwork energy input for the evaluated DSM strategies. Third week of January 2018.

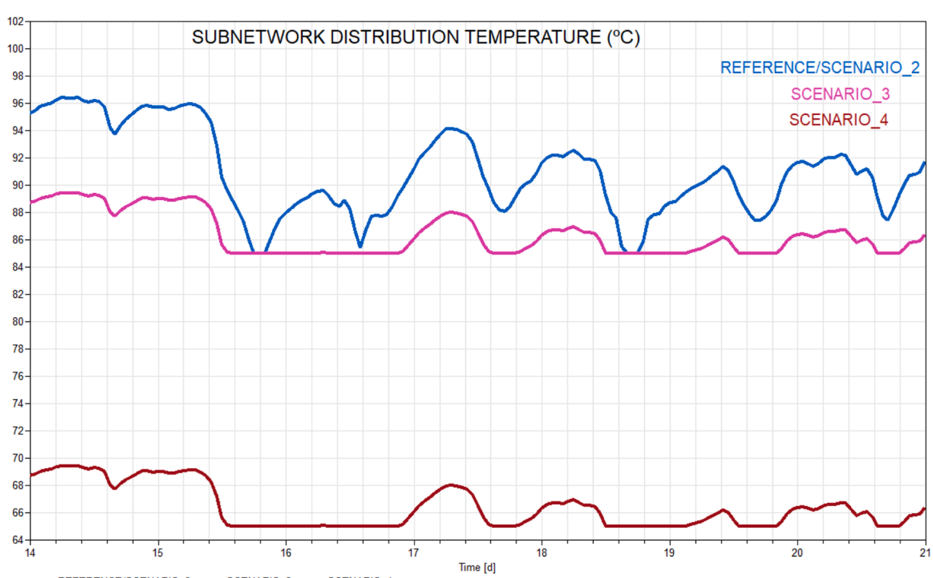

Fig. 19. Subnetwork distribution temperature. Reference/Scenario 2 vs Scenarios 3 and 4. Third week of January 2018.

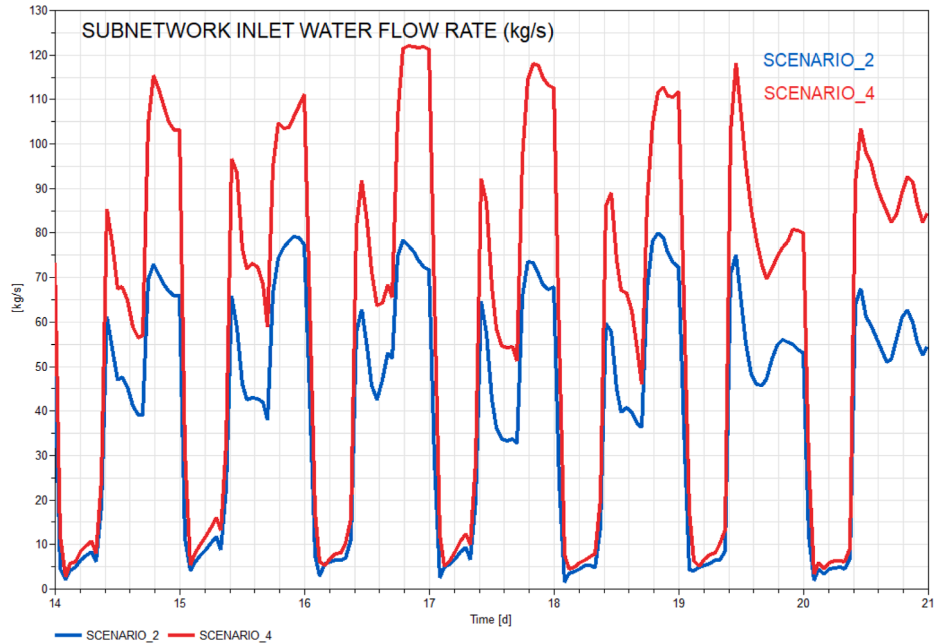

Fig. 20. Subnetwork inlet water flow rate. Scenario 4 vs Scenario 2. Third week of January 2018.

prediction DDM based on supervised ML techniques. It allows for the complete evaluation of new building operational strategies, without facing the burden of complete demand-side physical modelling.

Additionally, a new Modelica library is developed to enable a subsystem-based composition architecture. This dedicated library reduces the time required for DH system infrastructure physical modelling and minimises modelling errors, providing the flexibility and scalability required to define DH system infrastructure models of any size and distribution topology.

Finally, the described Stepa Stepanovic subnetwork use case shows the applicability of the developed IDM and new Modelica library to evaluating the unexploited energy savings potential available in existing DH systems through transitions to MPC operational strategies. With the restrictions and boundary conditions existing in the Stepa Stepanova subnetwork, the impact of the evaluated optimisation strategies allows for a reduction of up to 21% of the aggregated subnetwork energy input, and a reduction of the peak load of the district by 24.6%. According to the obtained results, adapting the designs of the building heating substations to the new low-temperature operational settings is recommended to fully exploit the existing distribution thermal loss reduction potential.

Regarding the applicability of the platform in real-world projects, low temperature DH systems with high penetration of distributed energy resources, provide the ideal framework to maximize the potential impact (e.g. demand flexibility exploitation, setpoint optimization through continuous commissioning) of the developed district management platform. In addition, the initial availability of modern control systems (at building and district level) and energy meters contributes to simplify the deployment of the platform as an additional layer on top of the existing control systems, reducing the cost of the developed solution. In this respect, the authors are already working to adapt the IDM concept to DH system design scenarios affected by a lack of proper energy consumption data. In the upgraded concept, the data-driven building demand forecasting model and demand correction functions will be completed by building energy behaviour metamodels produced through ML techniques. This new body of work will be presented in a subsequent paper.

CRediT authorship contribution statement

Víctor F. Sánchez: Conceptualization, Data curation, Investigation, Formal analysis, Methodology, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Antonio Garrido Marijuan:** Data curation, Validation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The research activities leading to the described developments and results, were funded by the European Unionś Horizon 2020 MOEEBIUS project, under grant agreement No 680517. Authors would like to express their gratitude to the operator of the Vozdovac district heating system (Beogradske elektrane) for the specifications used to develop and calibrate the models, and to Solintel M&P, SL for developing the initial versions of the EnergyPlus models (including only the geometrical and constructive definition of the buildings), in the framework of the MOEEBIUS project.

References

[1] S. Frederiksen, S. Werner, District heating and cooling, Studentlitteratur, Lund, 2014.
[2] Simone Buffa, Marco Cozzini, Matteo D'Antoni, Marco Baratieri, Roberto Fedrizzi, 5th generation district heating and cooling systems: A review of existing cases in Europe, Renewable and Sustainable Energy Reviews. 104 (2019) 504–522, https://doi.org/10.1016/j.rser.2018.12.059.
[3] Helge Averfalk, Sven Werner, Essential improvements in future district heating systems, Energy Procedia. 116 (2017) 217–225, https://doi.org/10.1016/j.egypro.2017.05.069.
[4] D. Mariano-Hernández, L. Hernández-Callejo, A. Zorita-Lamadrid, O. Duque-Pérez, F. Santos García. A review of strategies for building energy management system: Model predictive control, demand side management, optimization, and fault detect & diagnosis. Journal of Building Engineering. 2021;33:101692. 10.1016/j.jobe.2020.101692.

[5] Christian Johansson, Markus Bergkvist, Davy Geysen, Oscar De Somer, Dirk Vanhoudt, Operational Demand Forecasting In District Heating Systems Using Ensembles Of Online Machine Learning Algorithms, Energy Procedia. 116 (2017) 208–216, https://doi.org/10.1016/j.egypro.2017.05.068.

[6] J. Reynolds, M.W. Ahmad, Y. Rezgui, J.L. Hippolyte, Operational supply and demand optimisation of a multi-vector district energy system using artificial neural networks and a genetic algorithm, Applied Energy. 235 (2019) 699–713, https://doi.org/10.1016/j.apenergy.2018.11.001.

[7] Sam van der Zwan, Ivo Pothof, Operational optimization of district heating systems with temperature limited sources, Energy and buildings. 226 (2020), 110347, https://doi.org/10.1016/j.enbuild.2020.110347.

[8] Dirk Vanhoudt, Bert Claessens, Johan Desmedt, Christian Johansson. Status of the Horizon 2020 Storm Project. In: Proceedings of the 15th International Symposium on District Heating and Cooling. Seoul, South Korea, September 4-7, 2016. p. 170–180.

[9] The Modelica Association. https://www.modelica.org/.

[10] Anjukan Kathirgamanathan, Mattia De Rosa, Eleni Mangina, Donal P. Finn, Data-driven predictive control for unlocking building energy flexibility: A review, Renewable and Sustainable Energy Reviews. 135 (2021) 110–120, https://doi.org/10.1016/j.rser.2020.110120.

[11] MOEEBIUS Project (Modelling Optimization of Energy Efficiency in Buildings for Urban Sustainability). https://www.moeebius.eu/.

[12] Baetens Ruben, de Coninck Roel, Jorissen Filip, Picard Damien, Helsen Lieve, Saelens Dirk. OPENIDEAS - An open framework for integrated district energy simulations. In: Proceedings of the 14th IBPSA Conference. Hyderabad, India. December 7-9, 2015. p. 347–354.

[13] Modelica model environment for Integrated District Energy Assessment Simulations (IDEAS). https://github.com/open-ideas/IDEAS.

[14] Marcus Fuchs, Thomas Dixius, Jens Teichmann, Moritz Lauster, Rita Streblow, and Dirk Müller. Evaluation of Interactions Between Buildings and District Heating Networks. In: Proceedings of the 13th Conference of International Building Performance Simulation Association, Chambéry, France. August 26-28, 2013. p.96–103.

[15] Gerald Schweiger, Per-Ola Larsson, Fredrik Magnusson, Patrick Lauenburg, Stéphane Velut, District heating and cooling systems - Framework for Modelica-based simulation and dynamic optimization, Energy. 137 (2017) 566–578, https://doi.org/10.1016/j.energy.2017.05.115.

[16] S. Mohammadi, C. Bojsen, C. Milan, Identifying the Optimal Supply Temperature in District Heating Networks- a Modelling Approach 7–9 (September 2014) 189–195.

[17] Xiwang Li, Jin Wen, Review of building energy modeling for control and operation, Renewable and Sustainable Energy Reviews. 37 (2014) 517–537.

[18] Zhou D, Hu Q, Tomlin CJ. Model comparison of a data-driven and a physical model for simulating HVAC systems. arXiv preprint; 2016. https://arxiv.org/abs/1603.05951.

[19] Aurélie Foucquier, Sylvain Robert, Frédéric Suard, Louis Stephan, Arnaud Jay. State of the art in building modelling and energy performances prediction: A review. Renewable and Sustainable Energy Reviews, Elsevier, 2013, 23, pp.272 - 288. https://hal-cea.archives-ouvertes.fr/cea-01792021.

[20] J. Zhao, K. P. Lam, and B. E. Ydstie. EnergyPlus model-based predictive control (EPMPC) by using MATLAB/SIMULINK and MLE+. In: Proceedings of the 13th Conference of International Building Performance Simulation Association. Chambéry, France, August 26-28, 2013. p. 2466–2473.

[21] G.D. Kontes, G.I. Giannakis, V. Sánchez, P.D. Agustin-camacho, A. Romero-amorrortu, N. Panagiotidou, Simulation-based evaluation and optimization of control strategies in buildings, Energies 11 (2018) 1–23, https://doi.org/10.3390/en11123376.

[22] Maomao Hu, Fu Xiao, John Bagterp Jørgensen, Rongling Li. Price-responsive model predictive control of floor heating systems for demand response using building thermal mass . Applied Thermal Engineering. 2019;153:316-329. 10.1016/j.applthermaleng.2019.02.107.

[23] Jan Gasser, Hanmin Cai, Stavros Karagiannopoulos, Philipp Heer, Gabriela Hug, Predictive energy management of residential buildings while self-reporting flexibility envelope, Applied Energy. 288 (2021), 116653, https://doi.org/10.1016/j.apenergy.2021.116653.

[24] EnergyPlus building energy simulation program. https://energyplus.net/.

[25] eQUEST (the QUick Energy Simulation Tool). http://www.doe2.com/equest/.

[26] TRNSYS, Transient System Simulation Tool. http://www.trnsys.com/index.html.

[27] Wetter Michael, S. Bonvini Marco, Nouidui Thierry, Equation-based languages - A new paradigm for building energy modeling, simulation and optimization, Energy and Buildings. 117 (2016) 290–300, https://doi.org/10.1016/j.enbuild.2015.10.017.

[28] M. Wetter and C. Haugstetter. Modelica versus TRNSYS - A comparison between an equation-based and a procedural modeling language for building energy simulation. In: Proceedings of the second National IBPSA-USA Conference. Cambridge, MA, August 2-4, 2006. p. 262–269.

[29] Maile, Tobias & Fischer, Martin & Bazjanac, Vladimir. Building Energy Performance Simulation Tools - a Life-Cycle and Interoperable Perspective. 2007; Center for Integrated Facility Engineering (CIFE) working paper 107. https://www.researchgate.net/publication/237621385_Building_Energy_Performance_Simulation_Tools_-_a_Life-Cycle_and_Interoperable_Perspective.

[30] The DOE-2 software. https://doe2.com/.

[31] RIUSKA. https://www.magicad.com/en/mc_software/magicad-comfort-energy/#features-for-autoca.

[32] OPENMODELICA. https://openmodelica.org/.

[33] Dymola, Dynamic Modeling Laboratory. https://www.3ds.com/products-services/catia/products/dymola/.

[34] The Modelica Buildings library. https://simulationresearch.lbl.gov/modelica/.

[35] The Modelica open-source BuildingSystems library. https://github.com/UdK-VPT/BuildingSystems.

[36] AixLib - An Open-Source Modelica Library within the IEA-EBC Annex 60 Framework. Müller D., Lauster M., Constantin A., Fuchs M., Remmen P.. BauSIM 2016, p.3–9, September 2016. https://github.com/RWTH-EBC/AixLib.

[37] IEA EBC Annex 60. http://www.iea-annex60.org/.

[38] Wetter M, Fuchs M, Grozman P, Helsen L, Jorissen F, Lauster M, et al. IEA EBC ANNEX 60 Modelica library - an international collaboration to develop a free open-source model library for buildings and community energy systems. In: Proceedings of the14th IBPSA Conference, Hyderabad, India. December 7-9, 2015. p.395–402.

[39] IBPSA Project 1(BIM/GIS and Modelica Framework for building and community energy system design and operation). https://ibpsa.github.io/project1/.

[40] B. van der Heijde, M. Fuchs, C. Ribas Tugores, G. Schweiger, K. Sartor, D. Basciotti, D. Müller, C. Nytsch-Geusen, M. Wetter, L. Helsen, Dynamic equation-based thermo-hydraulic pipe model for district heating and cooling systems, Energy Conversion and Management. 151 (2017) 158–169, https://doi.org/10.1016/j.enconman.2017.08.072.

[41] Bram van der Heijde, Arnout Aertgeerts, Lieve Helsen, Modelling steady-state thermal behaviour of double thermal network Pipes, International Journal of Thermal Sciences. 117 (2017) 316–327, https://doi.org/10.1016/j.ijthermalsci.2017.03.026.

[42] Loïc Giraud, Roland Bavière, Mathieu Vallée, Cédric Paulus. Presentation, Validation and Application of the District Heating Modelica Library. In: Proceedings of the 11th International Modelica Conference, Versailles, France. September 21-23, 2015. p.79–88.

[43] Tobias Sommer, Matthias Sulzer, Michael Wetter, Artem Sotnikov, Stefan Mennel, Christoph Stettler. The reservoir network: A new network topology for district heating and cooling. Energy. 2020;199. 10.1016/j.energy.2020.117418.

[44] Francesco Casella, Alberto Leva1 Andrea Bartolini. Simulation of Large Grids in OpenModelica: reflections and perspectives. In: Proceedings of the 12th International Modelica Conference, Prague, Czech Republic. May 15-17, 2017. p.227–234.

[45] Loïc Giraud Massinissa Merabet Roland Baviere Mathieu Vallée. Optimal Control of District Heating Systems using Dynamic Simulation and Mixed Integer Linear Programming. In: Proceedings of the 12th International Modelica Conference. Prague, Czech Republic. May 15-17, 2017. p. 141–151.

[46] Giovanni Tardioli, Ruth Kerrigan, Mike Oates, James O'Donnell, Donal Finn. Data Driven Approaches for Prediction of Building Energy Consumption at Urban Level. Energy Procedia. 2015;78:3378–3383. 10.1016/j.egypro.2015.11.754.

[47] Mathieu Bourdeau, Xiao qiang Zhai, Elyes Nefzaoui, Xiaofeng Guo, Patrice Chatellier. Modeling and forecasting building energy consumption: A review of data driven techniques, Sustainable Cities and Society. 48 (2019), https://doi.org/10.1016/j.scs.2019.101533.

[48] Henrik Lund , Sven Werner, Robin Wiltshire, Svend Svendsen, Jan Eric Thorsen, Frede Hvelplund Brian Vad Mathiesen. 4th Generation District Heating (4GDH) Integrating smart thermal grids into future sustainable energy systems. Energy. 2014;68:1–11. 10.1016/j.energy.2014.02.089.

[49] Leo Laakkonen, Timo Korpela, Jyri Kaivosoja, Matti Vilkko, Yrjö Majanne, Maria Nurmoranta, Predictive Supply Temperature Optimization of District Heating Networks Using Delay Distributions, Energy Procedia. 116 (2017) 297–309, https://doi.org/10.1016/j.egypro.2017.05.076.

[50] S. Chen, Y. Ren, D. Friedrich, Z. Yu, J. Yu, Sensitivity analysis to reduce duplicated features in ANN training for district heat demand prediction, Energy and AI. 2 (2020), 100028, https://doi.org/10.1016/j.egyai.2020.100028.

[51] C. Zhang, Y. Zhao, C. Fan, T. Li, X. Zhang, J. Li, A generic prediction interval estimation method for quantifying the uncertainties in ultra-short-term building cooling load prediction, Applied Thermal Engineering. 173 (2020), 115261, https://doi.org/10.1016/j.applthermaleng.2020.115261.

[52] Jong Man Lee, Sung Hyup Hong, Byeong Mo Seo, Kwang Ho Lee. Application of artificial neural networks for optimized AHU discharge air temperature set-point and minimized cooling energy in VAV system. Applied Thermal Engineering. 2019; 153:726-738. 10.1016/j.applthermaleng.2019.03.061.

[53] Fan Zhang, Chris Bales, Hasan Fleyeh, Night setback identification of district heat substations using bidirectional long short term memory with attention mechanism, Energy. 224 (2021), 120163, https://doi.org/10.1016/j.energy.2021.120163.

[54] Caleb Robinson, Bistra Dilkina, Jeffrey Hubbse, Wenwen Zhang, Subhrajit Guhathakurta, Marilyn A. Brown, Ram M. Pendyala, Machine learning approaches for estimating commercial building energy Consumption, Applied Energy. 208 (2017) 889–904, https://doi.org/10.1016/j.apenergy.2017.09.060.

[55] Lei Lei, Wei Chen, Wu. Bing, Chao Chen, Wei Liu, A building energy consumption prediction model based on rough set theory and deep learning algorithms, Energy and buildings. 240 (2021), 110886, https://doi.org/10.1016/j.enbuild.2021.110886.

[56] The Functional Mock-up Interface (FMI) standard. https://fmi-standard.org/.

[57] Michael Wetter. A View on Future Building System Modeling and Simulation. Book chapter published in "Building Performance Simulation for Design and Operation," 2011, Jan L. M. Hensen and Roberto Lamberts (editors), Routledge, UK, ISBN: 978-0-415-47414-6. https://www.amazon.com/Building-Performance-Simulation-Design-Operation/dp/0415474140.

[58] Aertgeerts Arnout, Claessens Bert, De Coninck Roel, Helsen Lieve. Agent-based control of a neighbourhood: a generic approach by coupling Modelica with python. In: Proceedings of the14th IBPSA Conference, Hyderabad, India. December 7-9, 2015. p.456–463.

[59] Andreas Nicolai Anne Paepcke. Co-Simulation between detailed building energy performance simulation and Modelica HVAC component models. In: Proceedings of the12th International Modelica Conference, Prague, Czech Republic. May 15-17, 2017. p.63–72.
[60] Stephane Nouidui Thierry, Wetter Michael. Linking Simulation Programs, Advanced Control and FDD Algorithms with a Building Management System Based on the Functional Mock-Up Interface and the Building Automation Java Architecture Standards. In: Proceedings of the ASHRAE/IBPSA-USA Building Simulation Conference, Atlanta, USA. September 10-12, 2014.
[61] Edmund Widl, Benoit Delinchant, Svea Kübler, Li Dan, Wolfgang Müller, Victor Norrefeldt, S. Nouidui Thierry, Sebastian Stratbücker, Michael Wetter, Frédéric Wurtz, Zuo Wangda. Novel simulation concepts for buildings and community energy systems based on the Functional Mock-up Interface specification. Workshop on Modeling and Simulation of Cyber-Physical Energy Systems (MSCPES). In: Proceedings of the CPS Week. April 2014. p.1–6. 10.1109/MSCPES.2014.6842396.
[62] Torsten Schwan, René Unger B.A. Jörg Pipiorke. Aspects of FMI in Building Simulation. Proceedings of the 12th International Modelica Conference May 15-17, 2017, Prague, Czech Republic. p.73–78.
[63] Thierry Stephane Nouidui, Michael Wetter, Wangda Zuo, Functional mock-up unit for co-simulation import in EnergyPlus, Journal of Building Performance Simulation. 7 (2013) 192–202, https://doi.org/10.1080/19401493.2013.808265.
[64] Zeyu Wang, Ravi S. Srinivasan. A Review of Artificial Intelligence Based Building Energy Prediction with a Focus on Ensemble Prediction Models. In: Proceedings of the 2015 Winter Simulation Conference, California, USA. December, 2015. p.3438–3448.
[65] H. Zhao, F. Magoulès, A review on the prediction of building energy consumption, Renewable and Sustainable Energy Reviews. 2012 (16) (2012) 3586–3592, https://doi.org/10.1016/j.rser.2012.02.049.
[66] Aurélie Foucquier, Sylvain Robert, Frédéric Suard, Louis Stephan, Arnaud Jay. State of the art in building modelling and energy performances prediction: A review. Renewable and Sustainable Energy Reviews, Elsevier, 2013, 23, pp.272 - 288. https://hal-cea.archives-ouvertes.fr/cea-01792021.
[67] Saleh Seyedzadeh, Farzad Pour Rahimian, Ivan Glesk, Marc Roper, Machine learning for estimation of building energy consumption and performance: a review. Visualization, Engineering. (2018;6:5.), https://doi.org/10.1186/s40327-018-0064-7.
[68] The ThermoPower library. https://build.openmodelica.org/Documentation/ThermoPower.html.
[69] V. Sánchez, et. D3.3 Models of DER devices. MOEEBIUS project. 31/01/2017. https://www.moeebius.eu/images/MOEEBIUS_D3.3_Models_of_DER_devices_V1.0.pdf.
[70] V. Sánchez, et. D3.6 Local and Global Energy performance models. MOEEBIUS project. 31/03/2017. https://www.moeebius.eu/images/MOEEBIUS_D3.6_Local_and_Global_Energy_performance_models_V1.0.pdf.
[71] V. F. Sánchez, et al. Smart Dual Thermal Network. International Journal of Energy Production and Management. 2017;2:315–326. (DOI 10.2495/EQ-V2-N4) https://www.witpress.com/elibrary/eq-volumes/2/4/2077.