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An intelligent semantic system for real-time demand response management of a thermal grid

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ABSTRACT

"Demand Response" energy management of thermal grids requires consideration of a wide range of factors at building and district level, supported by continuously calibrated simulation models that reflect real operation conditions. Moreover, cross-domain data interoperability between concepts used by the numerous hardware and software is essential, in terms of Terminology, Metadata, Meaning and Logic. This paper leverages domain ontology to map and align the semantic resources that underpin building and district energy management, with a focus on the optimization of a thermal grid informed by real-time energy demand. The intelligence of the system is derived from simulation-based optimization, informed by calibrated thermal models that predict the network's energy demand to inform (near) real-time generation. The paper demonstrates that the use of semantics helps alleviate the endemic energy performance gap, as validated in a real district heating network where 36% reduction on operation cost and 43% reduction on CO_2 emission were observed compared to baseline operational data.

1. Introduction

The growing interest in thermal grids requires new business and technology platforms to handle the increasing amount of multi-aspects data and the level of complexity and diversity of the urban energy landscape (Howell, Rezgui, Hippolyte, Jayan, & Li, 2017; Reynolds, Ahmad, Rezgui, & Hippolyte, 2019). Moreover, the load profile fluctuation, from both heat demand and heat generation, requires informed decision-making to explore a wide range of configuration options that contribute to reduce heat energy demand and carbon emissions (Kuster, Rezgui, & Mourshed, 2017; Li, Rezgui, & Zhu, 2017; Reynolds, Rezgui, & Hippolyte, 2017). Therefore, the smart control of a thermal grid that factors in predicted changes is crucial to ensure effective real-time demand response. Conversely, the use of machine learning has paved the way to new ways of addressing the endemic energy performance gap (Wang et al., 2019; Wu, Shahidehpour, & Khodayar, 2013), while promoting flexibility and scalability of current generation of decentralized and multi-vector energy systems (Li et al., 2017; Petri, Yuce, Kwan, & Rezgui, 2018).

Intelligent systems involve reliance on smart sensors, monitoring and control devices, and computing networks, powered by machine learning (Talebi, Haghighat, Tuohy, & Mirzaei, 2019; Wang et al., 2019). However, current research in the energy management field reveals: a) difficulties in embracing the increasing complexity of current and future energy systems; b) limited potential in handling real-time dynamic conditions; and c) lack of holistic approaches to integrate seamlessly all hardware, protocols, software, and occupants involved (Howell, Rezgui, Hippolyte et al., 2017; Reynolds et al., 2019).

Moreover, managing a complex energy system such as a district heating (DH) network requires a holistic approach to elicit and represent the data structures of the underpinning hardware and software components (Li, García-Castro, Mihindukulasooriya, O'Donnell, & Vega-Sánchez, 2019). Ontology is a computer and human readable formalisation of a domain that can be used to interpret semantically related concepts using classes, relations and attributes. The development of ontology requires expert knowledge to conceptualize the underpinning domain artefacts. The constructed semantic maps are applied to illustrate the relationship and map the corresponding instances. The authors have successfully applied semantics to address building energy management (Howell, Wicaksono, Yuce, McGlinn, & Rezgui, 2018) and water urban management (Howell, Rezgui, & Beach, 2017).

This paper proposes an intelligent system for dynamic DH network monitoring to deliver real-time energy management through a dedicated ontology developed with the Web Ontology Language (OWL), augmented with semantic rules capable of handling heterogeneous data sources. The complex energy system is broken down into discrete but

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related elements, governed by dependent and independent variables and their interaction through mathematical approximations. The proposed system involves a building energy prediction engine to automatically calibrate building energy models and forecast building energy demand, a simulation engine to support distribution network heat loss modelling, and an optimization engine to optimize the operational schedule of the generation units. The proposed solution is tested and validated in a real case study, a brownfield development in Wales, UK.

The rest of the paper is organised as follows: Section 2 presents a critical review of related work. In Section 3, the overarching methodology and the underpinning components demonstrating the novelty of our approach is described. The subsequent section details the prediction, simulation and optimization engines. Section 5 presents the results, which are then discussed in Section 6. The last section provides concluding remarks.

2. Related work

Recent advances in smart sensors together with low cost communication solutions have paved the way for a wide range of smart management solutions of energy systems through artificial intelligence (AI), including prediction and optimization algorithms (Reynolds et al., 2017).

These techniques have been applied at building or district scale, and as such involve a bottom-up or a top-down approach (Kazas, Fabrizio, & Perino, 2017). The bottom-up models calculate the energy from a single building or a group of buildings and then aggregate or scale the results to the district level (Shimoda, Fujii, Morikawa, & Mizuno, 2004). The annual energy can be obtained by summing up simulation results from various household categories. Each category is simulated separately and then multiplied by the number of households. The top-down approach involves a data driven model to predict energy demand according to statistical techniques or machine learning (Mastrucci, Baume, Stazi, & Leopold, 2014; Tian & Choudhary, 2012). This approach studies the building stock at hand without investigating individual buildings, which are relegated as nodes in the complex urban fabric. A large amount of dataset is required to construct the prediction model (Howell, Rezgui, Beach et al., 2017).

The problem of mismatch between energy supply and energy demand is pronounced in the urban energy landscape (Zhang, Xu, Liu, Zang, & Yu, 2015), including in the context of district heating. A wide range of optimization models such as linear programming (LP), mixed-integer linear programming (MILP) and non-linear programming (NLP) have been applied for DH network optimization (Wang, Abdollahi, Lahdelma, Jiao, & Zhou, 2015). Cho et al. Cho, Mago, Luck, and Chamra (2009) developed a linear model for load dispatch with the purpose of reducing operation cost and carbon emission. Ameri and Besharati Ameri and Besharati (2016) developed a MILP model to identify the best energy mix in a complex district energy system to meet energy demand with minimum operation cost. Fonseca (Fonseca, Nguyen, Schlueter, & Marechal, 2016) developed a non-linear k-means clustering algorithm computational framework for the optimization of building energy systems in an urban scale. Significant savings in operation cost, primary energy and CO_2 emission were achieved. Ommen et al. Ommen, Markussen, and Elmegaard (2014) conducted a comparison of linear, mixed integer and non-linear programming to examine their impacts on energy dispatch. Results revealed that NLP and MILP exhibited better results than LP, corresponding to an improvement of 32% and 23%, respectively, in the performance of the generation units. The authors claimed that MILP is the best option from the runtime and accuracy perspectives.

Model Predictive Control (MPC) has been extensively applied in the energy optimization process to mitigate the negative impacts caused by predictive uncertainties (Reynolds et al., 2019). Reynolds et al. Reynolds et al. (2019) have examined the MPC for supply and demand management in a multi-vector district energy system. Zhang et al. Zhang, Zhang, Wang, Liu, and Guo (2015) compared the MPC with the traditional day-ahead control in a MILP based optimization process. Case study results demonstrated that MPC strategy provided more significant operation cost reduction.

Recent research has seen the development of dynamic district energy simulation solutions (Wang et al., 2015) capable of predicting energy demand of the building stock, while providing a wide range of functionality, including manipulation and analysis of collected data. Schiefelbein (Schiefelbein et al., 2019) developed an urban energy system modelling platform through OpenStreetMap, with simulated space heating demand reflecting measured consumption.

Interoperability and integration between the components of an energy system require the use of common or semantically aligned models to promote seamless data exchange between the constituents of these systems (Shang, Ding, Marianantoni, Burke, & Zhang, 2014). These semantic models are best reflected in the linked data and semantic Web efforts (W3C, 2019). The paper proposes an approach for DH energy management underpinned by semantics and powered by AI, to inform real-time management of a thermal grid. This paper takes the overarching hypothesis that an accurate simulation of a thermal grid and its associated buildings, augmented with machine learning techniques fed by real-time sensory data, can alleviate the endemic energy performance gap in thermal grids. This is elaborated in the following section.

3. Methodology

This section gives an overview of the methodology employed to develop the proposed intelligent semantic system to monitor and optimize thermal grids. i.e. DH networks. The objective is to deliver a holistic real-time energy prediction and optimization process. A semantic Web-based approach is adopted to conceptualize the DH network and its constituent buildings, factoring in the enhanced sensing and actuation infrastructure.

The developed solution represents an intelligent system to (a) collect and integrate real-time data from heterogeneous data sources, (b) analyse the collected data, and c) provide continuous feedback while informing decision making with the objective to reduce the gap between predicted and actual energy consumption. The proposed solution translates into three layers: the sensing and actuation layer, the data interoperability layer and the intelligence layer, as illustrated in Fig. 1.

The sensing and actuation layer represent energy and environmental sensing and actuation nodes in the complex energy system used to gather real-time data and apply, in response, adapted actuation strategies. Sensed data includes real-time supply and return temperatures of the distribution network, the amount of fuel available for use, the amount of hot water available in the storage tank, and energy demand of the connected buildings. This is augmented with environmental data from the UK Met Office weather service, including temperature, humidity, solar radiation, wind speed, and wind direction. The actuators are linked with devices for smart control and fault detection, e.g. the external shading blinds in windows (within buildings) are activated when the solar radiation reaches a certain level, or an alert is sent to the energy manager to signal that unoccupied spaces are being heated.

The interoperability layer integrates all sensed and heterogeneous data in a form that is exploitable by the intelligent analytics and visual components using data models in the form of semantics. The district energy management system (DEMS) and the building energy management system (BMS) can thus inter-operate, despite their different native communication protocols, through a proposed Web service interface. As such, the interoperability layer acts as a mediator to integrate diverse and heterogeneous data sources and bring them in a form exploitable by the intelligence layer. Moreover, data from smart devices and modelling tools are converted into computer readable language and shared in a common ontology, promoting interoperability and facilitating communication. The main concepts forming the resulting

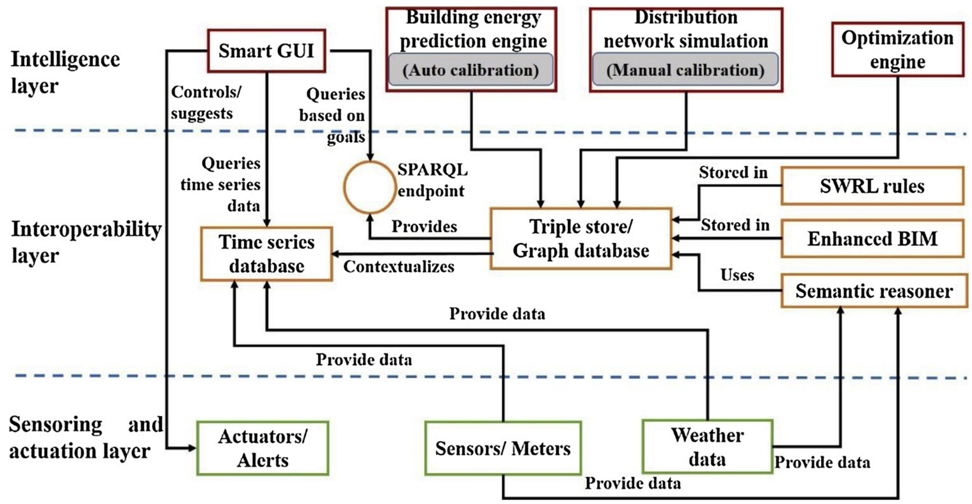

Fig. 1. Architecture of the proposed solution.

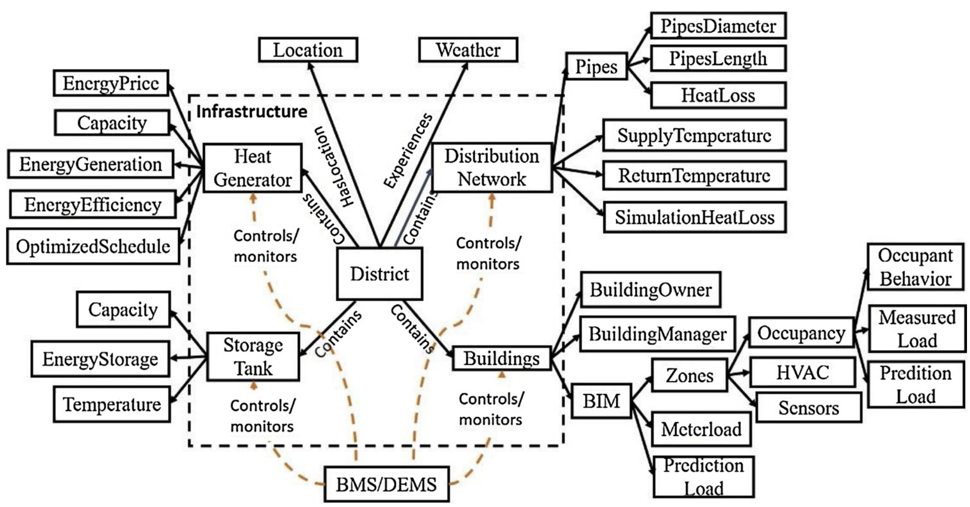

Fig. 2. Conceptualisation of main concepts in the district.

ontology are shown in Fig. 2. More details about the ontology development process are given in (Hippolyte, Rezgui, Li, Jayan, & Howell, 2018). The proposed solution is scalable and can be adopted in a wide range of buildings regardless of the data communication protocols used by the sensing and actuation nodes.

The intelligence layer involves a smart GUI (Graphical User Interface) and three discrete engines: the building heating demand prediction engine (Section 4.1), the distribution network simulation engine (Section 4.2) and the optimization engine (Section 4.3). The smart GUI is used to monitor and visualize real-time and historical data, monitor the performance of the systems in place, while providing a decision support capability in the form of actuation plans. The system can detect anomalies and suggest fault management plans. The state of the components of the energy system are analysed through the BMS/DEMS sensing nodes and acted upon through the energy system output control commands. As a result, the proposed system can send notifications to stimulate appropriate actions, and thus assists in the decision-making process.

The workflow that involves interaction between the three engines is illustrated in Fig. 3. A cluster-based infrastructure is used to deploy the proposed architecture to ensure scalability and increase efficiency. The objective of the implemented scenario is to inform the energy operators of the optimal operational schedules for operational cost optimization. A MPC framework is integrated into the optimization process. The

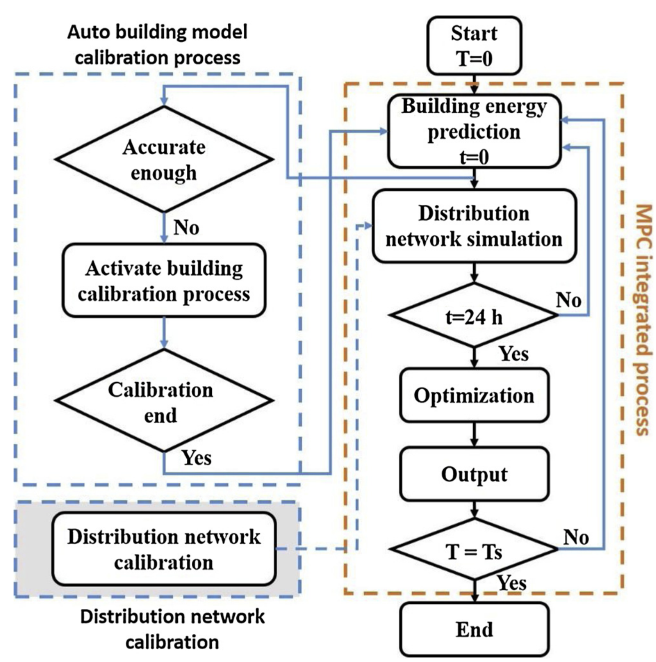

Fig. 3. The workflow for the interaction among the engines for optimization.

whole process is capable of producing a schedule for the following day provided it has 24-h weather and occupancy prediction. However, the optimization strategy only executes the result for the next time step (15 min. in this study). Thus, the optimization results are updated at each time step, which allows the system to react to a more up-to-date weather forecast and occupants' behaviour.

Two calibration processes can be achieved in the same cluster. The auto calibration process allows the building energy models to automatically calibrate sensitive parameters to improve prediction accuracy. This calibration is not performed on a time step basis but is instead triggered as a response to changing conditions that affect the accuracy of the simulated results. The distribution network calibration is conducted manually by adjusting the sensitive parameters to match simulation results with on-site measurements.

4. System modelling

The proposed methodology has been successfully tested and validated on a DH network in South Wales. The district was formerly occupied by a steelwork company that vacated the site in 1982. The site has since been developed into a vibrant and distinctive mixed-use (0.5 km wide and 3 km long) area, comprising an energy centre, a secondary school, a leisure centre, a learning zone, a general office and a multi-story car park. The energy centre was designed to provide heating for the above buildings and future planned developments. The installation includes one 400 kW gas engine CHP (Combined Heat and Power), two 450 kW biomass boilers, four 1900 kW gas boilers and two storage tanks. The electricity generated from CHP is sold directly to the national grid, which is not used locally. The electricity for the district is supplied by the national grid. The multi-story car park is not heated, thus it is not included in the DH network, as shown in Fig. 4. The general office was built in 1915 for the Iron and Steel Company and was refurbished in 2011. The other buildings were completed just after 2010.

4.1. Building energy prediction model calibration

Building energy models play a prominent role in the design and operation stage of a building (Li, Kubicki, Guerriero, & Rezgui, 2019). The developed simulation models are used in this research to predict building energy demand for the following day. The 3D semantic models of the buildings were reconstructed from point cloud data collected from a laser scanner. The models were then enriched based on archived documents. Zones and HVAC systems were added to each building simulation model.

Each building model was calibrated separately using the measured energy data. The time independent variables (U-values and air infiltration rate) were calibrated using an approach developed by the authors, presented in (Li & Rezgui, 2017). The calibration process for the time dependent variables (including indoor heating set point temperature, window opening schedules, occupancy etc.) is shown in Fig. 5. NSGA-II (Non-dominated Sorting Genetic Algorithm), which is one of the most popular multi-objective optimization algorithms (Yusoff, Ngadiman, & Zain, 2011), was employed to search for the optimal values for the time dependent parameters. If a chronic difference is detected between the simulation results and the measured results, a notification will be sent out to remind the energy managers to activate the auto calibration process as illustrated in Fig. 3.

The calibration was subsequently used to generate semantic rules. Two examples of the generated rules are shown in Fig. 6. A SWRL (Semantic Web Rule Language) includes an antecedent part and a consequent part, in the form of antecedent → consequent. If the antecedent is satisfied, then the consequent is satisfied as well.

The fitness function is to evaluate the CV-RMSE (Coefficient of Variation of Root Mean Square Error) and NMBE (Normalized Mean Bias Error) of the predicted results and measured results. NMBE and CV-RMSE are given by the following equations. yi and $\hat{y}_i$ denote simulation results and monitoring measurements.

$$NMBE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{(n-p)\bullet\bar{y}}\bullet 100 \tag{1}$$

$$CV - RMSE = \frac{\sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{(n-p)}}}{\bar{y}} \tag{2}$$

The building models are calibrated to the acceptable calibration tolerance of the ASHREA standard (ASHRAE, 2002). The well-calibrated building energy models provide reliable results for carrying out distribution network simulation.

4.2. Distribution network simulation

The distribution network is a piping system buried underground. The pipes are wrapped with insulation materials. Heat loss through the distribution network depends on the surrounding environment, distribution temperature, water flow regime, thermal physical properties of the pipe, insulation level, and the nature of the soil where the pipes are buried. The distribution network model was developed in Simulink, validated using on-site operation data, and presented in detail in (Li, Rezgui, & Zhu, 2016). The developed Simulink model is shown in Fig. 7. The calibrated model is thereafter used to generate the semantic rules that augment the developed ontology.

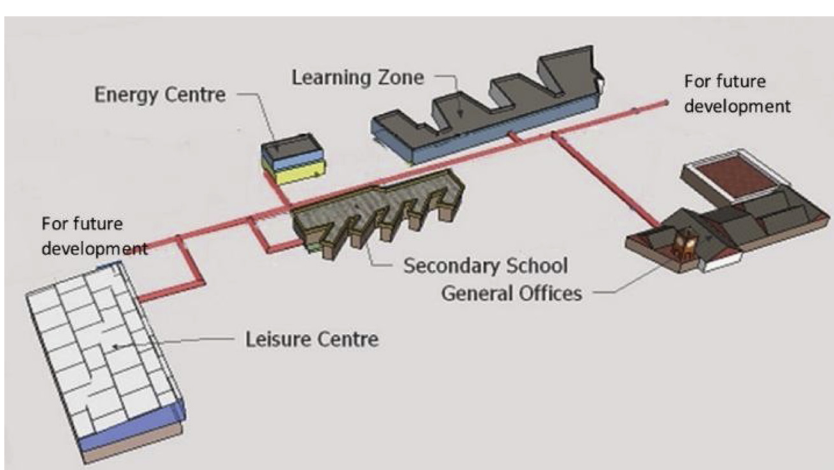

Fig. 4. The layout of heating network.

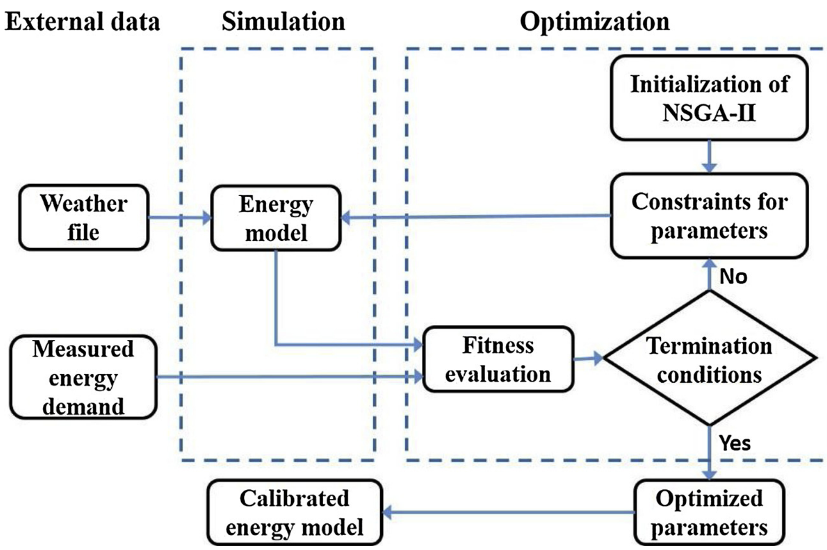

Fig. 5. GA based calibration process.

Rules definition	SWRL rules
1. IF NMBE>10% or *CV-RMSE* >30% of building (B1), then activate the calibration model (B1C)	1. BuildingSimulation(?B1) ^ hasNMBE(?B1,?NMBE) ^ greaterThan(?NMBE,?0.1) → Calibration_on(?B1C) BuildingSimulation(?B1) ^ hasCVRMSE(?B1,?CVRMSE) ^ greaterThan(?CVRMSE,?0.3) → Calibration_on(?B1C)
2. If a room (r1) is not occupied, then turn off the radiator (Ra1)	2. Radiator(?Ra1) ^ Occupied_room(?r1) ^ IsLocated(?Ra1,?r1) → Radiator_off(?Ra1)

Fig. 6. Two examples of the generated rules.

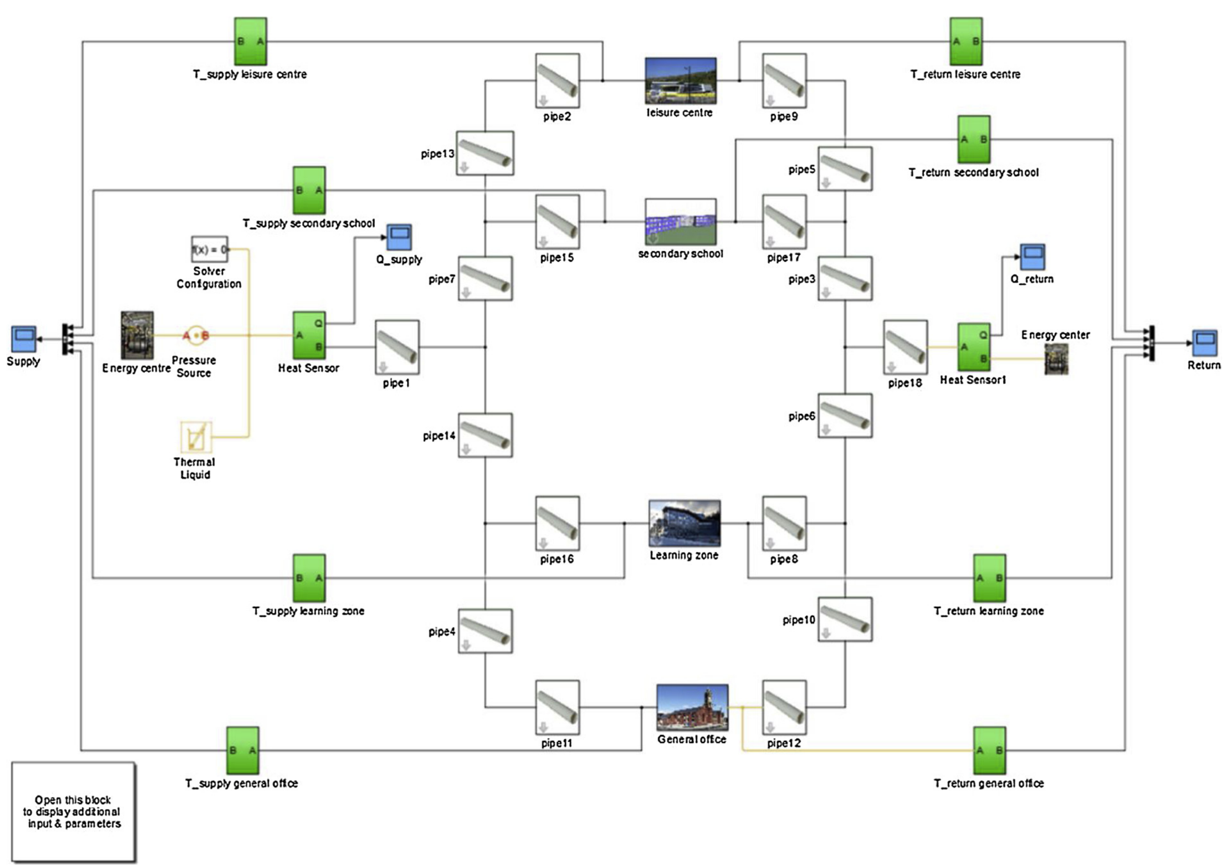

Fig. 7. The developed Simulink model for the distribution network.

Table 1
Energy price and CO_2 emission.

electricity price (sold to grid)	0.07	£/kWh
Renewable heat incentive (biomass)	0.0537	£/kWh of heat generation
purchase price of biomass	0.205	£/kg
purchase price of natural gas	0.0248	£/kWh
biomass calorific value	4.8	kwh/kg
CO_2 emission from biomass	15	kg/mwh
CO_2 emission from gas	185	kg/mwh

4.3. Operational optimization for cost minimization

The energy managers of the selected site used a load-tracking mode to control the generators, which resulted in low efficiency levels. The operating strategy used simplified the control of the generation units by assuming that the generators running at a lower output had the same efficiency as at a higher output. The energy managers turned on the generator(s) when there was a need for heating. The CHP had the highest priority, operating 24/7, to fully exploit its capacity to generate heat and power. The second option involves the biomass boilers. When the CHP and biomass boilers were not able to meet the heat demand, the gas boilers were put into operation. The storage tanks were installed in the energy centre but were not used efficiently.

The proposed optimization aims to reduce operation cost while maintaining the energy demand of the DH network by controlling the operational schedules of the generation units. Mix-integer linear programming, consisting of both binary and continuous variables, is chosen because of its computation speed in finding the optimal solution for near real-time management. The parameters that are used in the operation are shown in Table 1. The data were provided by the energy manager of the district. The electricity price refers to the price of selling electricity generated from the CHP to the national grid.

4.3.1. Constraints

The efficiencies of the generators vary under different output loads, which should be taken into account while investigating the operation cost from the energy centre. The efficiency profiles of the biomass boiler, gas boiler and CHP are illustrated in Fig. 8. The efficiencies of the generators vary over the operational profiles, performing better at higher output than lower output levels. In order to ensure the efficiency of the generators, the minimum output is defined at 20% of the rated power. The output levels are divided into 5 levels, corresponding to 20%, 40%, 60%, 80% and 100% of the rated power.

x(i,j,k) is a binary attribute to define the on/off status of the generators. x(i,j,k) = 1 indicates at time period i, generator j is operating at level k. At any time for any generator, it can only operate at one output level or be shut down. These constraints are applied to the entire optimization period.

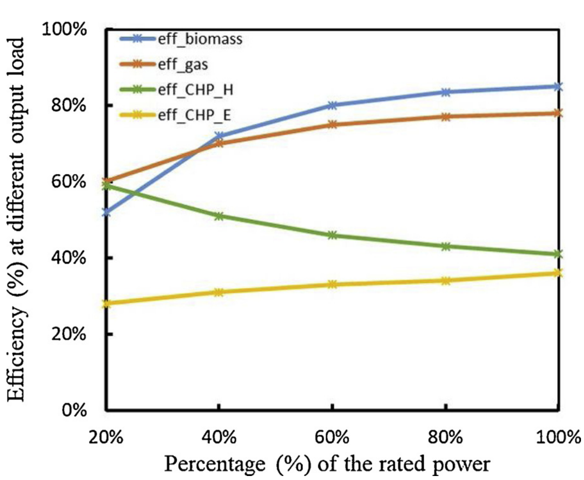

Fig. 8. Efficiency profiles of the generators.

$$\sum_{k=1}^{k=nlevel} x(i, j, k) \le 1 \tag{3}$$

$$x(i, j, k) = 0,\ 1 \tag{4}$$

The time step in this study is 15 min., so 24 h (one day) are equivalent to 96 periods. In order to represent the start-up status, another binary variable z(i, j) is introduced. More specifically, z(i, j) = 1 means generator *j* is off at time period i ($\sum_{k=1}^{nlevel}$ x(i,j,k) = 0) and it is on at i+1 time period ($\sum_{k=1}^{nlevel}$ x(i+1, j,k) = 1). The operation status of the generators is subject to the following constraints:

$$-\sum_{k=1}^{nlevel} x(i, j, k) + \sum_{k=1}^{nlevel} x(i+1, j, k) - z(i, j) \le 0 \tag{5}$$

$$z(i, j) = 0,\ 1 \tag{6}$$

z(i, j) is included in the objective function for cost minimization. Therefore, the solver will make sure z(i, j) = 1 on the condition that it satisfies the requirements.

The generators are numbered as CHP, gas boiler 1, gas boiler 2, gas boiler 3, gas boiler 4 and biomass 1, biomass 2. Different types of generators have the same priority for energy generation, but for the same type of boiler, biomass 1 has a higher priority than biomass 2, which means biomass boiler 2 is only turned on when biomass 1 is already in operation. The same principle is employed to gas boilers.

$$\sum_{k=1}^{nlevel} x(i, j, k) - \sum_{k=1}^{nlevel} x(i, j+1, k) \ge 0 \tag{7}$$

The heat stored in the storage tank ($Storage_i$) at time period i should be equal to the energy stored until time period i-1 ($Storage_{i-1}$) multiplied by the efficiency of the storage tank ($eff_{storage}$) and the energy generation at time period i, minus the energy consumption at time period i ($Demand_i$). The efficiency of the storage is assumed to be constant efficiency. PH(j, k) represents the energy production of operator j running at output level k.

$$Storage_i = (Storage_{i-1} \bullet eff_{storage} + \sum_{j=1}^{nGens} \sum_{k=1}^{nlevel} P_H(j, k) \bullet x(i, j, k) - Demand_i) \tag{8}$$

$$Storage_i \le Size_{tank} \tag{9}$$

When i = 1, $Storage_{i-1}$ is the measured energy storage from the storage tank.

4.3.2. Objective

The objective of the optimization is to minimize operation cost (C_{total}) from the energy centre while guaranteeing heat consumption of the DH network. The operation cost consists of fuel cost (C_{fuel}), start-up cost of the generation units ($C_{startup}$) and the positive revenue ($C_{electricity}$) gained from selling electricity to the grid taking into account the renewable heat incentive.

$$C_{total} = C_{fuel} + C_{startup} - C_{electricity} - C_{RHI} \tag{10}$$

$$\begin{aligned} C_{fuel} = \sum_{i=1}^{nPeriod} \Big(& \sum_{k=1}^{nlevel} \frac{P_H(1, k) \bullet x(i, j, k)}{\eta_{CHP}(j, k)} \bullet price_{gas} \\ & + \sum_{j=2}^{5} \sum_{k=1}^{nlevel} \frac{P_H(j, k) \bullet x(i, j, k)}{\eta_{gas}(j, k)} \bullet price_{gas} \\ & + \sum_{j=6}^{7} \sum_{k=1}^{nlevel} \frac{P_H(j, k) \bullet x(i, j, k)}{\eta_{biomass}(j, k)} \bullet price_{biomass} \Big) \end{aligned} \tag{11}$$

$$C_{startup} = \sum_{i=1}^{nPeriod} \sum_{j=1}^{nGens} (z(i, j) \bullet price_{start}(j)) \tag{12}$$

$$C_{electricity} = \sum_{i=1}^{nPeriod} \sum_{k=1}^{nlevel} P_{chp_e}(1, k) \bullet x(i, 1, k) \bullet\ Price \tag{13}$$

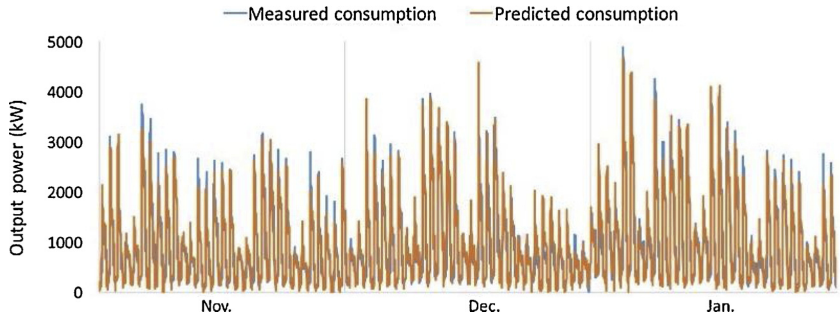

Fig. 9. Aggregated energy demand from the DH network, simulation VS metered data.

$$C_{RHI} = \sum_{i=1}^{nPeriod} \sum_{j=6}^{7} \sum_{k=1}^{nlevel} P_H(jj, kk) \cdot x(i, j, k) \cdot RHI \tag{14}$$

where $\eta_{CHP}(j, k)$, $\eta_{gas}(j, k)$ and $\eta_{biomass}(j, k)$ are the efficiencies of the CHP, gas boiler and biomass boiler operating at k level. $price_{gas}$, $price_{biomass}$, $price_{start}(j)$ and $Price_e$ represent the fuel cost for gas, biomass, startup cost for generator j and the price of electricity sold to the grid. $P_{chp_e}(1, k)$ represents the electricity generation from CHP boiler operating at level k, while RHI (Renewable Heat Incentive) represents the renewable incentive price for heat generation from biomass boiler.

5. Results

5.1. Energy demand from DH network

To evaluate the effectiveness of the developed solution, the proposed system was tested in a real site condition over a winter season from November to January. The prediction results are compared with the data collected from on-site measurements. Fig. 9 shows the dynamic behaviour of the DH demand over the optimization period. Eqs. (1) and (2) are used to evaluate the accuracy of the prediction results. The NMBE and CV-RMSE are -0.1% and 13.1% for 15 min interval data. The ASHRAE Guideline (ASHRAE, 2002) requires NMBE and CV-RMSE for monthly data to be within 5% and 15%, and for hourly data to be within 10% and 30%. Thus, from the statistical point of view, it can be concluded that the predicted results are in line with the measured data. Furthermore, the heat demand for working days are significantly different from the weekends and holidays. The operational schedules will be discussed based on one selected day from the working days and one selected day from the weekends or holidays.

5.2. Operational schedules for the generators

The optimization scheme is benchmarked with the load-tracking scheme. Figs. 10 and Fig. 11 illustrate the operational schedules of the generators for a typical day during working days and a typical day during weekends or holidays under load-tracking mode and after optimization. Under the load-tracking mode, the boilers' operation followed a predefined priority. Compared with the installed capacity of each generator, the generators operated substantially at partial loads. The CHP had the highest priority, which mainly operated at full load during daytime and partial loads during night time. The biomass boilers were mostly operating at or near their full load when in operation. These assured high efficiencies for the CHP and biomass boilers. The gas boilers mainly operated at partial loads, resulting in a low energy efficiency.

After optimization, the system took advantage of the storage tank for load shifting. The boilers mostly operated at or near full output loads, which ensures the energy performance of the whole system. It should be noted that the CHP and biomass boiler 2 operated exclusively at full load on weekends. During the working days, the CHP and biomass boiler 2 operated mainly at full load with exceptions that the CHP operated at 60% of the full load before shut down and the biomass boiler 2 operated at 80% of the full load at starting up. From the energy generation profiles after optimization, it can be seen that the heat generation before peak hours was more than the heat demand. The over generated heat was shifted to peak hours. The generators were normally designed to meet peak demand. If smart control had been introduced at the design stage, the installation capacity for the energy units could have been reduced. It should be noted that, after optimization, the biomass boiler is the most cost effective option for heat generation. As biomass is a carbon neutral energy source, this also leads to a reduction in CO_2 emission. Over the three-month period, the total CO_2 emission was reduced from 504 tons to 287 tons, corresponding to a reduction of 43%.

5.3. Operation efficiencies and costs

The efficiencies of the boilers after optimization are benchmarked with efficiencies under the load-tracking mode, as shown in Table 2. The efficiencies of the boilers under the load-tracking mode were obtained on-site from the annual operational efficiencies for the year 2016. The efficiencies after optimization are average efficiencies over the test period. After optimization, the performance of the gas boilers

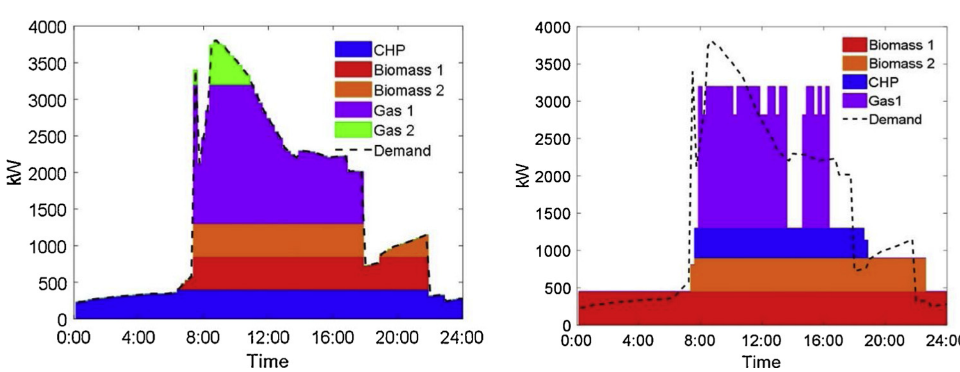

Fig. 10. Operational schedules for the generators for a typical day in the working days under the load-tracking model (left) and after optimization (right).

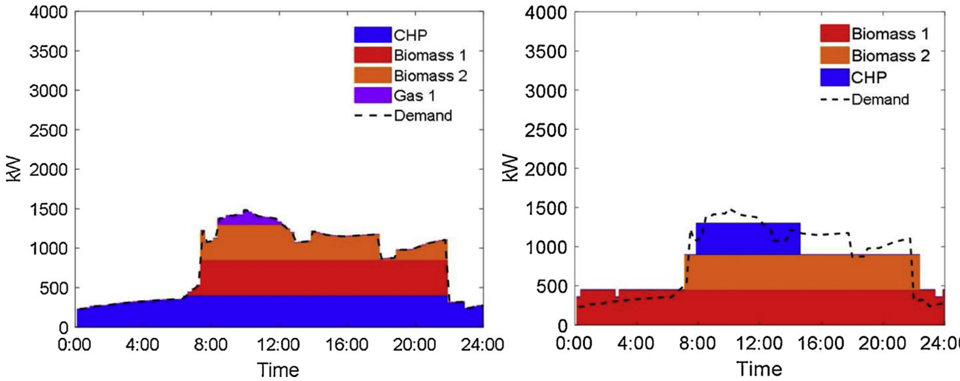

Fig. 11. Operational schedules for the generators for a typical day in the weekends or holidays under the load-tracking mode (left) and after optimization (right).

Table 2
Efficiencies of the generators under the load-tracking mode and after optimization.

	Load-tracking model	after optimization
CHP electricity	0.35	0.36
CHP overall	0.78	0.78
Biomass boiler	0.82	0.85
gas boiler	0.67	0.77

and the biomass boiler has been improved significantly. The overall efficiency for the CHP remains the same, but the efficiency for electricity generation showed a slight increase.

The daily operation costs under the load-tracking mode and after optimization are illustrated in Fig. 12. After optimization, 36% reduction in the operation cost has been achieved. The negative operation cost during holidays and weekends indicate that the system is capable of generating positive revenue, which is mainly due to the renewable heat incentive policy for heat generation from biomass boilers.

6. Discussion

A demand response energy management system is proposed, demonstrated and validated through a semantic approach. Although the proposed case study is specific, the proposed web-based system, underpinned by a comprehensive domain description through semantics, and augmented with intelligence through optimization, is generic and scalable. As such, the proposed system can be extended to connect further buildings to the thermal grid. Specifically, the prediction models are flexible for replacement of old building models and addition of new building models. For example, if a building changes (e.g. through a renovation process), this can be reflected in the corresponding calibrated simulation model used by the prediction engine. The network can be extended by adding new building models to quantitatively evaluate the possibility of integrating newly constructed buildings for cost effective management. For large scale district simulation, representative building models can be constructed to represent buildings with similar characteristics (including geometry), and then multiplied by the number of buildings to simplify the model generation process and reduce runtime requirements. The model size is only constrained by the computational power of the IT infrastructure. The simulation models can also be generated from data driven models if historical operation data are available. The large datasets are used to train and validate the prediction model through machine learning. The optimization algorithm can also be replaced or modified to achieve other objectives, such as enhancing renewable energy share and improving indoor thermal comfort.

The semantically enriched environment introduced in this paper supports the development of additional modules to support further use cases, including (a) anomaly detection, (b) automatic feature extraction for elicitation of performance gaps, and (c) informing decision making through tailored energy saving recommendations. For example, if a sensor attached to a window provides a state ‘open’ in cold winter, the energy sensor detects a significant energy increase within the room. The system will recognize this as an abnormal energy increase and sends a signal to remind the users to close the window. It is also capable of detecting pipe leakage in the distribution network by comparing the measured energy data with simulated network heat losses.

The semantic-enabled approach developed in this study for monitoring and optimization is not only limited to the thermal grid, it can also be used to integrate a thermal network with other networks in a multi-vector energy landscape.

7. Conclusions and future work

This paper presents a “demand response” management solution of a

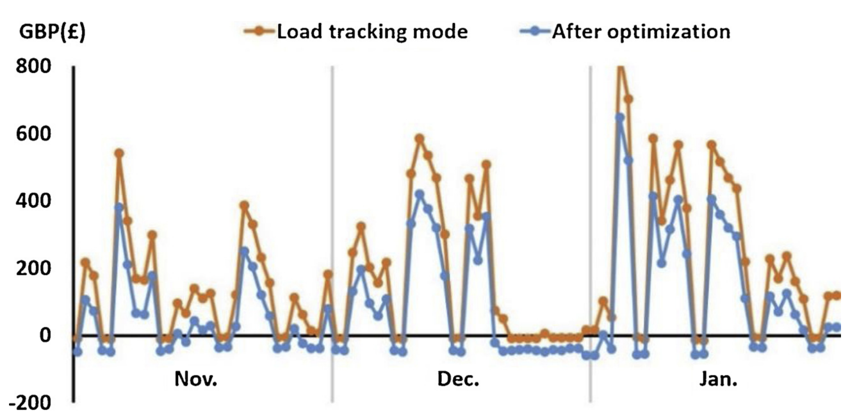

Fig. 12. Daily operation cost of the generators from November to January.

thermal grid by using a semantic middleware, that manages real-time data, augmented with machine learning techniques. Together with the novelty of the semantic approach, the solution presents an insight into real-time thermal grid monitoring and optimization, facilitating energy managers to make informed decisions based on real operation conditions of their energy system. The solution has been successfully implemented in a DH network, where 36% operation cost reduction and 43% carbon mitigation were observed within three months.

Whilst the individual components used in the proposed system delivered interesting performance improvement, key ongoing work includes further optimization of each. MINP is selected for the optimization because of its computation speed, which simplifies the operation of the generation units. For example, the MINP could be interchanged with a more advanced deep learning model, and its hyperparameters could be further optimized via a dense grid search or similar technique.

An automatic calibration process for the distribution network will be investigated in future development. Future work will also investigate optimization from the control of buildings such as zone energy demand, indoor temperature and indoor thermal comfort. Multi-objective optimization will be introduced to investigate operation cost together with thermal comfort, to be validated directly from occupants' feedback.

Declaration of Competing Interest

None.

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