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Upscaling energy control from building to districts: Current limitations and future perspectives

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ABSTRACT

Due to the complexity and increasing decentralisation of the energy infrastructure, as well as growing penetration of renewable generation and proliferation of energy prosumers, the way in which energy consumption in buildings is managed must change. Buildings need to be considered as active participants in a complex and wider district-level energy landscape. To achieve this, the authors argue the need for a new generation of energy control systems capable of adapting to near real-time environmental conditions while maximising the use of renewables and minimising energy demand within a district environment. This will be enabled by cloud-based demand-response strategies through advanced data analytics and optimisation, underpinned by semantic data models as demonstrated by the Computational Urban Sustainability Platform, CUSP, prototype presented in this paper. The growing popularity of time of use tariffs and smart, IoT connected devices offer opportunities for Energy Service Companies, ESCo's, to play a significant role in this new energy landscape. They could provide energy management and cost savings for adaptable users, while meeting energy and CO_2 reduction targets. The paper provides a critical review and agenda setting perspective for energy management in buildings and beyond.

1. Introduction

Reducing global energy demand and the greenhouse gases that stem from energy production is one of the most vital technological challenges that the world currently faces. Given that buildings represent a significant proportion of global energy consumption, 40% in the EU (European Parliament, 2010), this is a pivotal sector to target for efficiency savings. Key components within buildings such as the HVAC and lighting systems are estimated to account for around 55% and 15% of all building energy consumption although this is dependent on building uses and country (Pérez-Lombard, Ortiz, & Pout, 2008). However, recent research has shown that a significant proportion of this energy consumption is wasted due to poor management by controller systems (Hu, Weir, & Wu, 2012). It has been estimated that between 20% and 30% of building energy consumption can be saved through optimised operation and management without changing any hardware within the building (Guan, Xu, & Jia, 2010).

To tackle climate change there has been a recent surge in construction of renewable energy resources such as solar and wind power (Lins, Williamson, Leitner, & Teske, 2014). It is predicted that the future energy infrastructure will be much more decentralised, moving away from the current fossil fuel, central grid system in place (Kolokotsa, 2016). This new energy infrastructure will have a greater share of renewable generation and be closer to the communities that it supplies allowing local resources to be maximised and efficiency to be improved (Koirala, Koliou, Friege, Hakvoort, & Herder, 2016). In this new energy paradigm, more intelligent control systems are essential to manage the variable, stochastic renewable resources. The old model of demand led energy supply can no longer work in this scenario. Instead we must aim to become more supply led, shifting our energy demands to times when the supply is available (Ameri & Besharati, 2015; Di Somma et al., 2015; Ondeck, Edgar, & Baldea, 2015). This can be achieved through demand response, DR, or demand side management, DSM, techniques. It has been estimated that 93 GW of energy consumption can be brought forward and 247 GW delayed across Europe if we have smart enough controllers to exploit this (Gils, 2014). To achieve this vision of a smart grid, fast, reliable communication and intelligent, autonomous decision making is required between prosumers, storage devices, the central grid and end users. If implemented this could reduce electricity demand and CO_2 emissions by 10% to 15% (Mourshed et al., 2015).

Fortunately, volumes of research is being carried out into intelligent building controls which have great potential to reduce energy consumption and participate in demand response mechanisms. Current traditional building controls use Proportional or Proportional-Integral, PI, control. Rather than operating fully on or fully off, proportional control measures the error between desired value and the measured

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value and gives a proportional output response signal. PI control adds an integral term to remove permanent gains found in proportional only control and this is the most common system currently used in HVAC controllers (CIBSE, 2009). However modern advances in computational intelligence could allow direct digital control. Microprocessors could be programmed with artificial intelligence to provide advanced, adaptable and more optimal control. Furthermore, given the decentralisation of energy supply there is a requirement for building controllers to be more aware of their environment and adaptable to local circumstances to make best use of local generation capacity. The increased use of time of use tariffs or real time pricing gives an opportunity for engaged consumers to achieve real energy cost savings and in-turn help the grid reduce its peak demands.

This paper will critically review a number of peer-reviewed research papers on the topic of building energy management (Section 2) and wider scale district energy management (Section 3). An assessment of how integrated district and building level control are will be made as well as a number of proposed future research directions in Section 4.

2. Building energy management strategies

Most large complex buildings will be equipped with a Building Management System, BMS. These sense conditions in building zones and are programmed with internal logic to take action using various actuators depending on the conditions they perceive and the time of day. However, traditional BMS follow fairly static rules without the intelligence to try new, potentially more optimal, strategies. For example instead of turning on the heating at 8am to have the building at the appropriate temperature by 9am, could the building be pre-heated to avoid a morning spike and possibly reduce overall daily energy consumption? Can occupancy levels be better predicted and sensed to ensure that zones are only heated when necessary? Is the optimal strategy dependant on the outdoor conditions and does that need to be sensed more? These are the typical questions facing the development of BMS which are vital for reducing energy consumption and improving comfort within buildings. Lee and Cheng (2016) reviewed the impact of BMS over 35 years and found that during this period energy savings from BMS have increased from 11.39% to 16.22%. However a key challenge for the future BMS is the availability, cost and quality of sensors as well as the data management problems that arise from the increased sensing (Kumar et al., 2016). An excellent review of BMS is provided by De Paola, Ortolani, Re, Anastasi, and Das (2014), in which the author sets out the ideal BMS and how close current technologies are to that ideal.

2.1. Home energy management systems

Whilst most current BMS are installed in larger commercial buildings, smart energy management in residential buildings is also very important and a growing area of research. We are already seeing 'smart' thermostats like Nest (2016), which aim to learn users preferences and patterns to save energy as well as linking up with other smart devices using the Internet of Things, IoT. These products along with smart meters, which are increasingly being rolled out by energy suppliers (DECC, 2014), can also interact with users smart phones with the hope of engaging the consumer and encouraging behavioural change. Commercial systems are relatively new and the literature provides a number of suggestions for possible system architectures. Capone, Barros, Hrasnica, and Tompros (2009) presents the AIM gateway which proposes a communication architecture for devices and sensors within the home. The authors suggest that this could provide better monitoring and prediction for energy suppliers through user profiling. Son, Pulkkinen, Moon, and Kim (2010), Zhou et al. (2016) give a similar vision for a Home Energy Management System with a series of devices connected to a smart meter or controller. They suggest that the management and scheduling of these devices could be outsourced to a third party with intelligent analytics to save the consumer money. There is also emphasis that the scheduling strategies need to use demand response strategies. In Zucker, Habib, Blöchle, Wendt, and Schaat (2015), a cognitive architecture for building control is introduced. Cognitive algorithms aim to mimic the way the human mind thinks through storing experiences and basing decisions around previous actions.

An intelligent BMS is simulated in Missaoui, Joumaa, Ploix, and Bacha (2014). The BMS is assumed to control household appliances, the heating, local PV resources and sense outdoor conditions. A grey box, resistor-capacitance, RC, thermal model of a small house is created to simulate the indoor temperature depending on the heating strategy. By shifting the operation of controllable appliances, the smart BMS made significant cost savings. Smart household scheduling is also addressed in Chen, Wang, Heo, and Kishore (2013). This also controls the heating and controllable appliances but uses a Model Predictive Control, MPC, technique and utilises electrical battery storage which it theorises could come from a plug-in electrical vehicle. The solution is simulated in several climates and is shown to save the user up to 20%. However, this strategy assumes perfect weather forecasting so the saving, in reality, is likely to be reduced. In Yuce, Rezgui, and Mourshed (2016), Yuce combine the use of an Artificial Neural Network, ANN, and a Genetic Algorithm, GA, to schedule domestic appliances to ensure maximum utilisation of local renewable resources. The use case presented is based on a small holiday home in Southern England which has onsite PV and wind production. When grid energy reductions of 10%, 25%, and 40% are imposed on the building, the idle renewable generation is clearly reduced.

2.2. Optimal HVAC control

Given that HVAC systems account for a proportionately large share of building energy consumption a large amount of the literature focuses on better management of these systems. These studies often include setting the optimal start and end times for heating or cooling, a focus on sensing occupancy to improve efficiency, utilising the building thermal mass, and operational control of the components that make up the HVAC system.

2.2.1. Model predictive control management strategies

The dominant HVAC control method found within the literature is Model Predictive Control, MPC. A number of building control techniques were assessed in Shaikh, Nor, Nallagownden, Elamvazuthi, and Ibrahim (2014) and it concluded that MPC was an excellent strategy for managing building systems due to its ability to adapt to disturbances, exploit thermal mass, take account of price variations and shift load. MPC aims to optimise a decision variable (e.g. temperature set point) over a time horizon whilst considering outside disturbances such as outdoor temperature. It uses an internal model of the controlled system to be able to predict the outcome of its actions. It then re-evaluates at shorter time steps to be able to adapt to incorrect forecasts or unforeseen disturbances (Afram & Janabi-Sharifi, 2014; Kwadzogah, Zhou, Li, & Member, 2013). The model within MPC is obviously essential and this remains disputed within the literature. White box models are details physics based models such as Energy Plus or TRNSYS. These have the advantage of being highly detailed and customisable but have very long running times. Grey box models such as RC models are simplified physics models tuned using real data. Black box models such as ANN have no knowledge of the physical make-up of the system and are trained purely on available data. Unlike white box models they are quick and not computationally demanding but do require large volumes of data (Li & Wen, 2014). The complexity of the model is also a key consideration. It is required to accurately simulate the building in question whilst be as simple as possible to reduce computational time. Privara, Vana, Zacekova, and Cigler (2012) gives a methodology to provide the least complex yet adequately accurate building model for MPC.

MPC has been applied to a Czech university building in Prívara, Jan, Ferkl, and Cigler (2011), Široký et al. (2011). This MPC strategy took weather, occupancy, and price prediction into account and modelled the thermal conditions of the building with an RC model. In a 3 month trial the strategy achieved a 17% to 27% reduction in energy consumption. Traditional MPC was adapted in Oldewurtel et al. (2012) to take into account the uncertainties in the forecasts that it uses. The resulting Stochastic MPC reduced energy consumption and gave less comfort violations than traditional rule based control or normal MPC. Mahendra, Stéphane, and Frederic (2015), also aims to address the problems that stem from forecasting uncertainties. This solution runs a reactive algorithm in between the MPC time steps that can take swift action if the forecasts are clearly incorrect due to an unexpected spike in occupancy for example.

Aside from the use of RC models, Ma, Qin, Li, and Salsbury (2011) used an Energy Plus model of a fairly simple one storey building which was coupled with a MATLAB MPC procedure using the Building Controls Virtual Test Bed, BCVTB, as a middleware. This strategy found pre-cooling was effective to shift load off peak to cheaper times hence saving money over traditional strategies. Salsbury, Mhaskar, and Qin (2013) also exploited the thermal mass of the building using a MPC algorithm that considered price fluctuations throughout the day. A genetic algorithm is utilised in Molina, Lu, Sherman, and Harley (2013), in conjunction with a state space model to optimally control an ideal heating and cooling system. It aims to balance the economic cost of energy and discomfort measured using Predicted Percentage Dissatisfied, PPD, however fails to find a solution where both criteria are improved. Ferreira, Silva, and Ruano (2012), aimed to control both temperature and humidity to minimise the energy consumption and maintain conditions within an acceptable Predicted Mean Vote, PMV, range. The strategy was deployed in a classroom and was found to activate the AC unit far fewer times giving a predicted energy saving of over 30%. An explicit MPC strategy was developed in Parisio, Fabietti, Molinari, Varagnolo, and Johansson (2014) to control both CO_2 and indoor temperature whilst minimising energy costs.

In Figueiredo and Sá da Costa (2012) the authors aimed to develop an intelligent MPC layer above the traditional SCADA based building controls. Current SCADA systems lack the computational power to carry out any data analytics or advanced control strategies. The paper proposes that the interactive layer holds the intelligence and the legacy SCADA system is used to sense and actuate. A decentralised approach has been used in Moroşan, Bourdais, Dumur, and Buisson (2010). This allows independent MPC controller to be deployed in individual zones which are not computationally complex or time consuming. The heat transfer that is likely to be transferred from one zone to another is communicated to the relevant zone controller. This is then used to avoid temperature overshoots compared to independent zone level controllers. MPC can be formulated to also consider predictions of local renewable generation and variable energy prices to allow greater saving over traditional rule based control. This was applied in Lee, Horesh, and Liberti (2015) and energy savings of 15% to 30% were achieved over basic cooling strategies.

2.2.2. Other optimisation strategies

Whilst MPC is the dominant control strategy found in the literature, other smart scheduling or rule based controls can be found. Older HVAC energy minimisation methods were based on full audits of the system and then applying different control rules to try and reduce energy consumption. An example of this can be found in Mathews, Arndt, Piani, and van Heerden (2000), where a number of additional rules and fine tuning around start and stop times could lead to a 53% reduction in energy consumption. The building thermal mass is utilised in Lee and Braun (2008) by pre-cooling to avoid on-peak energy consumption. The building is held at a lower temperature until 1 p.m. and allowed to linearly increase during the peak energy period. However, these types of rule based controls will only work for the particular room or building they are tuned for. For these types of rule based controls to succeed on a wider scale they must be more intelligent, autonomous and learn from the conditions they perceive and the actions that they take. For example, they must predict the conditions to assess whether pre-cooling is a suitable strategy for that day. An intelligent, rule based, decision support system was created in Doukas, Patlitzianas, Iatropoulos, and Psarras (2007) to control indoor temperature, humidity, luminosity and air quality. It had a stored knowledge base and a wide array of sensors allowing it to choose the best course of action for the specific conditions. This led to a reduction in energy consumption of around 10% in a real trial. A care facility in the Netherlands is modelled and controlled in Yuce and Rezgui (2015). A validated Energy Plus model is used to generate vast quantities of training data which is used to train an ANN. A genetic algorithm then chooses the optimal rules through semantic mapping based on environmental conditions, the time and date.

As has already been alluded to throughout this paper so far, there is a growing use of computational intelligence techniques to tackle the problems of building energy management. Increasingly machine learning methods such as ANN can be used to predict important variables. They can also be tuned to continue learning and adapting after their initial creation using sliding window training techniques (Chae, Horesh, Hwang, & Lee, 2016). An excellent review of computational intelligence techniques such as machine learning, fuzzy logic, multi-agent systems and metaheuristic algorithms, applied to HVAC control can be found in Ahmad, Mourshed, Yuce, and Rezgui (2016). ANN have been used in Moon and Kim (2010) to maximise occupant comfort by controlling indoor temperature and humidity. The ANN could predict future indoor conditions based on current indoor and external conditions and then take appropriate action. Yamada (1999) also used neural networks to calculate predicted PMV. It then aimed to maintain PMV at $\pm$ 0.3 rather than 0 and this reduced energy consumption by 18%. Liang and Du (2005), also created a neural network controller that used PMV as its control objective rather than temperature or humidity. The ANN measures the error between set point and measurement. The error is used as an ANN input and it outputs an appropriate control action. It was found to provide more stable control and provide better comfort for occupants.

Papantoniou uses a number of computational intelligence techniques in Papantoniou, Kolokotsa, and Kalaitzakis (2015). ANN are used to predict the outdoor and indoor air temperature over the next 8 h. Then a genetic algorithm and real time fuzzy logic control are used to set fan coil operation and speed within a hospital. A Web-based dashboard is also set up to display several variables over a given time range for technical hospital staff. Whilst this is only trialled on 3 simulated rooms, if extrapolated to the whole hospital energy savings of up to 35% are predicted. A fuzzy logic controller based around the control of PMV is developed in Gouda, Danaher, and Underwood (2001). The authors argue that fuzzy logic controllers are more adaptable to different building conditions compared to traditional PID controllers. Whilst PID controllers work well for the conditions they have been tuned for, they perform poorly if building characteristics change. The controller developed in this paper outperforms the PID controller in these conditions. Building operation and HVAC control is highly dependent on occupancy patterns. Pisello, Bobker, and Cotana (2012) shows that simply by understanding and auditing the occupancy patterns within the building you can alter the HVAC schedules which provide significant energy savings compared to when the building is first commissioned. An occupancy based optimisation strategy is proposed in Erickson and Cerpa (2010). This pays particular attention to sporadically occupied zones to achieve energy savings of around 20%.

2.2.3. Operational control

Slightly beyond the scope of this review, but nevertheless important for the reader to be aware of, is a class of operational level optimisation strategies. These tend to focus of specific HVAC components and ensure that they are run at maximum efficiency. HVAC components have very complicated interrelationships and balancing the COP (Coefficient of Performance) of the different components is not necessarily intuitive. The chilled water and supply air temperature set points are optimised using evolutionary algorithms in Fong, Hanby, and Chow (2006), Fong, Hanby, and Chow (2009). MPC is used to control set point of shared, University campus, cooling towers, chillers and thermal storage in Ma et al. (2012) achieving around a 20% increase in overall COP. A genetic algorithm is used in Lu, Cai, Xie, Li, and Soh (2005) to minimise the overall energy consumption from fans, chillers, and pumps by controlling the chilled water temperature, cooling coil and chilled water pump pressure, and the sequences of pumps and chillers used. This kind of system efficiency optimisation is important in reducing overall building energy consumption and can be improved in conjunction with intelligent, wider scale, building control strategy found in the other sections of this paper. Interested readers can find more detail in the above references and in Komareji et al. (2008), Rehrl and Horn (2011), Xu and Li (2007), Yuan and Perez (2006), Yang and Wang (2012).

2.3. Multi-variable zone level optimisation

A more detailed class of building optimisation can also be found in the literature that aims to not only to control heating or cooling devices but also ventilation and lighting systems. Due to the complexity that comes from managing these highly coupled systems, they tend to be focussed at a room or zone level rather than an entire building level. An example can be found in Ahmad, Hippolyte, Reynolds, Mourshed, and Rezgui (2016), which aims to minimise energy consumption of a UK classroom whilst maintaining good indoor air quality, thermal and visual comfort using a genetic algorithm. The decision variables included the operation of a window blind, window opening and ventilation unit operation. Mossolly, Ghali, and Ghaddar (2009), aimed to control the fresh air flow rate depending on the CO_2 levels within the room. A GA was used to minimise a cost function comprising three components, the thermal comfort, the energy consumption and the indoor air quality. A study by Kim, Jeon, and Kim (2016) combines the use of Energy Plus simulations, artificial neural networks (ANN) and a GA to control a blind slat angle and the HVAC operation to satisfy thermal and visual comfort. A Langrangian relaxation – Dynamic programming technique was used in Sun et al. (2013). The study aimed to control the HVAC, lighting, shading and natural ventilation systems by reducing the problem and solving sub problems. Their solution was found to save up to 9.3% of energy cost when compared to conventional strategies. A further paper, (Yan et al., 2014), builds on this work by considering a combined cooling, heat and power unit, CCHP, and energy storage capacity. Yang, Wang, and Wang (2011) presents a GUI platform to manage lighting, CO_2 and temperature within a building whilst minimising energy cost using a particle swarm optimisation, PSO, algorithm.

2.4. Discussion

Many of the optimisation papers discussed so far are summarised in Table 1. It is immediately clear that there is no real consensus around which type of building model to use in building control optimisation. RC and ANN appear to be the leading candidates and the best choice is likely to be dependent on a number of case by case factors such as the availability of data and the optimisation method used. Table 1 also shows the need for advanced building control strategies to be tested in the field and implemented in real buildings. Only after this stage can this work become truly validated and begin to be accepted by the wider public. Furthermore, most of the optimisation strategies reviewed this section do not explicitly consider DR controls. This is a vital research gap that needs to be filled given global energy trends towards more decentralised use of uncontrollable renewable resources.

There is a clear difference between the detailed HVAC control and the home energy management systems which seem to be particularly focussed on domestic appliances. Given the increasing electrification of heating in residential properties, through rising popularity of devices like heat pumps, thermal control and appliance control will need to become more integrated in the future. Even with gas based heating systems, HVAC systems consume electricity through fans and pumps so holistic management of electricity is likely to be advantageous in most future buildings. The increasing interconnection of devices through IoT technology is greatly encouraging in this field. However, users' privacy concerns must be addressed and consumers must be better educated in their energy choices and feel as though they are kept informed.

In the authors' opinion, operational optimisation is something that will continue to develop alongside the improvement of smart building control strategies to provide efficiency savings. It is also encouraging that the vast majority of reviewed work considers outside influences such as the weather when optimising building energy consumption. External conditions have a large influence on the ideal building control strategy and therefore systems must move away from static, rule-based, strategies that carry out the same actions each day regardless of conditions.

3. District level energy management

As alluded to in the Section 1, the energy landscape and infrastructure is changing. Energy generation is becoming increasingly decentralised to take advantage of local energy resources. This is partly due to the concept of the 'prosumer', one who both produces and consumes energy, gaining popularity. Furthermore, district heating systems are gaining popularity partly due to improved efficiencies that come through use of combined heat and power, CHP, units. These generate electricity but can utilise the heat produced in a district heating network. Waste heat from industrial processes and waste incineration plants could also be exploited with these systems. Managing energy resources at a wider district level rather than a building level could provide greater flexibility, energy and cost savings to all users. Buildings of different uses, e.g. residential and commercial, could have mutually beneficial demand profiles and could therefore be better managed in a 'microgrid' setting. This does encourage the development of district level controllers to optimally manage the energy flows and does require building level controllers to be more perceptive of their neighbours. Clusters of buildings also have more chance to collectively participate in grid DR events. Single buildings can rarely shift enough load to qualify for these types of events but a group of collectively managed buildings may have more bargaining power with the grid (Aduda, Labeodan, Zeiler, Boxem, & Zhao, 2016).

3.1. Optimal operation of a microgrid

Much of the district level energy optimisation is focussed around the supply side. Many studies consider a cluster of buildings with shared energy production units, some of which may be uncontrollable renewable sources like solar or wind, energy storage capacity and a demand source. Staino, Nagpal, and Basu (2016), demonstrated a cooperative model predictive control, MPC, framework to manage the use of a shared heat pump between a cluster of buildings. A cooperative algorithm takes advantage of greater flexibility in the larger buildings to reduce overall district cost. However, despite an overall reduction in cost the smaller buildings face an energy cost increase raising questions of fairness and billing. A microgrid equipped with solar PV, batteries, a CHP and grid backup is considered in Guan et al. (2010). The optimisation strategy is based on Mixed Integer Linear Programming, MILP, and maximises the use of solar energy to avoid energy consumption during peak price periods. An 'islanded' microgrid is considered in Marzband, Sumper, Ruiz-Alvarez, Luis Dominguez-Garcia, and Tomoiaga (2013) with wind power, PV, a CHP and battery storage. The proposed optimisation reduces energy cost by 15%. MPC is applied to a smart residential microgrid in Zhang, Zhang, Wang, Liu, and Guo

Table 1
Summary of Building Optimisation Literature.

Reference	Model Type	Aims to Control	Objective	Disturbances Included	Real Case Study?	Load Smoothing Considered?
Missaoui et al. (2014)	RC	Indoor Temperature, Domestic Appliances	Minimise Energy Cost	Weather, Occupancy, Energy Prices	No	Yes
Chen et al. (2013)	Linear Equations	Indoor Temperature, Domestic Appliances	Minimise Energy Cost	Weather, Energy Prices	No	No
Yuce et al. (2016)	ANN	Domestic Appliances	Minimise Grid Reliance	Weather, Renewable Output	No	No
Široký et al. (2011)	RC	Indoor Temperature	Minimise Energy Consumption	Weather, Occupancy, Energy Prices	Yes	No
Oldewurtel et al. (2012)	RC	Indoor Temperature	Minimise Energy Consumption	Weather	No	No
Ma et al. (2011)	Energy Plus	Indoor Temperature	Minimise Energy Cost	Weather	No	Yes
Salsbury et al. (2013)	System Identification	Indoor Temperature	Minimise Energy Cost	Weather, Occupancy	No	Yes
Molina et al. (2013)	State Space	Indoor Temperature	Minimise Energy Cost and Discomfort	External Temperature, Solar Irradiance	No	No
Ferreira et al. (2012)	ANN	Indoor Temperature and Humidity	Minimise Energy Consumption	External Temperature, Irradiance, Humidity	Yes	No
Parisio et al. (2014)	Explicit Model	Indoor Temperature and CO_2	Minimise Energy Cost	Weather, Occupancy	Yes	No
Figueiredo and Sá da Costa (2012)	RC	Indoor Temperature and Luminosity	Minimise Energy Cost	External Temperature and Luminosity	No	No
Moroşan et al. (2010)	State Space	Indoor Temperature	Minimise Energy Consumption	Occupancy	No	No
Lee et al. (2015)	ANN	Indoor Temperature	Minimise Energy Cost	DR signals, Energy Storage, Energy Generation	No	Yes
Lee and Braun (2008)	RC	Indoor Temperature	Minimise Peak Energy Consumption	External Temperature, Irradiance	No	Yes
Doukas et al. (2007)	–	Air Quality, Luminosity, Temperature and Humidity	Minimise Energy Consumption	External Temperature, Humidity, Air Quality, Luminosity	Yes	No
Yuce and Rezgui (2015)	ANN	Indoor Temperature	Minimise Energy Consumption	Weather, Occupancy	Yes	No
Moon and Kim (2010)	ANN	Indoor Temperature and Humidity	Maximise Comfort	External Temperature and Humidity	No	No
Yamada (1999)	ANN	PMV	Minimum Deviation from PMV Set Point	External Temperature, Irradiance, Occupancy	Yes	No
Papantoniou et al. (2015)	ANN	Indoor Temperature	Minimise Energy Consumption	External Temperature	No	No
Erickson and Cerpa (2010)	State Space	Indoor Temperature, CO_2	Minimise Energy Consumption	External Temperature, Occupancy	No	No
Ahmad et al. (2016b)	Energy Plus	Indoor Temperature, Luminosity, CO_2	Minimise Energy Consumption and Discomfort	Weather, Occupancy	No	No
Mossolly et al. (2009)	RC	Indoor Temperature, CO_2	Minimise Energy Consumption	Weather	No	No
Kim et al. (2016)	ANN and Regression	Indoor Temperature, Luminosity	Minimise Energy Consumption	External Temperature and Luminosity	No	No
Sun et al. (2013)	State Space	Indoor Temperature, Luminosity, CO_2	Minimise Energy Consumption	Weather, Occupancy	No	No

(2015). When compared to a static day ahead scheduling strategy the MPC gives a 64% reduction in cost and manages uncertainties in prediction better. A MPC framework for managing multiple residential buildings in a microgrid is developed in Parisio, Wiezorek, Kyntäjä, Elo, and Johansson (2015). Shared energy generation and storage are best utilised to flatten peak loads and hence reduce the cost of energy for the district. The demand response potential of a power to heat microgrid is also assessed in Rodriguez, Hinker, and Myrzik (2016). In Yan et al. (2013) branch and cut methodology is used to optimise the operation of a small eco-district in China with PV, a CHP, waste to energy and storage capacity.

The growth in smart meters which can in greater detail inform the consumer of their energy consumption as well as provide the utility company with finer granularity consumption data has enabled an increased use of time of use or dynamic energy pricing tariffs. However, whilst consumers may have more information at hand it is impractical to expect them to constantly check the energy prices for the next day and continue to adjust the scheduling of their household appliances to minimise their energy costs. This must be automated and controlled to a large degree by a bi-directional communicating smart controller that can communicate with the energy supplier and control household devices such as washing machines, dishwashers and possibly electric vehicle charging points (Hatami & Pedram, 2010). This gives consumers an opportunity for reductions in energy costs and aids the energy network due to a flatter load profile with less extreme peaks. Barbato and Capone (2014) gives a generic guide of the procedure for mathematically modelling the components of a smart grid or smart house for the purposes of optimisation using linear, quadratic or dynamic programming. Energy consuming devices, energy storage, energy generation, user comfort, and interactions with the energy market or supplier must be modelled including all the associated constraints. An objective function could relate to minimisation of cost, discomfort, emissions, or maximisation of local resources.

The control logic behind a proposed smart scheduler is presented in Mohsenian-Rad and Leon-Garcia (2010). It provides a linear programming, appliance control optimisation method that considers predicted energy pricing fluctuations from the energy supplier. It schedules appliances to minimise the cost to the consumer and the waiting time for the appliances to complete the user requested task. They achieve a cost reduction of around 25% and reduce the peak to average ratio by 38% meaning the control strategy benefits both the consumer and the energy supply network. This method is simulated on several networked residential buildings and cost savings by all households are reported although the level of saving is determined by the load flexibility of each consumer. A similar appliance scheduling optimisation strategy is developed in Deng, Yang, and Chen (2014) with specific consideration for electricity price uncertainty in the real time market. The user can reserve energy a day in advance at wholesale cost or can purchase from the real-time energy market. The overall problem is decomposed into a set of solvable sub problems and the future electricity price uncertainty is managed using a stochastic gradient approach.

Barbato et al. (2011) also uses linear programming to schedule household appliances but also considers the effect PV panels and battery storage could have in this optimisation. They consider both single house optimisation and a group of houses working cooperatively. Significant cost savings can be achieved by consumers if they are more flexible with their device usage and have PV and battery storage. Furthermore, if the district works cooperatively it can achieve significant reductions in the peak load and peak to average ratio which considerably removes stress on the energy supply network. Local, small scale, residential renewable energy resources could be used to provide ancillary or balancing services to the local energy network provided they can accurately forecast the electricity they will provide a day ahead. Clastres, Ha Pham, Wurtz, and Bacha (2010) presents a MILP optimisation strategy to maximise the profit from selling surplus electricity through optimal management of storage capacity and shifting demand. However, the profit achievable is highly dependent on the accuracy of the forecast as inability to meet the pre-agreed energy supply would lead to penalties from the transmission system operator.

Gruber, Huerta, Matatagui, and Prodanovic (2015) aims to improve on the typical MPC strategy to create a 2 stage MPC process. A short-term optimisation takes place every 5 min in between hourly optimisations to react and adjust to real time information and any errors in initial predictions. MPC is used for a different purpose in Hu, Zhu, and Guerrero (2014), the controllers' objective is to maintain power quality within the microgrid despite the variable renewable supply. Electric vehicles are specifically exploited in Battistelli, Baringo, and Conejo (2012). This study develops an aggregation and optimisation model for the inclusion of vehicle to grid battery storage in a local microgrid. Whilst one electric vehicle could only provide a small storage capacity, if aggregated it could be substantial. However, it is questionable as to whether users would accept their vehicle batteries being used like this and some form of financial incentive would be necessary. A multi-objective GA is used to minimise energy consumption and emissions from 3 potential heat production units supplying a district heating system in Jayan, Li, Rezgui, Hippolyte, and Howell (2016). The site is equipped with a biomass boiler, a gas boiler and a gas CHP. The optimisation algorithm can produce a 24-h schedule of which production units to use based on demand. A memetic algorithm, an extension of a genetic algorithm, is used in Hu et al. (2012) to control the set point of two buildings that share an ice storage system. Each building is responsible for solving its own sub problem and the solutions are brought together by an aggregator to eventually converge on an overall cluster solution. The proposed decentralised optimisation provides a better solution that 'greedy' solutions dominated by one building.

3.2. Inter-district energy trading and aggregation

Due to increasing grid decentralisation, some authors have developed business models for inter-district energy trading and bidding. This moves beyond time-of-use tariffs, which set fairly static pricing conditions each day, to a more real-time energy market. The most developed standard on an integrated energy future is given in the Universal Smart Energy Framework by the USEF Foundation, (USEF, 2015). It clearly defines several stakeholders including the prosumer, the balance responsible party (BRP), the distribution system operator (DSO) and the transmission system operator (TSO). It outlines the interactions the stakeholders' have with each other (Fig. 1) and the role an energy aggregator can play to provide flexibility in the system. The grid can request flexibility at specific times from a series of aggregators which in turn manage a portfolio of prosumers from which it can leverage flexibility. Once agreement is reached and the decisions have been actuated the grid must financially compensate the prosumer for their flexibility service according to pre-agreed conditions.

Fanti, Member, Mangini, Roccotelli, and Ukovich (2015), develops a district energy management system based on day-ahead pricing schemes and real-time power monitoring. In this model buildings are required to submit day ahead energy consumption predictions. Then the actual consumption of the buildings is monitored and compared to the estimations to determine rewards or penalties. A DR aggregator for a group of residential buildings is presented in Siano and Sarno (2016). The controller bids for energy based on real-time pricing fluctuations set by the DSO. This allows empowered consumers to shift their load, avoiding peak prices, to achieve cost savings. This is also greatly beneficial to the DSO as overall peak demands on the system will be reduced. In Anees and Chen (2016) a community controller acts as a virtual DSO to implement real time price variation to a group of smart homes. Domestic appliances operation times are shifted to reduce the peak energy demand. However, in their case study some residences receive increased costs even though the overall cost for the district is reduced. This raises crucial issues of potential unfairness that could arise.

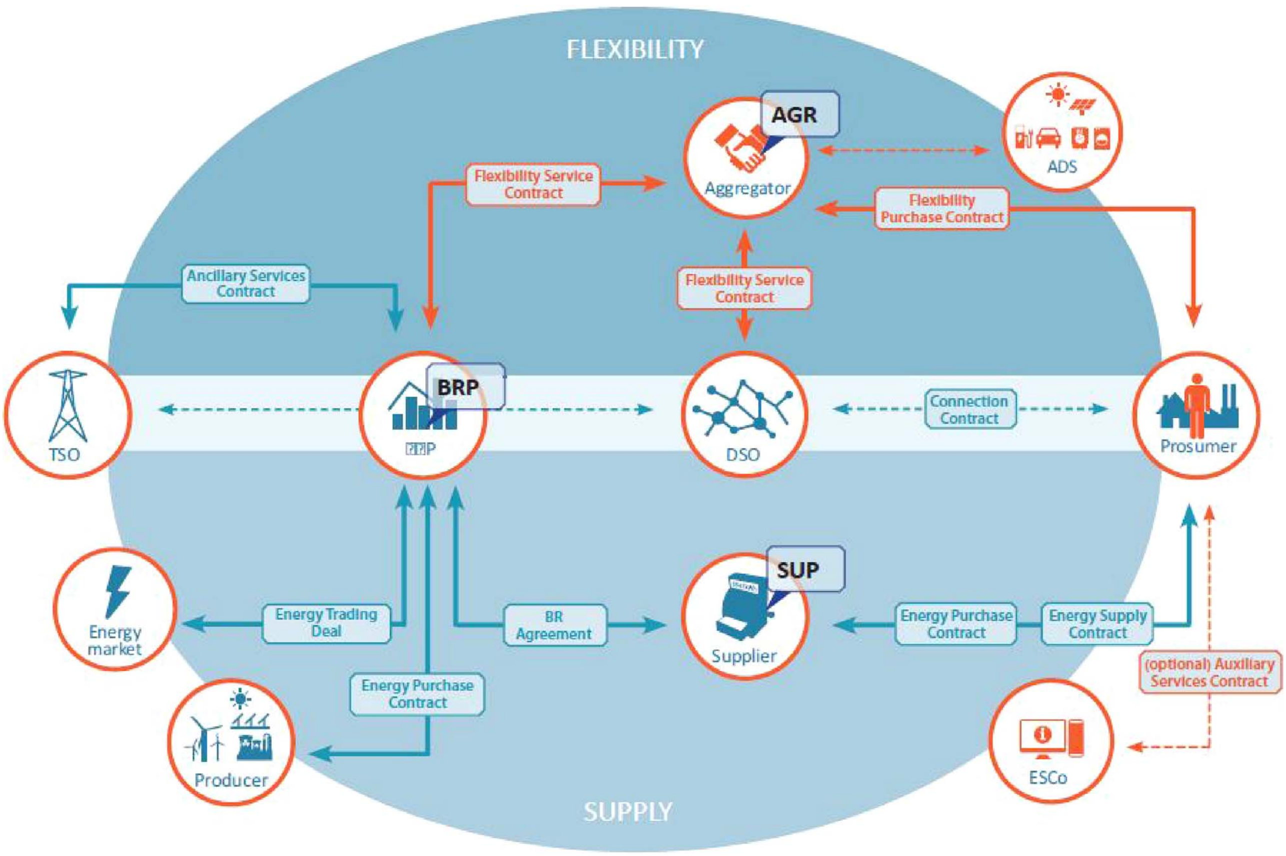

Fig. 1. USEF Interaction Model (USEF, 2015).

Agent-based, real-time price variation controllers can also be found in the literature. The PowerMatcher software is detailed in De Ridder, Hommelberg, and Peeters (2009). In this study the author proposes that consuming and producing appliances are represented by intelligent agents. These agents submit the price that they are willing to pay or receive for their energy. Once all bids are assembled, the market clearing price is calculated. If this price is higher than the consumer agent is willing to pay, then it does not consume energy and waits for the next round. In a case study the rate of over or underproduction from a wind farm is reduced by 50% and peak load is reduced. PowerMatcher is also used in De Ridder et al. (2009). It finds that if you increase the percentage of intelligent loads within a large district you get an almost linear decrease in peak power up to 20%. PowerMatcher is enhanced in Booij and Kamphuis (2013) to consider both electricity and heat in an integrated way which is important considering the increasing electrification of heat through devices like heat pumps.

3.2.1. Game theoretical approaches

Traditional optimisation focussed at a district level could lead to overall system optimal e.g. minimum total cost of district energy but could lead to cost rises for specific individuals within the district. These issues of unfairness could potentially be resolved by instead using a game theory approach to solving district energy management problems. Game theory approaches can more fairly model individual "players" rational desire to minimise their own energy costs. Saad, Han, Poor, and Basar (2011) provides an excellent review of the game theory applications in a smart grid environment. The autonomous, distributed, and heterogeneous nature of the smart grid make game theory well suited to smart grid problems. The review argues that interactions and energy trading between microgrids and the wider network can be modelled as well as interactions between the consumer and utility company regarding demand side management and load shifting.

A two-level demand side management game is developed in Chai, Chen, Yang, and Zhang (2014). The lower level evolutionary game composes of a population of residential, household consumers choosing how much energy to purchase at specific hours from different utility companies based on their prices. The upper game is a non-cooperative game between the utility companies where they determine their generation amount and future energy price. Both games are proven to converge quickly, the method is shown to be scalable and results in a lower average price for the consumers and a lower peak to average ratio. Gkatzikis, Koutsopoulos, and Salonidis (2013) investigates the role an aggregator can play in a future smart grid setting. A three-level scenario involving 10000 households, several aggregators and a single utility is investigated. A day ahead the utility advertises a demand shifting target and a price they are willing to pay for this. The aggregator then bids a certain level of demand shifting on behalf of their portfolio of households whom they compensate for their flexibility. The system is shown to be highly dependent on the reward the utility is likely to offer and the level of flexibility shown by the residential consumer. However, the study did show potential for a 15% reduction in operating costs where all three parties gain compared to a baseline, flat price scenario. A combined MILP and game theoretical approach is used in Zhu et al. (2011) to optimise the scheduling of controllable appliance to minimise the cost to a group of residential consumers working cooperatively. Wu, Mohsenian-Rad, Huang, and Wang (2011) uses game theory to optimally control household appliances of several residential consumers in an islanded microgrid with wind and gas generation. Using this method reduces the community energy bill by 38% even with imperfect, Markov chain, wind generation forecasts. If the forecasts are improved a further 21% saving could be achieved.

Rather than considering appliance scheduling, Atzeni, Ordóñez, Scutari, Palomar, and Fonollosa (2013a), Atzeni, Ordonez, Scutari, Palomar, and Fonollosa (2013b) use a game theoretical approach to optimise a smart grid in which a small percentage of users have dispatchable electricity generation and/or storage capacity. It assumes day ahead knowledge of user demands from which a pricing tariff is set. The active users then use their flexibility to minimise their own electricity bills which results in a flatter demand profile and hence lower prices. The users with greater flexibility (generation and storage) achieve very high savings around 80% but even the passive users see a reduction in cost around 15% simply due to the reduction in peak prices. Mohsenian-Rad, Wong, Jatskevich, Schober, and Leon-Garcia (2010) suggests that dynamic pricing set by the utility encourages each individual user reduce their energy cost by reducing their peak to average ratio. However, the author argues that this is not necessary providing a district works cooperatively to ensure their collective peak to average ratio is small. To achieve this the authors' develop a distributed, game theoretical approach to minimise a collective district energy bill by scheduling their appliances iteratively and broadcasting their forecasted energy consumption to their neighbours. This results in a 17% reduction in peak to average ratio and 18% reduction in cost.

3.3. Communication infrastructure and data organisation

All proposed intelligent building control systems at both building and wider district level must share large quantities of data. This comes from multiple different sources and sensors in different locations possibly with different owners. These data streams are often produced in incompatible formats especially if systems have been retrofitted at later dates. Furthermore, this data must be kept secure and private to maintain consumer trust. Therefore, robust communication architectures are essential in district energy management.

A cluster energy management system is developed in Kamiyoshi, Mine, and Nishi (2010). This system has a collective energy data collection system through connected terminals deployed around a university. The advantage of collecting such volumes of data is to allow higher level data analytics to take place. For example, in this study the collated data is used to generate energy demand predictions. A split HVAC system across multiple university buildings was also considered in Escrivá-Escrivá, Segura-Heras, and Alcázar-Ortega (2010). The systems are linked using the common Ethernet network and TCP-IP protocols. The information is gathered in a central server where the control centre and SQL database is kept. This system then allows data to be accessed through a simple web interface to provide support for technical staff and facility managers. A similar communication network is utilised in Kolokotsa et al. (2016) taking advantage of the common university internet structure and replacing all sensors so they can use Internet Protocols to communicate with a central university controller. In this study, an ANN is trained to predict building energy consumption. Using this a GA optimises the building's lighting and HVAC strategies. Barbato et al. (2016) is also focussed on university campuses. This study presents a data collection and communication architecture to capture building energy characteristics. From this base, prediction models and optimal schedulers can be created and implemented to save energy. Iwamura creates an information platform that gathers data from smart communities from the user and utility side. From this they can implement data analytics to monitor trends and produce predictions. This could allow implementation of DR measures in response to natural disasters or faults.

3.3.1. Sematic interoperability

Interoperability and communication between different heterogeneous data sources could be addressed utilising Semantic Web technology. An ontology can allow the formation of a machine readable, multi domain knowledge base. They could potentially provide the means to facilitate data retrieval, interoperability and decision support in the built environment (Hu et al., 2014). Curry, Battistelli et al. (2012), argues that 'linked data' techniques are needed within buildings as they are producing more data than ever and these are often contained in different data silos. This paper uses Semantic Web technology to extract relevant information to the cloud and then proposes to offer users cloud based building data services.

Wagner, Speiser, and Harth (2010) argues that sematic web technologies are well suited to be applied to the smart grid given that it can support heterogeneous data, it is flexible, it is extendable to new additions and the smart grid is distributed in its nature. Also within the field of smart grids and urban planning Keirstead, Samsatli, and Shah (2010), created SynCity which contains a generic ontology describing an urban energy systems. This ontology could easily be adapted and applied to different urban case studies. The paper then demonstrates the usefulness of a shared information model by using it to optimise the layout of a proposed eco-town in the UK. DR events can also be modelled and represented in an ontology as demonstrated in Zhou, Natarajan, Simmhan, and Prasanna (2012). The authors also argue that ontologies have the advantages that they can be re-used and they can be extended. Different ontologies can be defined separately for different domains of the built environment. They can then be linked together by an upper level ontology that map the concepts between domains resulting in a holistic urban knowledge model.

Ontologies have been demonstrated in two FP7 EU projects, RESILIENT and WISDOM. In RESILIENT a district energy ontology was produced to represent the electricity system, shared district heating network, production units, stakeholders and the interactions between them (RESILENT Project, 2013). WISDOM applied smart ICT and semantic modelling to aid the management of the water network (Duce et al., 2014). An ontology for use in multi-agent systems which aligns and expands on existing standards and the USEF framework is detailed in Hippolyte, Howell, Yuce, and Mourshed (2016). Smart grid roles such as the customer energy management system, the aggregator, the distribution system operator are defined as well as the interactions between these autonomous stakeholders. A district energy ontology is used as the backbone for a web-based, urban, decisions support system in Howell, Hippolyte, Jayan, Reynolds, and Rezgui (2016). The developed platform aims to engagingly and visually display buildings utilising existing building information models, apply background data analytics and machine learning, and employ optimisation through web services.

3.3.2. Multi-agent systems

Multi-agent systems, MAS, have achieved significant attention and growth in recent years. MAS involves several distributed, intelligent agents that can implement bottom-up control. These agents are programmed with internal logic or intelligence to manage the operation of selected components such as a generation unit, a HVAC component, or a storage device. As well as aiming to achieve their set objective they are also perceptive of their environment and able to communicate and cooperate with neighbouring agents. Advantages to MAS include a completely scalable computing architecture, resilience to failures in communication, and potentially increased security as no agent will have access to every piece of information.

Lagorse, Paire, and Miraoui (2010), applies MAS to a hybrid renewable system. Each device has internal rules and a 'token' is passed between devices to indicate which agent is in control of the system based on their individual internal states. Ramchurn, Vytelingum, Rogers, and Jennings (2011) studies agent based control of domestic appliances on a wide scale. An agent is based in the smart meter of each home representing the aggregation of several controllable and uncontrollable household appliances. A connected system of 5000 homes is theorised and if the developed agent based system is implemented energy peaks could be decreased by up to 17%. Similarly, Joumaa, Ploix, Abras, and De Oliveira (2011), creates an agent-based architecture for controlling household appliances. Services are categorised as either energy supply, storage or end use and end use services were further broken down into temporary, controllable or permanent consumers. The GRENAD, MAS framework is detailed in Ductor, Gil-

Quijano, Stefanovitch, and Mele (2015). This aims to simulate and control smart power grids using MAS through a generic, modular and flexible platform. Jun, Jie, Jun-feng, La-mei, and Min (2008) defines a MAS architecture for an eco-house that could operate on or off grid due to a number of agent controlled renewable resources.

3.3.3. Peer to peer networks

Lasseter (2011), argues that microgrid components should conform to peer-to-peer concepts. As opposed to centralised control schemes, a peer-to-peer based system can be highly scalable, extensible, resilient to failure of single components and more secure. (Dorri, Kanhere, Jurdak, and Gauravaram (2017) demonstrates the use of Blockchain technology, a key underpinning component of the Bitcoin cybercurrency, to enhance the security and privacy of a IoT based smart home system. In Rusitschka, Gerdes, and Eger (2009), the authors propose that installation of intelligent smart meters would be very expensive and this fixed infrastructure is not necessary or adaptable for the future. Instead they propose a peer to peer network of homes system containing digital electricity meters. These homes would form self-organising, scalable, networks large enough to be able to provide DR, load balancing, or power quality services to the grid operator and hence benefit from the financial rewards currently only available to large scale consumers. The equipment needed to construct such a network is far cheaper than current smart meter models and the operator has no installation, maintenance or operating costs due to the self-organising nature of peer-to-peer networks. Due to the increasing number of prosumers in the future smart grid, the availability and opportunity for transactions between peers and utilities is increasing (Ipakchi, 2011). Mature technologies such as Blockchain could provide a solution to ensuring security, fairness and consumer confidence in a proposed energy and money trading system.

3.4. Discussion

Table 2 summarises the literature reviewed in Section 3. As demonstrated in Table 2, optimisation from the point of view of the supply side and the demand side is considered. Many of these papers consider assumed knowledge of a fixed heat or electric demand profile over the optimisation time horizon. Many also assume perfect knowledge of future renewable energy generation. In reality, these profiles can be difficult to accurately predict and are highly dependent on disturbances such as weather conditions and building occupancy. New prediction methodologies are being applied to overcome this challenge such as the use of ANN or random forest algorithms (Ahmad, Mourshed, & Rezgui, 2017). To be implemented in real case studies, prediction of these variables should be further improved and the control algorithms themselves should take into account the inherent uncertainty within the prediction. If this is not the case, frequent breaches of comfort constraints will arise and contingency control algorithms will need to take over.

The management of highly heterogeneous data and the sheer volume of data required for district level control must be addressed. Whilst this is manageable within an environment with shared ownership and ICT infrastructure it remains a problem for multi-use, multi-owner districts. These more diverse districts are likely to have a wider number of systems, which use different communication protocols, are different ages, and have dissimilar privacy issues. From the reviewed literature, the use of semantic web technologies such as ontologies appears to provide an adequate solution to ensure the interoperability of this diverse data. These can then be used as a base from which intelligent data analytics and control platforms can be developed. Indeed, they have already been used as the platform to build MAS which is a rapidly increasing field of knowledge. MAS seem particularly applicable to the smart grid architecture due to their inherently decentralised structures and scalability.

Finally, interesting work is taking place on virtual energy trading schemes possibly facilitated by an energy aggregator. However, the applicability of these types of aggregators is likely to be highly dependent on the type of buildings that make up the district in question. A district of public sector office buildings with single ownership will have very different privacy and engagement challenges than a residential district with hundreds to thousands of different owners and stakeholders. In the authors' opinion government policy and regulation in this area is lacking. Strict controls are required to ensure that any energy trading system works fairly for all consumers. Furthermore, significant effort will be required to persuade the public to participate in such programmes and clear information on the trade-off between sharing private information and possible financial gains must be well communicated. Some consumers may be reluctant to cede any control over their personal appliances and accept any level of discomfort that is required for financial gain. A strong period of demonstration and persuasion will be required before these strategies can become mainstream.

4. Future research directions

This paper has reviewed a wide breadth of peer-reviewed research papers on the topic of building energy management at both a building and district level. It has emphasised the need for smarter energy control, improving on current static, rule-based management systems. Given the evolution of energy infrastructure there is an urgent need for predictive control and implementation of demand response measures to match fluctuating demand with fluctuating supply introduced by renewable energy sources. However, this review has identified a number of gaps in the current body of research that give rise to future research directions.

4.1. Holistic energy management

The district level microgrid control, examples of which are shown in Section 3.1, are generally much more aware of demand response and include it as a stated objective of their control schemes. However, they generally consider the building demand as perfectly predicted and uncontrollable. They often model building profiles as a constraint which their optimisations must meet. There is a real need for there to be a bi-directional link between a building level controller that is aware of demand response and a district level controller that actively views buildings as potential demand response sources. This could be a two-tiered optimisation model. At a building level, it could optimise the control of HVAC systems or domestic appliances similar to many of the studies in Section 2. It would send the predicted schedule to a district level controller but crucially include a degree of flexibility in the energy profile. The district level would aggregate a number of demand profiles from several buildings and optimally manage any shared generation resources and storage capacity. It could then engage in negotiations to seek further flexibility if necessary. This sort of bi-directional, iterative approach would keep the level of detail at a building level but also have the wider awareness of the districts energy needs, providing a more holistic approach to energy management.

4.2. Semantic representation of the district energy environment

To manage and control a modern, complex district, information and characteristics from various heterogeneous, multi domain, data sources must be linked. This can be achieved through semantic web technology which allow machine interpretable descriptions of the district to be defined. This can allow domains which have been considered in isolation to each other to be optimised in a holistic way. Leveraging semantic modelling could provide the tool to enable the exchange of data between different data models and software's which may not use the same communication protocols to allow truly holistic energy management approaches. As shown in Section 3.2.1 they can also provide the

Table 2
Summary of District Optimisation Literature.

Reference	Optimisation Method	Aims to Control	Objective	Predictions Included	Real Case Study?	Load Smoothing Considered?
Guan et al. (2010)	MILP [1]	Scheduling Generation	Minimise Energy Cost	Weather, Renewable Supply, Demand	No	No
Staino et al. (2016)	Economic MPC	Shared Heat Pump Operation	Minimise Energy Cost	External Temperature, Electricity Prices	No	No
Marzband et al. (2013)	MINLP [2]	Scheduling Generation	Minimise Energy Cost	Weather, Renewable Supply, Demand	No	No
Zhang et al. (2015)	MILP	Scheduling Generation and Energy Storage	Minimise Energy Cost	Renewable Supply, Demand, Electricity Price	No	Yes
Parisio et al. (2015)	MILP	Demand Scheduling and Energy Storage	Minimise Energy Cost	Renewable Supply, Demand, Electricity Prices	No	Yes
Rodriguez et al. (2016)	Linear Programming	Heat Supply and Thermal Storage Operation	Minimise Temperature Set Point Error and Peak Power Flow	Indoor Temperature, Thermal Comfort	No	Yes
Yan et al. (2013)	Branch and Cut	Scheduling Generation and Building Demand	Minimise Energy Cost	Indoor Temperature, Energy Prices	No	No
Hatami and Pedram (2010)	Dynamic Programming	Demand Scheduling	Minimise Energy Cost	Electricity Prices, Demand	No	Yes
Mohsenian-Rad and Leon-Garcia (2010)	Linear Programming	Appliance Scheduling	Minimise Energy Cost and User Dissatisfaction	Electricity Prices, Demand	No	Yes
Deng et al. (2014)	Stochastic Gradient	Appliance Scheduling	Minimise Energy Cost	Electricity Prices, Demand	No	Yes
Barbato et al., (2011)	Linear Programming	Appliance Scheduling	Minimise Energy Cost	Electricity Prices, Demand, Solar Energy Supply	No	Yes
Clastres et al. (2010)	MILP	Scheduling Generation and Energy Storage	Minimise Energy Cost	Electricity Prices, Demand, Solar Energy Supply	No	Yes
Hu et al. (2012)	Memetic Algorithm	Building Temperature Set Point	Minimise Energy Cost	Weather, Demand, Renewable Supply, Electricity Prices	No	No
Gruber et al. (2015)	MILP	Scheduling Generation, Demand and Energy Storage	Minimise Energy Cost	Renewable Supply, Demand, Electricity Prices	Yes [3]	Yes
Battistelli et al. (2012)	Robust Optimisation	Scheduling Generation and Energy Storage	Minimise Energy Cost	Renewable Supply, Demand, Electricity Prices	No	No
Jayan et al. (2016)	Genetic Algorithm	Scheduling Generation	Minimise Energy cost and Emissions	Energy Prices, Demand	No	No
Fanti et al. (2015)	Linear Programming	Demand Scheduling	Minimise Energy Cost	Electricity Prices, Weather, Demand	No	Yes
Siano and Sarno (2016)	D-LMP [4]	Demand Scheduling	Minimise Energy Cost	Electricity Prices, Demand, Building Temperature	No	Yes
Anees and Chen (2016)	Linear Programming	Demand Scheduling and Real Time Pricing	Minimise Energy Cost	Electricity Prices, Demand	No	Yes
De Ridder et al. (2009)	Agent Based	Appliance Scheduling	Minimise Energy Cost	Renewable Supply, Demand, Electricity Prices	No	Yes
Booij and Kamphuis (2013)	Agent Based	Scheduling Generation	Minimise Energy Cost	Renewable Supply, Demand, Electricity Prices	No	Yes
Chai et al. (2014)	Game Theory	Demand Scheduling	Minimise Energy Cost, Maximise Profit	Electricity Prices, Demand	No	Yes
Gkatzikis et al. (2013)	Game Theory	Demand Scheduling	Minimise Energy Cost, Maximise Profit	Electricity Prices, Demand	No	Yes
Zhu et al. (2011)	Game Theory	Demand Scheduling	Minimise Energy Cost,	Electricity Prices, Demand	No	Yes
Wu et al. (2011)	Game Theory	Appliance Scheduling	Minimise Energy Cost,	Renewable Supply, Demand, Electricity Prices	No	Yes
Atzeni et al. (2013a)	Game Theory	Demand and Generation Scheduling	Minimise Energy Cost, Minimise Peak to Average Ratio	Renewable Supply, Demand, Electricity Prices	No	Yes
Mohsenian-Rad et al. (2010)	Game Theory	Appliance Scheduling	Minimise Energy Cost,	Electricity Prices, Demand	No	Yes

platform from which district level optimisation can be implemented. Furthermore, utilising semantics and ontologies allows a scalable and flexible approach to district modelling as additions can be made to adapt to unforeseen future changes to the district.

Future research in semantic-based modelling could provide the link between the currently available Building Information Modelling, BIM, models and real time, operational data collected by sensors embedded within the building. A centralised ontology that has knowledge of the buildings physical components and characteristics as well as access to BEMS sensory information would allow truly powerful and useful data analytics for a facility manager. This can provide the platform to allow prediction of future energy consumption, behaviour patterns and occupancy. Smart control algorithms could also be built on top of the central ontology allowing resulting schedules and instructions to be sent for the BEMS to action. The base provided by the semantic modelling of a district could lead to a 3D visualisation of the district for facility managers, local authorities, or urban planners. The link with the sensory information of the district could allow relevant data, depending on the user, to be displayed in a more dynamic, clear and useful manner compared to current BEMS interfaces.

4.3. Computation urban sustainability platform

The Computational Urban Sustainability Platform, CUSP, is currently under development by the authors' research group. Its interface and architecture is displayed in Fig. 2. This project aims to implement the vision set out by this paper. CUSP presents real time, actionable information in a web based platform for facility managers or urban planners (Howell et al., 2016). An engaging, 3D user interface of district visualisation and decision support is provided in the form of a web-based application, which uses the Unity game engine. Note the Unity engine only displays data and visuals to the user, the data processing is performed in the HPC, cloud-based infrastructure. The CUSP platform couples data analytics and prediction services with BIM models. A key, underpinning, feature of the CUSP architecture is the ontology server which effectively can link the previously isolated information. Ontologies bring context, meaning and provenance to the data. For instance, external weather data or internal sensor readings through the BMS can be gathered and stored in the time series server. The CUSP platform aims to provide intuitive controls to access the district or building level data and decision support from a selected date range, including future dates. A simulation server utilising Energy Plus models or machine learning, surrogate models can produce day ahead forecasting which may influence facility managers' decision making. Given the collection of large quantities of useful information, optimisation procedures must be deployed utilising powerful, cloud-based, high performance computing which could provide energy and cost savings to the consumer. CUSP also aims to simply display various key performance indicators, KPI's, such as energy consumption per unit area, CO_2 emissions, or economic running costs. This, alongside automatic anomaly detection alerts can quickly inform a facility manager if the district is performing as expected.

4.4. Business models and energy policy

Given the rise in implementation of smart metering devices, time of use or real time energy pricing tariffs are likely to become more available and popular with consumers. This is possible as smart meters

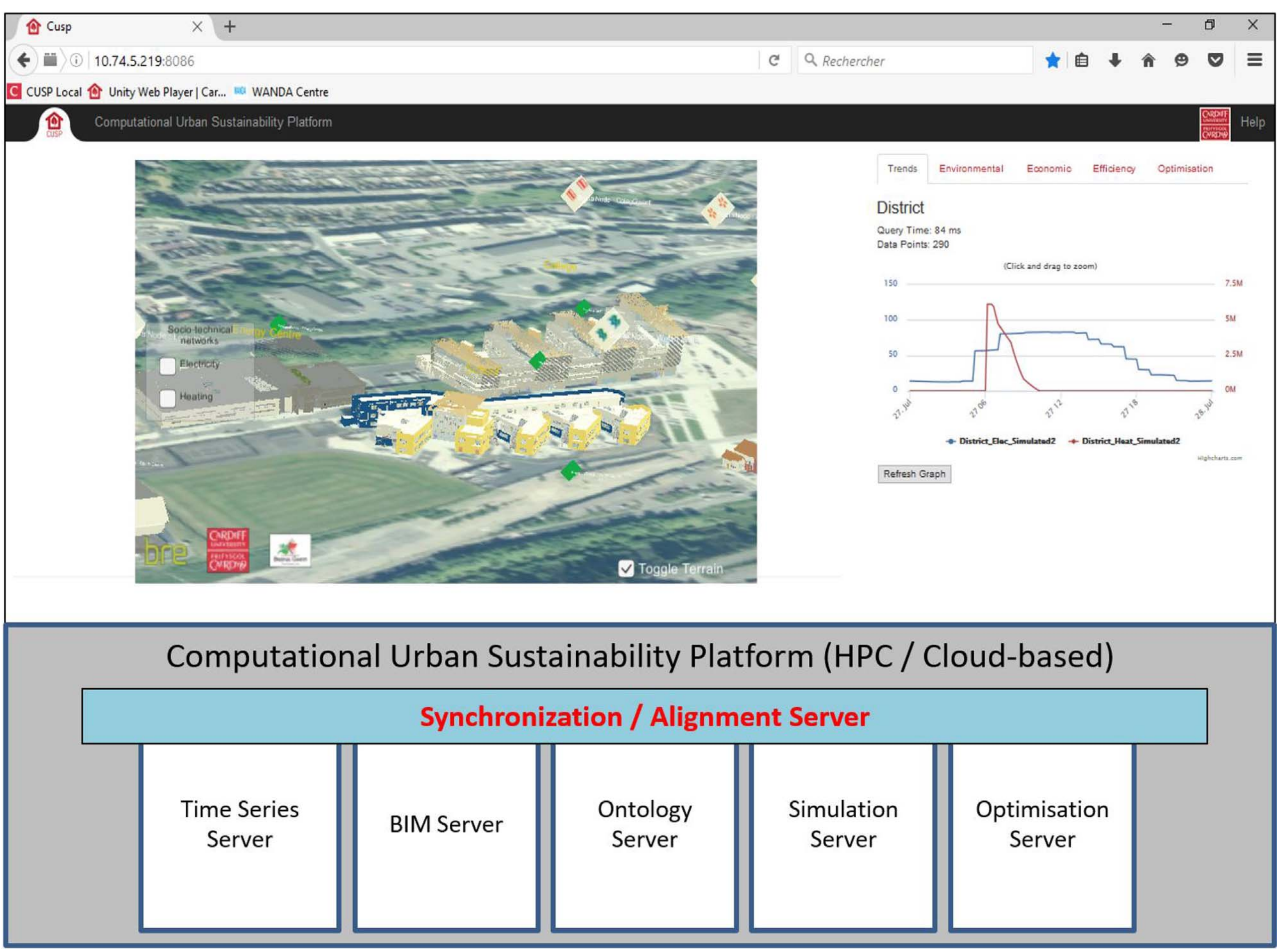

Fig. 2. CUSP Interface and Architecture.

will give utility companies greater detail on the quantity and the time of energy consumption. These tariffs will allow engaged and empowered users to gain substantial cost savings over fixed rate energy tariffs by intelligently shifting their consumption to advantageous times. However, we cannot expect the average consumer to constantly monitor or understand energy price fluctuations and manually reset many of their devices to consume or stop consuming. This leads to opportunities for so called Energy Service Companies, ESCo's. Consumers could effectively outsource their energy management and relevant data to 3rd party companies which would aim to provide energy cost reductions for the consumer and in return take a proportion of that saving. ESCo's would have to gain access to large amounts of user data and could provide virtual, cloud-based energy management. The recent introduction of commercially available, on demand, high performance computing, HPC, from cloud services companies such as IBM, Google, Amazon and Penguin could revolutionise what is achievable in building energy management. It could allow greater levels of data analytics, improved prediction models or even the use of detailed, white box energy models in real-time optimisation (Petri et al., 2014; Yang et al., 2014). Several different control approaches could be implemented by ESCo's:

- Internal Energy Markets – Similar to some of the studies in Section 3.2, an internal energy market between the ESCo's clients could be formed. Users with complimentary load profiles or excess renewable generation could combine to form virtual energy sharing partnerships facilitated by the central grid and the ESCo. These consumers could be in different geographic locations and provide mutual savings for all parties and achieve greater prices for excess energy rather than selling back to the grid.
- Centralised Control – This control architecture would be more applicable for, natural, self-contained, districts with a single owner and a single utility bill such as University campuses, industrial estates or public sector buildings. In this situation, direct, advanced, MPC could be applied utilising the existing SCADA based system for data collection and actuation. The intelligence and decision making would be held in a control layer above the SCADA system.
- Intelligence Update – A more passive approach that ensures the user feels in control of their systems. The ESCo could carry out data analytics and feedback simple suggestions to the user based on the data available. These could be slight adjustments to the current rules, for example to turn off the HVAC system an hour earlier. The user would then decide whether to implement this.
- Demand Response Coordinator – This architecture is much closer to USEF. Initially each BMS would locally optimise their own day ahead demand. This would be fed to a district level controller to build a district demand profile. Using this knowledge and predictions of generation capacity, it could make decisions on how to flatten the overall demand profile. An iterative, negotiation based arrangement would take place to lead to a more optimal district demand profile.

5. Conclusion

This paper has reviewed a large number of publications on the topic of building energy management. Crucially, it has also assessed building energy management from a district level. This is necessary due to the increasingly distributed and localised nature of the energy infrastructure as well as the changing mix of supply sources. The review has found that most district level optimisation procedures consider the optimal supply of a district. They generally consider the demand profile from the buildings as known, perfectly predicted and unalterable. Therefore, there is a requirement for a holistic district energy management controller that finds the right balance between the type of papers found in Sections 2 and 3. The district level management needs to consider buildings as an active demand response participant and the building level controls needs a mechanism to adjust and respond to demand response instructions from a district level controller. The vast majority of the literature reviewed is simulation based. Whilst this is an excellent method to prove concepts there is now a desire to demonstrate that these strategies can be applied in real time and do provide their estimated savings. The review has also found a demand for the use of semantic web technology to effectively manage the heterogeneous data streams that modern, complex, building control requires. This has been demonstrated by the Computational Urban Sustainability Platform, CUSP, which aims to provide 3D visualisation, simulation and KPI indication for facility managers all underpinned by an ontology. Finally, there is a need for adjustment in energy policy through the increased use of real time pricing or time of use tariffs. These will allow engaged users to save money on their energy bills and will help the grid to lower peak demand. In the authors opinion, this will lead to increased opportunity for ESCo's to manage households (including prosumers) energy in a number of business models outlined in Section 4.3.

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