Decentralised Energy Optimisation
For Blocks of Buildings

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ABSTRACT
Policy and new technologies are transforming the energy landscape in the UK. Centralised control of electrical generation and unidirectional distribution have a finite part in a sustainable energy system. Subsidies have encouraged an increase in distributed resources. At the same time closure of larger fossil-fuelled power plants is reducing system inertia on energy networks. In this study, a decentralised proactive approach to demand-side response exploiting building thermal inertia is presented using machine learning methods and a real-time adaptation algorithm. This paper proposes a dynamic 2-step energy consumption prediction scheme that can be configured to provide efficiency opportunities and the potential to reduce energy costs in buildings. The approach adopted optimises energy usage through existing demand-side response mechanisms utilising decentralised frequency regulation. The paper concludes with a discussion on the future direction of research.

Keywords
Decentralised, machine learning, Dijkstra, thermal inertia, frequency regulation.

1. INTRODUCTION
An increasing number of distributed generation resources have helped steer the energy sector on a pathway towards a low carbon future [19]. Closure of larger traditional fossil-fuelled power plants, driven mainly by environmental considerations, advances in technology and geopolitical influence, is reducing system reserve capacity on energy networks [27]. Consequentially, the amount of system inertia available to help balance out supply and demand is reduced. A situation aggravated by more diverse and volatile distributed renewable electricity generation (DREG) being deployed within larger centralised energy networks [28]. High value infrastructure development projects can exist in both a centralised and decentralised framework [21]. However a decentralised approach offers greater regional flexibility when balancing supply and demand. As a means to distinguish between centralised and decentralised, we apply the concise definition concerning decentralised electricity generation put forward by Ackermann et al [1]. They state that “In general, distributed distribution can be defined as electric power generation within distribution networks or on the customer side of the network.”

At certain times of the day access to additional electricity resources are required to maintain grid reliability and stability. In the UK, the Electricity System Operator (ESO) is responsible for managing system balancing and operability of its networks [34]. In this context the ESO has access to different resources that can be made available depending on the urgency and scale of the imbalance. Integrating elements of smart-grid technologies and improved coordination between ESO and distribution network operator (DNO) has the potential to unlock new flexible decentralised control measures and encourage more active customer participation in demand-side response (DSR) programs [36].

The International Energy Agency World Energy Outlook 2017 statistics show energy consumed in residential and commercial buildings accounts for 21% of the globally delivered energy [25]. The same data shows this figure is set to increase by 32% before 2040, predominately in emerging non-Organisation of Economic Co-operation and Development (OECD) countries. In contrast, energy consumption in OECD countries is much less at 7.5%. Therefore, opportunities for improved efficiency in buildings are enormous. The UK government remains committed to a low-carbon economy, reducing its greenhouse gas (GHG) emissions by 80% by 2050 (against a 1990 baseline) [12]. A Transition Pathway that examined the interaction of technological and social factors was aligned with a multi-level perspective for analysing socio-technical transitions [7]. In conclusion, the pathway identified that in order to reach GHG emission targets and energy efficiencies, both technological and behavioural energy measures are required.

Space heating continues to account for the highest proportion of energy consumption in the household sector in EU-27 countries [18]. The use of air conditioning consumes most of the energy required to achieve reasonable thermal comfort in the workplace [3,8]. Although temperature is a significant contributing factor to energy consumption in optimising space heating, relative air humidity, meteorological parameters (seasonal variations) and geographical location also influence the electrical demand profile [33].

Given energy consumption in buildings has risen in recent years, advances in data science and control technologies has attracted much attention [29]. Businesses are looking for solutions that help to cut costs; better energy management is an obvious choice. A building energy management system (BEMS) can reduce energy consumption and boost building health and performance [22,26]. Literature on BEMS is extensive [37]. As technology advances, building health systems become ever more sophisticated. Smart devices and positioning equipment designed to collect occupancy behaviour and state, and participation in DSR events co-exist with more traditional approaches that consider the building in isolation [35].

A key consideration when taking part in a predefined energy reduction strategy must empower customers to use energy in the lowest price period accessible, at the same time as offering participation in DSR events. This study offers a novel perspective by placing the building as an integral part of a much wider energy optimisation system. There is a tangible link between electricity demand and grid frequency excursions in power networks [30]. A recent study concluded that a decentralised approach to energy curtailment by exploiting thermal inertia in building stock can be achieved while participating in proactive demand response using frequency
regulation [39]. This paper is a continuation of previous work and proposes to minimise the reliance on data collection from external sources by presenting only feasible data (feature selection) in real-time to an energy optimisation solution (EOS). The EOS contribution to a facilities energy management strategy is to decompose the overall optimisation into 2 main parts: the first uses machine learning, creating a grid frequency prediction model. The second is based on a modified Dijkstra’s algorithm, credited for finding the shortest path between nodes in a directed acyclic graph (DAG). An optimisation scheme that formed part of a Pareto optimal frontier, based on probabilistic methods for creating a population of feasible routes (shortest paths) for a shipping vessel, utilised an evolutionary multi-objective optimisation technique [31]. Here, a scalarization function reduces a multi-objective function to a single objective problem [23]. Therefore, a unique solution that optimises all objectives simultaneously calculates the optimal temperature setpoint, thus adjusting the energy consumption of thermostatically controlled loads (TCL) required to regulate indoor space heating and air conditioning.

This paper focuses on frequency measurement, data types and feature selection. Specific attention is given to a dynamic 2-step energy consumption prediction method. Firstly, Section 2 reviews previous studies in frequency measurement. Section 3 gives a brief description of an energy optimisation solution in terms of building energy management and contribution to proactive demand response through frequency regulation. Section 4 introduces the 2-step energy consumption prediction method. It includes a discussion of how the edge weight between any two nodes in a Dijkstra’s algorithm is manipulated in real-time, and the application of machine learning. In conclusion, Section 5 discusses future direction of the research presented.

2. FREQUENCY MEASUREMENT

Grid frequency is a measure of the balance between energy generated and consumed. It is constantly shifting and requires management and control at all times. Decentralised demand-side frequency regulation when used to control TCLs in building stock can help regulate short-term frequency excursions in demanded electrical energy. When the TCL is used to control space heating and air conditioning, arresting the measured frequency excursion, through load shifting in real-time can have a positive influence on reserve generation capacity without compromising user comfort. This is achieved by exploiting heat transfer dynamics present in buildings.

The reliance on advanced communication networks to convey frequency information from remote nodes to centralised control at sufficient resolution while maintaining real-time accuracy is problematic [38]. Design of a low-cost microcomputer frequency measurement and control element that can operate independently at the building or block of building scale, in either islanded or on-grid has been validated [39]. Hardware in the Loop (HIL) tests demonstrate small excursions in measured space temperature will not compromise indoor comfort levels but are capable of providing a positive contribution to the restoration of frequency equilibrium during network stress events. This opens up the possibility of greater customer participation in Demand Response (DR) at reduced cost. The scale of benefit depends on the business. When energy demands reach a critical level the ESO will provide a dispatch notification, typically 4-hours in advance to the projected shortfall, to those businesses and organisations in its DR network. On receipt, customers can initiate agreed curtailment plans that ultimately result in energy load reduction for the duration of the DR event. In return, financial rewards are provided; the amount dependant on the scale of energy reduction.

3. ENERGY OPTIMISATION SOLUTION

Advanced BEMS have changed the way building custodians manage the health and performance of buildings [11]. Smart sensors and monitoring assure the longevity of existing building infrastructure and help regulate occupant comfort by sending control actions according to occupant’s activities and expectations. A building energy automation system may include the following assets: photovoltaic (PV); space heating and air conditioning system: chiller; fan control unit (FCU) and air handling unit (AHU); backup generators and an energy storage solution (ESS). The contribution to new knowledge this paper describes is shown in Figure 1.

Figure 1. Energy optimisation solution (EOS) context

The conceptual framework places the EOS as part of an extant BEMS but crucially makes use of decentralised grid frequency; i.e. measurements that are recorded locally. Connectivity to a DNO opens participation in potential DSR opportunities. The EOS objectives are sympathetic to a multistakeholder governance model, sharing solutions to common problems or goals. Here, a building custodian maintains overall responsibility of system operation. The level of participation and subsequent influence on aspects of building energy control and optimisation is determined by the EOS mode of operation; each configured with an emphasis on either energy saving or money saving. An option to participate in a demand response program is also supported. Furthermore, a proposed frequency prediction model opens opportunities to automatically respond to a change in grid frequency (i.e. a decentralised proactive demand response mechanism) that would ordinarily prompt a local grid operator or utility to send a demand response dispatch notification.

Traditionally, BEMS strategies for space heating and air conditioning have considered occupants as passive components having little or no real-time influence on thermal comfort [6]. Set points range from those embedded inside equipment logic, which are rarely changed, to space temperature set points, which need constant adjustment; usually by building managers. Often, the possibilities of reducing the cost of energy for space heating and air conditioning are ignored for fear of adversely affecting thermal comfort. However, smart technologies that empower building occupants to actively participate in the thermal comfort of an occupied space are readily accessible. The EOS considers building occupants as a collective active component, promoting well-justified multi-layered near real-time decision making of adjustments to zonal space heating. Low level decision points that automatically adjust temperature set points and energy consumption prediction are determined using a dynamic 2-step energy consumption prediction.

4. 2-STEP ENERGY CONSUMPTION PREDICTION

A generalised block diagram that illustrates the proposed information flow between the initial step (frequency prediction)
and subsequent optimisation step in the 2-step energy consumption prediction process is shown in Figure 2. The scope of this discussion limits the control action to a single TCL: an electric space heating system. Its operation is controlled by means of a temperature setpoint adjusting the energy consumption using a variable frequency drive (VFD). Remote temperature sensors provide closed feedback control. A decentralised energy storage system (ESS) offers substantial opportunities for storage. When used as part of an EOS, customers could shift their primary power source depending on economic gain, limiting their overall energy spend.

4.1 Frequency Prediction

Transmission network operators in the UK are learning the consequences of the open access paradigm. A complex energy landscape means the demands placed on the system in terms of capacity and diversity are very different from those initially envisaged during its inception. Excessive stress and sudden natural or malicious physical events on modern power systems may degrade grid reliability and stability. Grid frequency measurement provides system operators a good indicator of system status and performance. Small frequency stability determination can be realised using centralised automated generation control (AGC): automatic voltage control (AVC) and primary load frequency control (LFc). Depending on the rate of change and magnitude of frequency deviation, DR and activation of load shedding relays can improve resilience before more drastic emergency measures are imposed in order to maintain continuity of supply.

In the area of building energy management, machine learning (ML) continues to attract much attention. A growing number of case studies describe how ML is used to monitor and optimise operations and maintenance costs [24]. More recently, ML has been used to help identify energy consumption patterns to create more informed energy management strategies [4,32]. ML methods with their ability to learn pattern recognition and create more informed energy management strategies [41]. A commonly used strategy that yields the optimal train-test-validation split ratio with circa. 68% of data assigned for training will be applied [16].

A systematic review of types of ML algorithms identifies the merits of using SVD when dealing with nonlinear problems [13]. However, among the proposed prediction models to be considered, linear regression is arguably the most widely used. Furthermore, the multiple linear regression (MLR) learning method that studies the relationship between multiple independent arguments and one dependent variable appears to be a viable candidate that requires further investigation.

4.2 Optimise

The principle component at work in the EOS optimisation step offered is based on the Dijkstra’s shortest path finding algorithm [14,15]. Its application in optimisation continues to attract much attention [5,17]. Traditionally the algorithm is used to calculate the shortest path(s) in a weighted directed acyclic graph (DAG) (Figure 3(a)) and is based on the following assumptions: (1) all edge costs are non-negative, (2) the number of vertices is finite, and (3) the source is a single vertex, but the target may be all other vertices [9]. Since the objective here is to optimise the transition between multiple non-negative features in real-time over a finite period, the construct of the Dijkstra’s algorithm is of particular interest.

Recasting of vertices to represent predicted temperature set points, manipulating the distance between each pair of valid vertices and adding a time dimension, the more common DAG visualisation is transformed to a \( m \times n \) matrix, where \( m \) is the frequency horizon that bound the prediction window varies. Recent studies demonstrate a yearly, weekly and daily forecast horizon [2]. The originality of this research is based on optimising energy consumption using grid frequency as the predominant feature. Firstly, a real-time measurement and reporting of grid frequency (decentralised) assists in the restoration of frequency equilibrium triggered by an imbalance in demand on the grid. This can be achieved by direct load control of thermostatically controlled loads. Furthermore, assuming a demand side provider has committed to participate in a demand side response service (turn up, turn down, or shift demand in real-time), they are obliged to contribute to the economic load dispatch problem during DSR events. However, a secondary goal of this research is to set the frequency prediction model forecast horizon to enable automatic participation in a bespoke energy reduction strategy - a decentralised proactive demand response mechanism. This offers energy consumers an opportunity to adopt a more active approach to the supply and demand imbalance conundrum, decreasing energy costs and help improve security of supply across the energy network.

Numerous methods of ML are available: linear regression, decision tree, support vector machine (SVD) and artificial neural networks (ANN); practitioners sometimes combine multiple techniques (ensemble learning) [40]. However, it is argued that feature engineering is the most important part of the modelling process [10]. The perceived random structure of grid frequency makes the task of identifying parameters that characterise its behaviour challenging. This research proposes to first establish a credible feature list and determine the contribution of each variable using correlation analysis. Preliminary candidate features include: time (seasonal variation), rolling system demand, daily energy transmitted, generation (by fuel type), meteorological variables and cost (price tariff). Knowledge of severe system disturbances and robust validation datasets will reduce the risk of over-fitting and under-fitting. The balancing mechanism reporting service (BMRs) provides access to historical operational energy related data [41]. A commonly used strategy that yields the optimal train-test-validation split ratio with circa. 68% of data assigned for training will be applied [16].
range of meaningful predicted temperature set points and \( n \) is the number of finite time periods, Figure 3(b). To sustain acceptable thermal comfort over a prolonged period, and remain an active participant in a DSR program, the energy demands up to 24-hours ahead are considered.

The shortest (optimal) path from source vertex to target vertex in a standard Dijkstra's algorithm presentation is represented by the summation of individual edges that exist between two adjacent vertices that are on the selected (optimal) path. The unit of measure of each edge being fixed, e.g. distance between two places of interest. The proposed algorithm is a modification to this arrangement such that the unit of measure between two adjacent vertices is dynamic. A change in the edge weight influences the calculation that determines the shortest path between the source vertex and target vertex. Here, the optimisation problem is expressed as a multi-objective problem.

The value (weight) of each edge is a function of predicted frequency, cost of energy (price tariff) and ESS state of charge (SOC). Furthermore, occupant’s feedback on relative comfort (space temperature) is a factor that influences the value of each edge. The subsequent control action is modified at the end of each cycle. The steps in the proposed modified algorithm are described in the pseudocode set out below:

```plaintext
for all \( w \in W \)
    do \( w \leftarrow \text{weight}(u, v) \)
for all \( v \in V - \{s\} \)
    do \( \text{dist}[v] \leftarrow \infty \)
    \( S \leftarrow \emptyset \)
    \( Q \leftarrow V \)
while \( Q \neq 0 \)
    do \( u \leftarrow \text{minimumdist}(Q, \text{dist}) \)
        \( S \leftarrow S \cup \{u\} \)
        for all \( v \in \text{adj}[u] \)
            do if \( \text{dist}[v] > \text{dist}[u] + \text{w}(u, v) \)
                then \( \text{dist}[v] \leftarrow \text{dist}[u] + \text{w}(u, v) \)
        return \( \text{dist} \)
```

Maintaining the shortest path information using this approach is consistent with static shortest path problems, i.e. update operations are performed at the beginning of each iteration. This is in contrast to the dynamic version of the same problem which requires the shortest path information to be maintained after each update to the graph [20].

### 4.3 Simulink Model

A computer model of a simplified linear power system and building thermal control system shown in Figure 4. The model includes a decentralised frequency control (DFC) element; which has been shown to potentially have a positive influence on reserve generation capacity [39]. The arrangement of EOS is shown, including frequency prediction and optimise subsystems.

To demonstrate correct operation of scheduling of power source, early testing is limited to using simulated real-time frequency measurement and manual manipulation of adaptive algorithm parameters that affect the value (weight) of each edge (i.e. energy cost (price tariff), SOC and comfort parameters).

![Figure 3. (a) Shortest path (b) Energy optimisation scheduler](image)

Further work is now required to introduce a frequency prediction model and automated optimisation of building energy resources scheme.

### 5. CONCLUSIONS

This paper presents a foundation for a dynamic 2-step energy consumption prediction method that offers optimisation of space heating and air conditioning using decentralised proactive frequency regulation. The dependency of frequency prediction in optimised energy consumption in building stock is considered in this work. Several interesting features described in this paper suggest that combining frequency prediction using machine learning and optimisation of building energy consumption provides a promising avenue for an alternative proactive balancing service mechanism (decentralised demand response). In the context of evolving energy landscape with depleting system inertia and reserve generation capacity is at risk, this study may have important implications for both energy suppliers and custodians of building stock.

### 6. ACKNOWLEDGEMENTS

The first author wishes to acknowledge the financial support provided by Teesside University and the Doctoral Training Alliance (DTA) scheme in Energy. The authors also acknowledge elements of the work was carried out as part of the DR-BOB project (01/03/16–28/02/19) which is co-funded by the EU’s Horizon 2020 framework programme for research and innovation under grant agreement no. 696114.

### 7. REFERENCES


