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Minimising the Electricity Interruptions Using Artificial Intelligence and Demand Side Management Approach to Achieve SDGs

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Session 3: Energy Interventions and the SDGs

Chaired by Dr. Rupert Gammon, IESD

Minimising the Electricity Interruptions Using Artificial Intelligence and Demand Side Management Approach to Achieve Sustainable Development Goals

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Abstract

Accessing affordable, reliable, sustainable, and modern energy for all and making cities and human settlements inclusive, safe, resilient, and sustainable are the seventh and the eleventh targets of the sustainable development goals (SDGs) for 2030. The consistent supply of electricity is a fundamental requirement to ensure overall developmental growth within local communities by using appropriate, accessible, and affordable technologies. Some countries have accessible electricity most of the time but struggle with interruptions due to shortages in the generation and typically apply load shedding schemes as a solution. This research presents a novel method of using artificial intelligence techniques with smart grids equipment to offer more controlled load management and load shedding scheme to minimise interruptions on communities.

***Keywords**: Sustainable Development Goals, Demand-side-Management, Demand-Side-Response, Reliable Supply.*

Introduction

Demand Side Management (DSM) was proposed in the early 1980s by EPRI (Electric Power Research Institute) and the defined as “the planning, implementation, and monitoring of those utility activities designed to influence customer use of electricity in ways that will produce desired changes in the utility’s load shape, i.e., changes in the pattern and magnitude of a utility’s load.” (Arteconi, Hewitt and Polonara, 2012). Figure 1 shows a categorisation of DSM approaches. These can be categorised to two groups (1) energy efficiency (EE) and (2) demand response (DR). EE aims to decrease energy consumption while achieving the same tasks, and DR aims to modify load profile via applying different methods such as load shedding and load shifting, motivated by market changes (Charles River Associates, 2005).

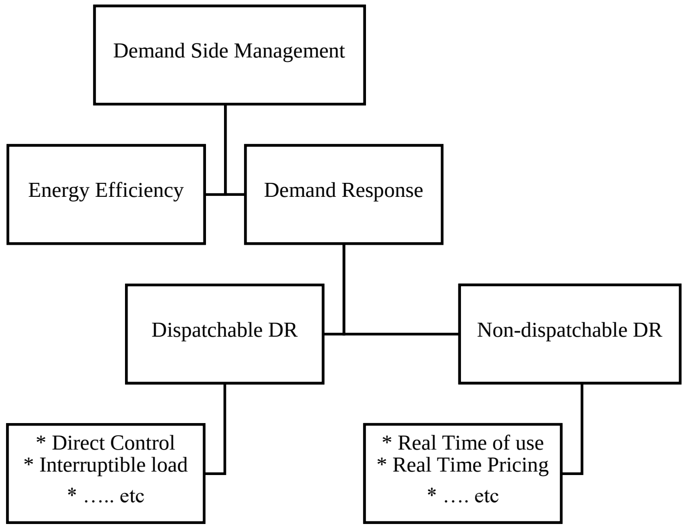

Figure 1 DSM Approaches Classification

Demand Side Response (DSR) defined as: "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardised." (Balijepalli et al., 2011). DSR can decrease the overall investment and plant capital cost via grid improvements (Siano, 2014). Smart Grids (SGs) can be defined as the additional hardware and software tools added to the power system to accomplish a more self-sufficient sensitivity to incidents that affect the electrical grid, and optimal day to day operating efficiency of distributed energy (Mortaji et al., 2017). SG independent system operator (ISO) or regional transmission organisation (RTO) make use of DR schemes to govern supply and demand. Smart DR methods include direct load control (DLC) programs which give the capability to power companies to monitor and control electrical appliances during peak periods using smart plugs and smart appliances that operate under internet data platforms. The concept and objectives of the proposed intelligent connections in the Smart DR are related to the Internet of Things (IoT) theory. IoT is defined as making the use of web platforms to link, monitor, and control the objects of daily life (ZORZI et al., 2010). The combination of SG and IoT is referred to as the Internet of Energy (IoE) (Bui et al., 2012). Artificial Intelligence (AI) cloud controllers can be used under IoT configurations. AI is the study of enhancing computers and machines to do things in the same sense that humans make something done (Simmons and Chappell, 1988). Previous researches provided a strong hypothetical approach for smart grids, machine-to-machine (M2M), and human-to-machine (H2M) collaborations in the residential areas (Niyato, Xiao and Wang, 2011).

The majority of DSR schemes assume that the load profile has the flexibility to be shifted somewhere else over time. However, in some developing countries, the problem is not about load shaping but capping the load appropriately to meet the available generation capability regardless of the time. As such, the key mechanism for DSM is not load shifting or load management, but load shedding. Most of the published literature in the area of load shedding focuses on a scheme illustrated in Figure 2-a. where the substation is monitored and if the voltage/frequency drops below the relay setting the load downstream is switched off. The hypothesis described and simulated in this article aims to use Artificial Intelligence (AI) to reduce the influence of load shedding to neighbourhoods of clients. So, as a substitute for substation disconnection; load within communities is decreased based on current sets of conditions as shown in Figure 2-b. Furthermore, the load shedding procedure suggested in this paper is undertaken by looking at the real-time load measurements on the substation instead of stability perspective (frequency/voltage) measurements.

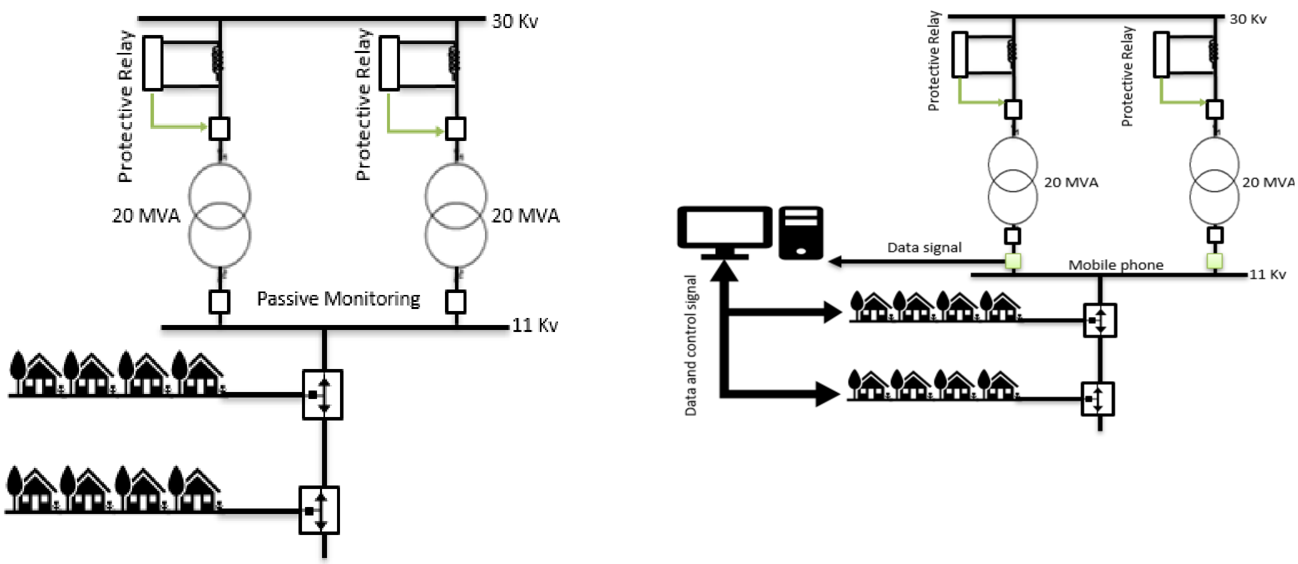

Figure 2 -a. Example of Load Shedding Schematic *-b. Proposed Load Shedding Schematic*

Background

There have been several research papers studying DSM and AI implementation in the SGs approach published. DSM for large clients number was examined via studying the effect of demand flexibilities, time of use (TOU) prices, and Emergency Demand Response Program (EDRP) (Aalami, Yousefi, and Parsa Moghadam, 2008). Load shifting and the optimal scheduling scheme for typical home appliances were also examined (Setlhaolo, Xia, and Zhang, 2014). Energy management approaches in a smart home with the respect to demand response (DR) investigated(Zhang *et al.*, 2016). These researches studied DSM from scales of individuals to large scale aggregators. Additionally, centralised management approaches were applied to achieve the control signals with fixed electricity tariffs. Focusing on the load shedding strategies, a method claiming to offer a minimum volume at a good location (Moors, Lefebvre, and Van Cutsem, 2000). The suggested method applies a multi-stage and non-linear technique to achieve the lowest load shed at each step (Irving, Luan, and Daniel, 2002). The decentralised control methods utilise the deployed control components in the neighbourhood area. They can make determinations with a limited quantity of data accessible and limited coordination. Smart devices are fitted out with essential optimisation and logics procedures. Such a design based on multi-agent systems (MAS), is utilised in voltage control approaches and claims to deliver delivers a regional division of the distribution system depending on the electrical distance concept (Dolan *et al.*, 2013) and (Zabaiou, Dessaint, and Kamwa, 2014). A fully distributed MAS based on the reinforcement learning method is applied for online optimum reactive power dispatch. This technique does not need the correct system model. Recently, the decentralised control systems have attracted small-scale applications and have been implemented in several sites. For instance, the tests of the MAS application for the decentralised DGs resources installed in Kythnos island was claimed to be effective, but with a disadvantage of expensive infrastructure for a small group of DGs resource owners (Fei He *et al.*, 2010). Hybrid methods provide the advantages of both centralised and decentralised methodologies at larger investment costs (Larik *et al.*, 2018; He *et al.*, 2019). To avoid the costs of complex control and to guarantee that load shedding is undertaken in the most convenient way possible where there are no opportunities for shifting of load, this work is an extension work of AI concept for load shedding in Libya (Alarbi, Strickland and Blanchard, 2019). The research looks at an AI approach with decentralised control at substation level to implement load shedding. This work is novel because it does not look to load shed the smallest amount of load, but the most convenient amount of load.

Methodology

This research looks to determine how best to load shed in a community using AI techniques to minimise the disruption to the householders. To understand the load demand, this research uses the CREST demand model to generate loads for several houses and the appliances inside them (McKenna and Thomson, 2016). The reason behind the use of the CREST model is the uncertainty of appliances operation and the capability to simulate different occupancy profiles as well as week and weekend days. These loads will be applied to train and test the load shedding approach accuracy. The methods suggested in this paper give rise to the most straightforward prediction technique due to the high level of information available from the residential areas. Therefore, less data is required to train the AI function compared to the other methods. In this research, communication tools are a necessary element of the process as data will be transmitted online to the local control unit rather than having a central control unit. The strategy in this paper can be applied in two different ways. The methodology is divided into two sections: the load shedding calculation, and the load shedding control.

A) Load Shedding Value Prediction

The load shedding calculation is separated into two computation approaches. The first step is fitting the community load curve as close to the substation load limit as possible by determining the load shedding value. Secondly, a classification approach can be used to predict the targeted house and targeted appliance. To solve the issue of calculating the load shed value at the substation with the lowest computing capacity, neural networks can be utilised to train a model that forecasts the load shed value. The inputs on this model will be the substation load, substation limit, and the calculated load shed. Using this input data, a function that can predict the load shed value can be obtained. Using AI instead of straightforward subtraction at this stage allows the research to be adapted more easily in the future to use dynamic asset rating to estimate the rating of the substation and therefore using AI in this way produces a better path to DAR in the future. The inputs of this function will be the substation load and substation limit as illustrated in Figure 3.

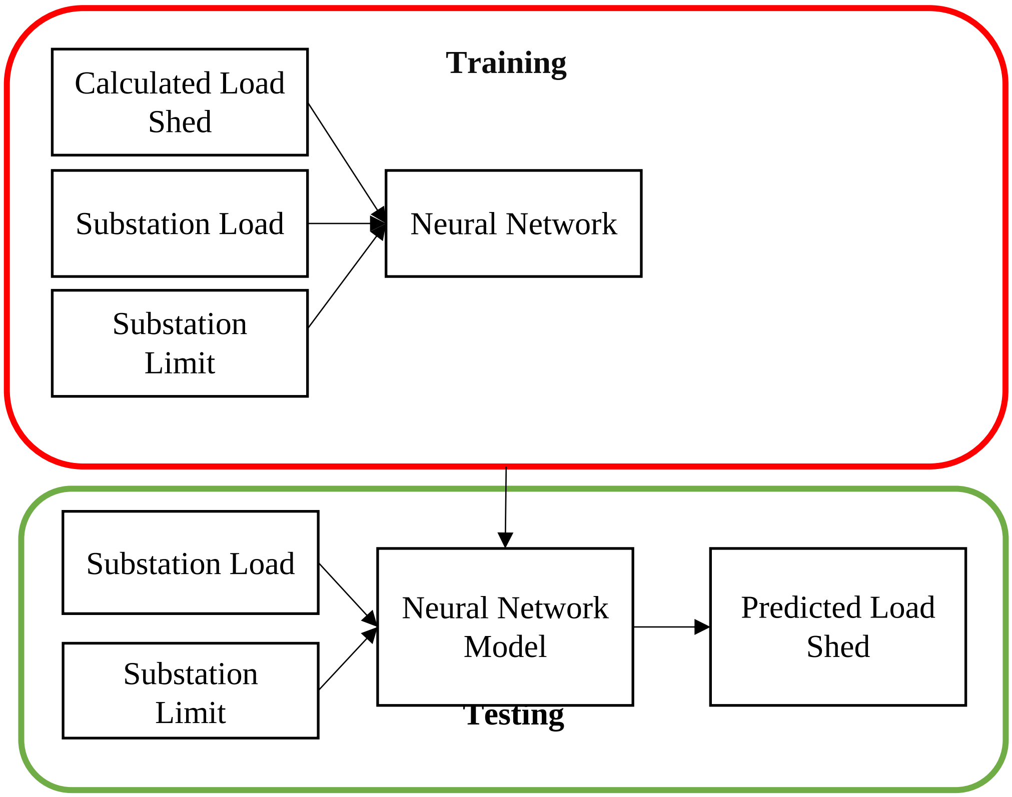

Figure 3 Load Shedding Training and Testing Approach

For the training stage, three different training algorithms were tried.

- “trainlm” is reportedly the quickest backpropagation algorithm in the MATLAB toolbox (Riadi, Wirawan, and -, 2017; Hartono, Marifa Ahmad, and Sadikin, 2018). This algorithm is proposed as a primary-preference supervised algorithm. However, it does involve more memory than other algorithms.
- “trainbr” is a training process that updates the weight and bias values according to Levenberg Marquardt's optimization (Riadi, Wirawan, and -, 2017). It reduces a sequence of squared errors and weights and then verifies the correct pattern to deliver a generalised quality network.
- “trainscg” is a training tool that updates the weight and bias values corresponding to the scaled conjugate gradient method (Riadi, Wirawan, and -, 2017; Hartono, Marifa Ahmad and Sadikin, 2018).

10, 20, and 30 hidden layers were implemented on the training stage to obtain the best solution. The performance of the training algorithm using different hidden layers is illustrated in Table 1.

	Trainlm	**Trainbr**	**Trainscg**

Hidden Layers	10	20	30	10	20	30	10	20	30
Training	0.99993	1	1	1	1	1	0.9969	0.99954	0.98533
Validation	0.99993	1	1	1	1	1	0.99855	0.99971	0.98231
Testing	0.99998	1	0.92259	1	1	1	0.99679	0.99859	0.99049
Target	0.99993	1	0.96611	-	-	-	0.99672	0.99944	0.98231

Table 1 The values of R during the training, validation, testing stages using different hidden layers.

B) Load Shedding Control

Load shedding relies on information from three main data sources. Firstly, the substation load of a specific area. However, this data is not representing the detailed layers (houses consumption). The second type of data is real-time monitoring of the house's load which gives comprehensive and larger understanding to load inside houses. Finally, the appliances state on/off delivers a better understanding of the consumer behaviour that can be used for the Smart-DSM approach. Table 2 Illustrates the investigated methods in this paper. The following two sections will go through the training stages of houses selection and appliances selection functions.

Method Reference Number	Substation Load	Houses Load	Appliances State	DR Strategy	Time-based Training
1	✓	✓	✓	Knowledge	No
2	✓		✓	Knowledge	No

Table 2 The Investigated Methods.

Method 1 Methodology

Method (1) The Substation, Houses and App State method will comprise of a controller which aims to develop smart load shedding technique based on the data sharing between the substation, houses, and appliances in the residential areas. The control framework of load shedding is shown in Figure 4. The highest appliances loading will be disconnected first.

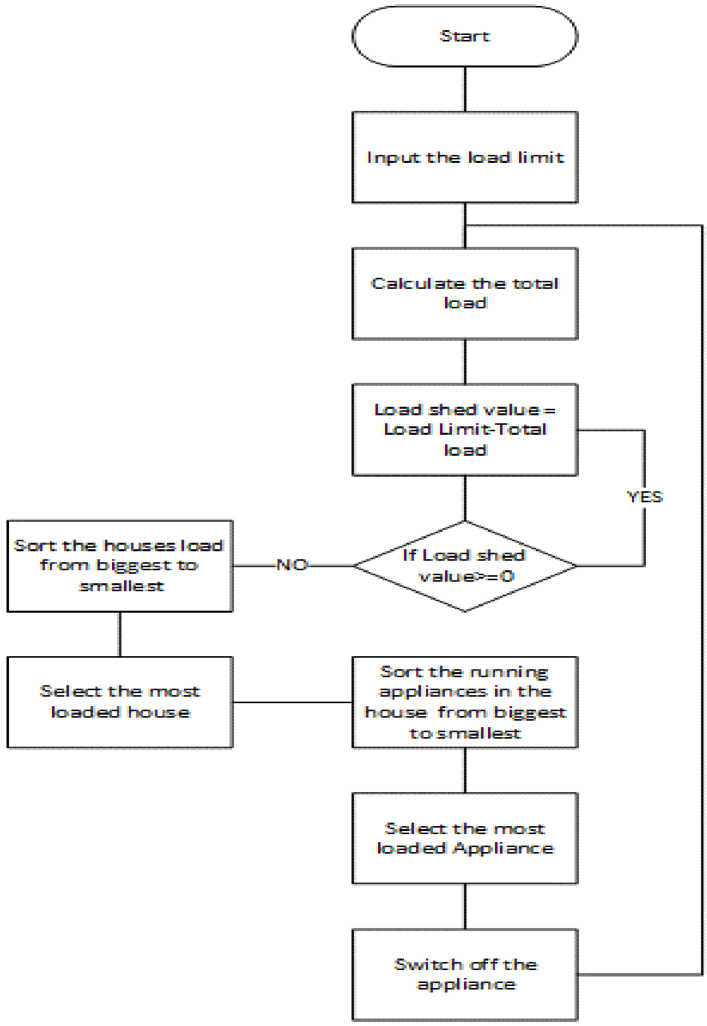

Figure 4 The Top-Level Algorithm of Load Shedding Using Substation, House, and Appliances Data.

<u>1) Houses Selection</u>

For the residential level, it is necessary to understand different ways of selecting houses and appliances for load shedding that will be most convenient to the customer. This study focuses on choosing to reduce load at the house with the highest demand as a way of initially determining this choice: then deactivating the appliance with the highest load value in that house until the system reaches the required load shed value, by way of example. Other methods would be equally applicable, and it is envisaged that a weighting factor based on customer preference and reinforcement learning will eventually be used. The training data for house selection used in this method are the load shed value and the house power as (0,1) which is a logical method to identify the largest and smallest loaded house. When the load shed value is equal to zero the targeted house will be zero so no actions will be needed to load shed. Once the load shed value is greater than zero the system will pick up the largest house load by real-time reading from smart meters that is only applicable to method 1.

Load shedding Value   Houses data   Target

$$\begin{pmatrix} \mathbf{0} \\ \vdots \\ \mathbf{1} \end{pmatrix} \qquad \begin{pmatrix} \mathbf{1} & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{1} \end{pmatrix} \quad \begin{pmatrix} \mathbf{0} \\ \vdots \\ \mathbf{5} \end{pmatrix}$$

Using the MATLAB classification toolbox, the previous matrixes was used for training a prediction function. The accuracy of this function was 100% and training time for this function is 0.81911 seconds, and the function can do 590 observation every second. The next step will be choosing the appliances to shed.

2) Appliances Selection

In Method (1) Substation, Houses, and App State are known, in the training stage, the system uses a 33x33 identity matrix for training and the column matrix from 1 to 33. The 33x33 identity matrix is representing the logical relation between the largest and the smallest real-time power consumption for appliances in the selected house. This function will operate only if one of the houses was triggered for load shedding occasions.

	Training data	Target
Method (1)	$\begin{pmatrix} \mathbf{1} & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{1} \end{pmatrix}$	$\begin{pmatrix} \mathbf{1} \\ \vdots \\ \mathbf{33} \end{pmatrix}$

The MATLAB classification application was used to develop an AI function that was trained over two stages. Firstly, finding the targeted house as presented in the house selection stage. Secondly, within the targeted house, the house appliances state in (1,0) will be inputted to determine the targeted appliances. The predicting function was created with 100% classification accuracy by fine KNN appliances selection and the spent time to train this function was 0.91439 seconds, and the function can do approximately around 3700 observations every second.

Method 2 Methodology

Method (2) Substation and App State method will involve a controlling process that seeks to develop smart load shedding techniques based on the data sharing between the substation and appliances in the residential areas without the use of house metered data. The control framework for load shedding is shown in Figure 5. The highest appliances will be disconnected first if the load shedding scheme is required.

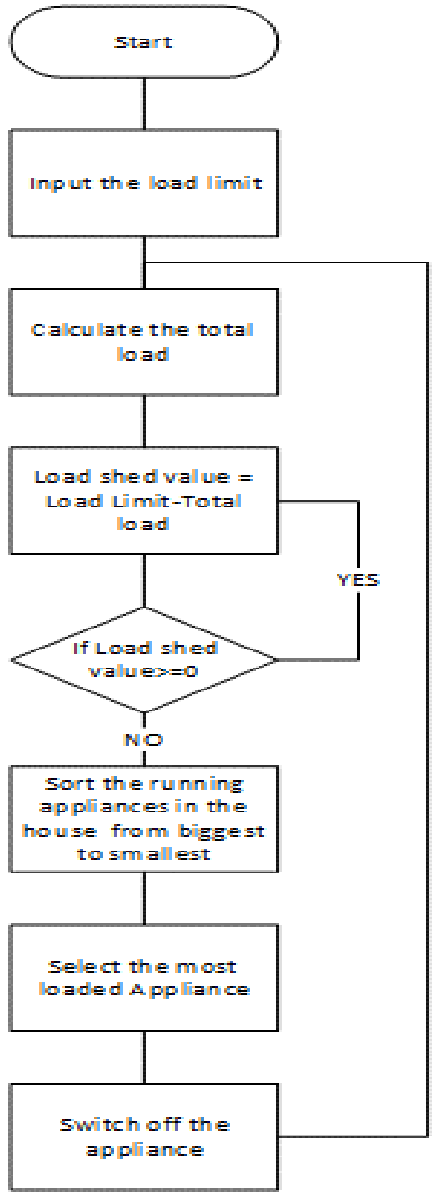

Figure 5 The Top-Level Algorithm of Load Shedding Using Substation and Appliances Data

1) Appliances Selection

In method (1) Substation and appliances data, the system training step uses the 165×165 identity matrix for training and the targeted appliances from 1 to 165 as the system designed for 33 appliances in 5 houses. The MATLAB classification tool is used to develop an AI function that is trained by inputting the prepared identity matrix to determine the target appliance for load shedding. The appliances states are a defined as (1,0) that means the logical representation of the largest and the smallest real-time power consumption for all appliances, chosen for convenience as a way of selecting a load that is considered least disruptive, these states are used to train the forecasting function and 100% classification accuracy is achieved by k-nearest neighbours algorithm KNN for appliances selection. This function will operate only if the load shedding value is more than zero. This method does not involve house load monitoring via smart meter but involves the smart appliance real-time power consumption.

$$\text{Method (2)} \qquad \begin{array}{c} \text{Training data} \\ \begin{pmatrix} \mathbf{1} & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{1} \end{pmatrix} \end{array} \qquad \begin{array}{c} \text{Target} \\ \begin{pmatrix} \mathbf{1} \\ \vdots \\ \mathbf{165} \end{pmatrix} \end{array}$$

The spent time to train this function was 1.9935 seconds, and the function can predict around 7900 observations every second.

Systems Simulation and Results

All simulations in this section are operated on a PC with Intel(R) Core (TM) i5-3570M CPU @3.4 GHz and 12.00 GB memory and MATLAB 2019a were used for AI function creation and simulating the proposed models. This study considers a smart grid structure with five houses. Using the CREST demand model each user, an assumption of the number of appliances that will be operating in the houses is made represent different types of loads and assuming that each appliance is capable to be disconnected (McKenna and Thomson, 2016). The maximum power capacity for these houses is set to 4 kW for testing proof of concept and the load without load shedding is presented in Figure 6.

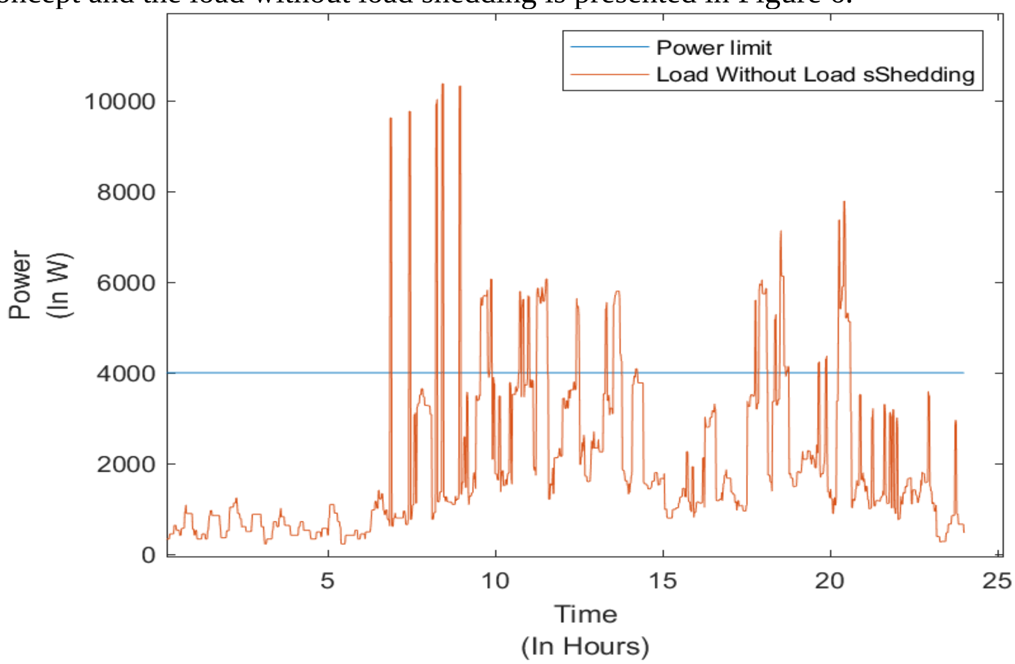

Figure 6 The Maximum Power Capacity and The Load Without Load Shedding

Method 1 Results

The total load after applying load shedding is illustrated in Figure 7, this data shows the results of the model under the knowledge of the substation, houses, and the power consumption of the appliances.

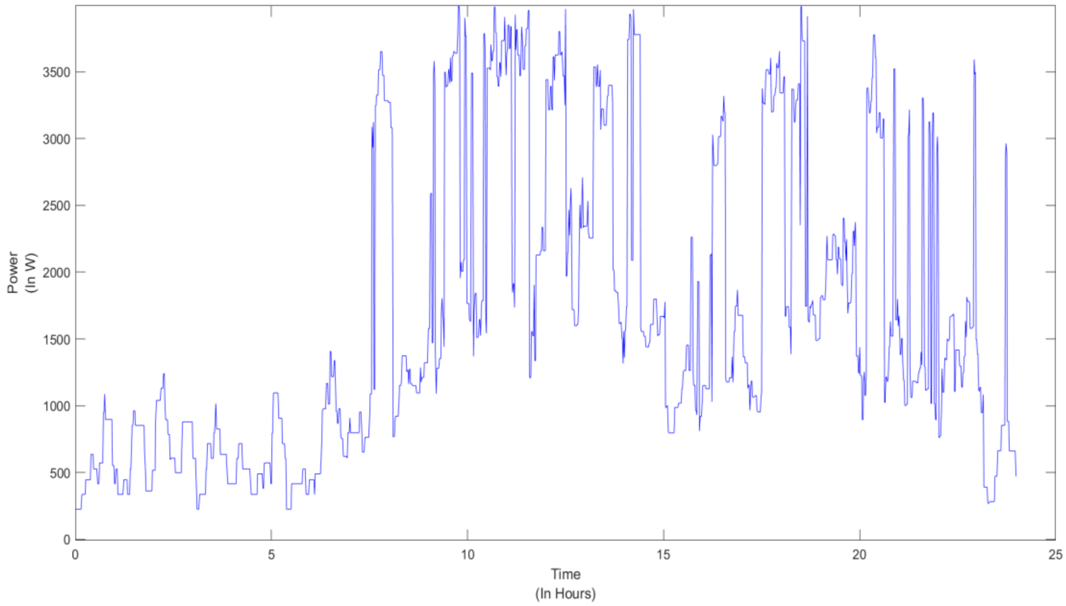

Figure 7 The Total Load With Load Shedding Method 1

Method 2 Results

The power balance using this method was achieved by keeping the total load below the generation limit. Figure 8 illustrates the load after applying load shedding and using the AI approach under the knowledge of the substation and the power consumption of the appliances.

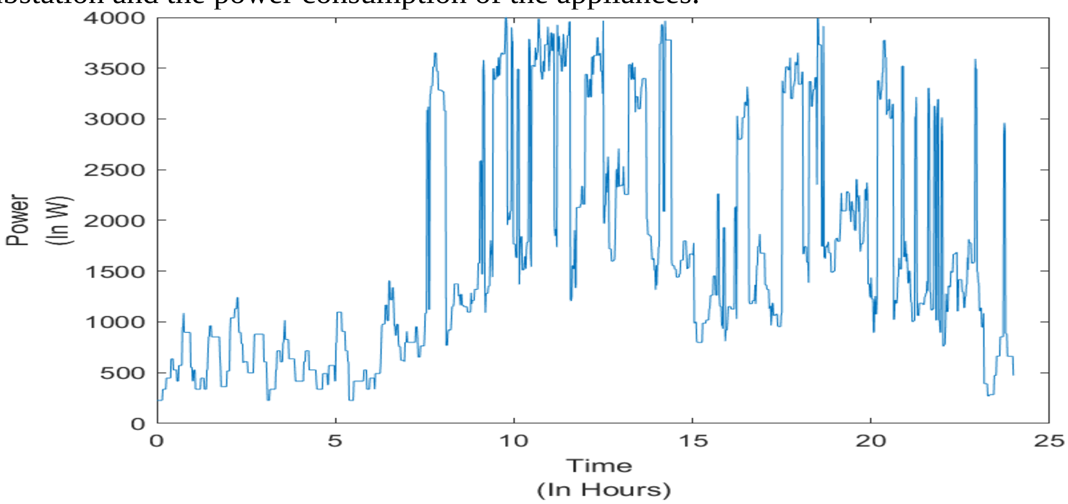

Figure 8 The Total Load With Load Shedding Method 2

The achieved load shedding value in both methods was quite similar over the day with little differences due to methodology variation. Making the point clearer, in the first method the algorithm targeted the highest loaded house and then marked the largest appliance to be switched off. However, the second method algorithm observed the entire appliances level and predict switch off the largest appliances.

Conclusion

In this research, a smart distributed demand-side management approach is proposed to deliver reliable energy for costumers in residential areas. The users are connected via the community substation fed by limited power capacity. For this area, demand-side management (DSM) is used to regulate the operation scheme of dispatchable elements and the collaborating to keep the utility in operation. Simulation results showed that the two methods of smart-DSM were able to achieve the optimal control system. Load shedding value calculation using prediction software at the substation was achieved using different algorithms. Load shedding control via the first method utilising substation, houses, and appliances real-time power consumption information, and the second method using substation and appliances real-time power consumption data determined a very good performance. However, different appliances were triggered sometimes due to different methodologies. Since, in the first approach, the entire level of appliances was assessed by AI function, whereas the second method assessed the houses and then goes to the appliances level. The next stage for the research is to adapt these models for lab testing. both methods produced equally valid results but that not having a house smart meter is a saving in complexity, time and cost.

Acknowledgements

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Minimising the Electricity Interruptions Using Artificial Intelligence and Demand Side Management Approach to Achieve SDGs,

By Ali A. A. Alarbi (on behalf of Ali A Alarbi, Richard Blanchard, Dani Strickland of Loughborough University)

Conference on Aligning local interventions with the UN SDGs

Minimising the Electricity Interruptions Using Artificial Intelligence and Demand Side Management Approach to Achieve Sustainable Development Goals

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Conference on Aligning local interventions with the UN SDGs

The Outline

- Introduction.
- The Previous Work.
- Methodology.
  - Load Shed Value Calculation.
  - Load Shedding Control.
- Results.
- Conclusion and Further Research

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Introduction

- Problem
  - Electricity Shortages.
  - Inequality in Accessing Power.
- Research Tools and Techniques
  - SDGs.
  - Demand Side Management.
  - Artificial Intelligence and Power System.

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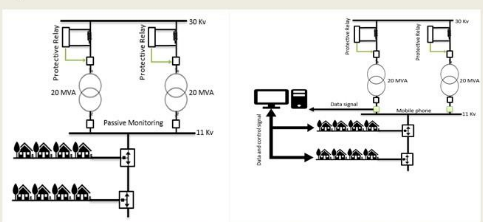
Previous work

- Load shedding literature review.
- The system structure:-



a. Example of Load Shedding Schematic

-b. Proposed Load Shedding Schematic

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Methodology

- Data Preparation.
  - CREST Demand Model for UK.
- Artificial Neural Network Algorithm.
  - Load Shed Calculation
    - Levenberg-Marquardt Backpropagation (Trainlm).
    - Bayesian regularization Backpropagation (Trainbr).
    - Scaled Conjugate Gradient Backpropagation(Trainscg).
  - Load Shedding Control
    - K-Nearest Neighbours Algorithm (KNN).

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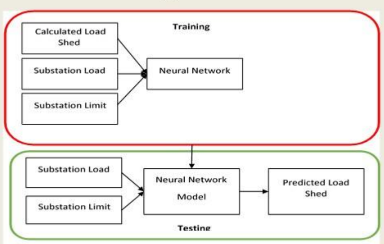
Methodology

- Load Shedding Value Prediction



Load Shedding Training and Testing Approach

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Methodology

- Load Shedding Control (Knowledge)
  - Method 1 (Substation-Houses-Appliances)
    - Requirements
      - Substation Sensing, House Smart Meter and Smart Plug.
  - Method 2 (Substation-Appliances)
    - Requirements
      - Substation Sensing and Smart Plug.

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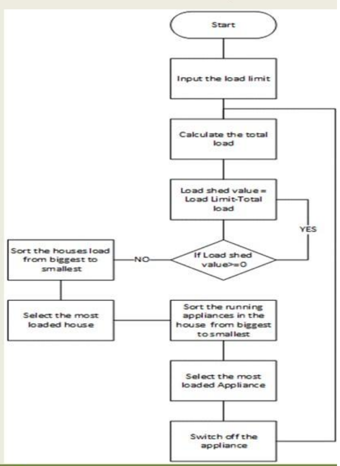
Methodology

- Method 1 Training
  - House Training

Load shedding Value: $\begin{pmatrix} 0 \\ \vdots \\ 1 \end{pmatrix}$ Houses data: $\begin{pmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{pmatrix}$ Target: $\begin{pmatrix} 0 \\ \vdots \\ 5 \end{pmatrix}$

  - Appliances Training

Training data: $\begin{pmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{pmatrix}$ Target: $\begin{pmatrix} 1 \\ \vdots \\ 33 \end{pmatrix}$



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Methodology

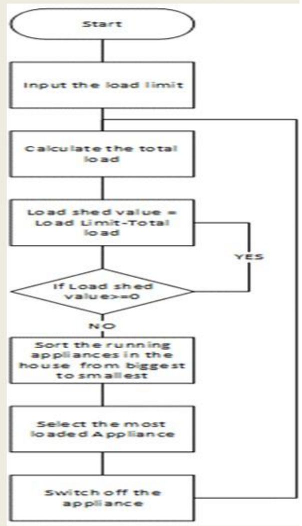
- Method 2 Training
  - Appliances Training

Training data

$$\begin{pmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{pmatrix}$$

Target

$$\begin{pmatrix} 1 \\ \vdots \\ 165 \end{pmatrix}$$



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Simulation and Results

- Load Shedding Value Prediction

	Trainlm			Trainbr			Trainscg		
Hidden Layers	10	20	30	10	20	30	10	20	30
Training	0.99993	1	1	1	1	1	0.9969	0.99954	0.98533
Validation	0.99993	1	1	1	1	1	0.99855	0.99971	0.98231
Testing	0.99998	1	0.92259	1	1	1	0.99679	0.99859	0.99049
Target	0.99993	1	0.96611	-	-	-	0.99672	0.99944	0.98231

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Simulation and Results

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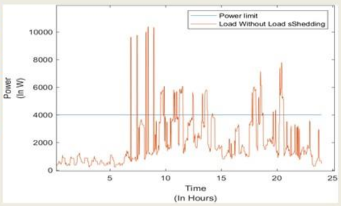
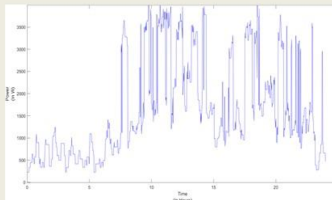
- Load Shedding Control
  - Method 1





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Simulation and Results

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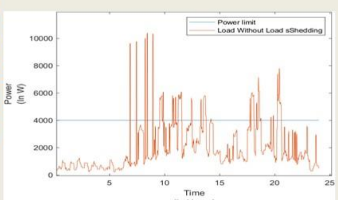
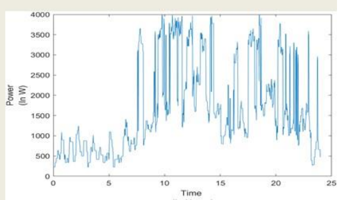
- Load Shedding Control
  - Method 2





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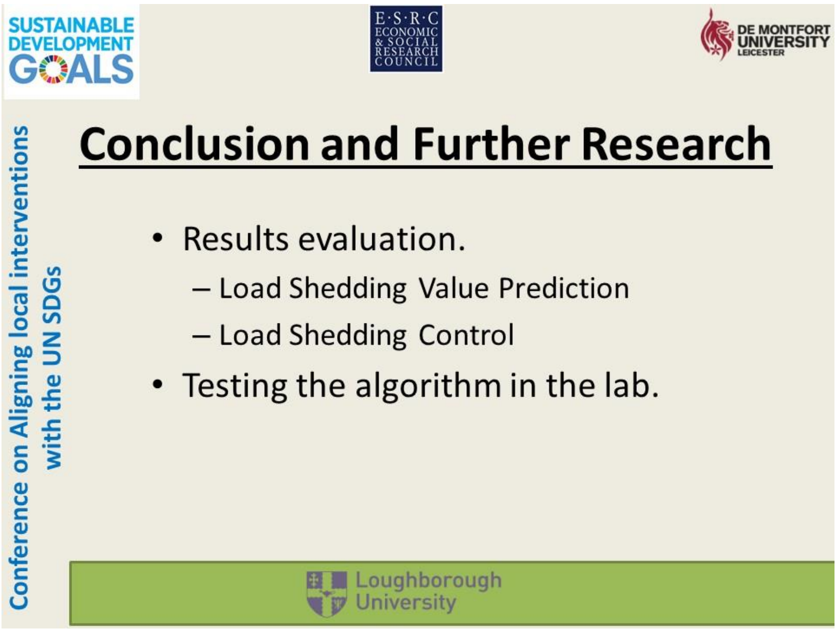
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Conclusion and Further Research
• Results evaluation.
– Load Shedding Value Prediction
– Load Shedding Control
• Testing the algorithm in the lab.
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Q & A Time
?
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