A Brief Review of Methods to Simulate Peer-to-Peer Trading in Electricity Networks

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***Abstract*— The threat of climate change has caused countries to begin the decarbonization of the energy chain; the broader adoption of renewable energy technologies is playing a pivotal role in achieving this goal. The closing of the feed-in tariff and the unattractive rates offered by the new smart export guarantee has resulted in a decline in the number of new solar installations. Peer-to-peer energy trading markets have the potential to get renewable energy installations back on track by increasing the value of the generated energy to all parties involved. The move from centralized to distributed energy systems brings its own set of potential challenges, including reverse power flows and islanding. Accurate simulations of both the peer-to-peer network and the broader distribution network need to be developed and integrated for the impacts of peer-to-peer energy trading markets on the energy transmission grid to be made apparent. This paper looks at the methods and technologies used to simulate each aspect in a grid-connected peer-to-peer energy trading network and attempts to draw some comparisons between the methods used in the reviewed literature.**

Keywords—Simulation, Peer-to-Peer, Distributed Generation, Local Energy Markets, Photovoltaics, Distribution Network, Modelling.

I. INTRODUCTION

In order to meet the growing electrical demands while reducing our greenhouse gas emissions, new sustainable forms of energy generation must be developed, and existing renewable sources more widely adopted. Solar panels are probably one of the most accessible types of renewable energy sources available to the general public. Hartley [1], reveals that early adoption was stimulated by the Feed-in Tariff (FiT) scheme, which offered a financial incentive to those installing photovoltaic solar panels. In [2], Ingham discusses the impact of the closing of the FiT scheme to new applicants at the end of March 2019. The result has been a decline in the number of installations; June 2019 saw an 18% reduction when compared to June 2018. 90% of these installations were of low capacity panels with a rating of less than 4kW, resulting in a fall in the installed capacity during June 2019 of 56% when compared June 2018.

Cui et al. [3] state that excess power generated by solar panels installed after the closure of the FiT scheme would still be fed back into the grid; however, homeowners would not be paid for the power exported, and this is illegal under current legislation. The UK government is attempting to fill the gap by implementing the Smart Export Guarantee (SEG) from 1st January 2020. Energy suppliers with more than 150,000 domestic customers will have to pay their customers for the power that they export to the grid. However, it does not specify how much the unit price they will receive, nor does it guarantee the length of any contract.

According to Ingham [2], solar power is vital to the United Kingdom achieving its renewable energy targets, and the government needs to introduce regulations that stimulate the growth of the installed solar capacity. Hartley [1] states the UK Government's figures show that the Smart Export Guarantee will only result in around an additional 3000 new Photovoltaic installations each year; this is comparatively insignificant to previous installation rates.

In [3], Cui et al. compared the annual savings and payback time of the modeled Photovoltaic System for the FiT and two versions of the new SEG. The two SEG tariffs considered were provided by Octopus Energy, a UK supplier. Fixed Outgoing Octopus (FOO) offers a fixed rate for the power exported, and Agile Outgoing Octopus (AOO) pays a varying rate based upon, in part, the day ahead wholesale prices. The authors concluded that the annual savings of each scheme were: FiT £300.88, FOO £84.16, and AOO £146.43. The Payback Period under the FiT scheme was also much shorter at 9.34 years than the AOO Tariff at 26.93 years, and the FOO Tariff at 46.85 years.

According to Aggarwal [4], the industry rates the useful lifespan of solar panels to be 25 – 30 years. At this time, the solar panels could still be producing 82.5% of their original rated capacity. At the 0.8% degradation rate, calculated as the average by the National Renewable Energy Laboratory (NREL) in 2012, a solar panel will produce 72.5 of its rated power after 40 years and 66.9 after 50 years, so the lifespan could be considered to be much longer. These lifespans show that with the SEG tariffs considered above, the solar panels will be at or near the end of their useful lifespan when they have reached their payback period.

In order to incentivize consumers to invest in solar and renewable energy products, there must be an opportunity for them to reclaim the money invested and also to benefit financially from their investment. A move towards peer-to-peer energy trading will allow prosumers to take advantage of an open market in order to meet their social and economic goals when selling their excess energy. Consumers are also able to take advantage of the peer-to-peer market, allowing them to choose carbon-free power from their neighbors instead of relying on traditional fossil fuels.

Section II of this paper investigates the methods used in simulating the Prosumers' energy consumption and production. Section III focuses on the simulation of Peer-to-Peer trading systems, and Section IV discusses simulating the

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impact of peer-to-peer energy trading on the broader power grid.

II. HOME ENERGY MODELS

Simulating the power profile of the home requires modeling any power generation at the property and the energy consumption characteristics of the homeowner.

A. Modeling Home Energy Production.

The modeling of home energy production will mainly mean modeling the power profile of a solar PV system as these are much more common than domestic wind turbines. The FiT installation Report for 2020 gives the number of domestic wind turbine installations from 1st April 2010 to 31st March 2020 as 4,354. In the same period, the number of Domestic PV installations recorded by Ofgem was 823,945 [5]; therefore, this report will only consider the modeling of PV generation.

Cui et al. [3] demonstrate the modeling of PV panels in two ways the "PV model" gives the periodic power production $P(W)$ of a solar panel of an active area $A_{pv}(m^2)$ and with solar irradiance incident to its tilted surface of $G\ (W/m^2)$, described by Eq. (1):

$$P = \eta_{PV} \cdot \eta_{inv} \cdot A_{pv} \cdot \psi \cdot \frac{G}{G_{STC}}[1 + \psi_T(T - T_{STC})] \quad (1)$$

The equation allows for the effect of the temperature variation of the cells, which is necessary as the PV module produces less power at a given irradiance as the cell temperature rises.

In (1), $\eta_{PV}(\%)$ and $\eta_{inv}(\%)$ represent the efficiency of the photovoltaic module and inverter, respectively. ψ represents the derating factor. The derating factor is used to adjust the power output based upon real-world operating conditions. These losses occur due to the age of the module, external factors such as the weather or shading, losses in the AC interconnection and DC wiring, module mismatch, losses in the DC connections, and diodes. $\psi_T(\%/°\text{C})$ is the maximum power temperature coefficient, $T(°\text{C})$ represents the operating temperature of the cell while $T_{STC}(°\text{C})$ is the temperature at standard test conditions, usually 25°C. [3] [6]

The second method used to model a PV module, "one-diode mathematical model," gives the instantaneous power production for any given solar incident irradiation. The model is developed from the eq. (2) which is the equation for the ideal PV Cell.

$$I_{Cell} = I_{pv,cell} - I_{0,cell}\left[exp\left(\frac{qV}{\Theta k T_{Cell}}\right) - 1\right] \quad (2)$$

The equation of the ideal PV Cell requires additional parameters to represent the characteristics seen at the terminals of a PV array the equation for a practical PV array is eq. (3)

$$I = I_{pv} - I_0\left[exp\left(\frac{V + I \cdot R_S}{\Theta N V_{th}}\right) - 1\right] - \frac{V + I \cdot R_S}{R_{Sh}} \quad (3)$$

The thermal equivalent voltage V_{th} is given by eq. (4)

$$V_{th} = \frac{kT_{Cell}}{q} \quad (4)$$

I_{pv} (A) is the light generated current of the photovoltaic cell, the current flowing from the cell is given by eq. (5)

$$I_{pv} = (I_{pv,STC} + K_I \Delta_T)\frac{G}{G_{STC}} \quad (5)$$

K_I is the short circuit current temperature coefficient and is usually found on the data sheet.

Δ_T is the difference between the cell temperature and the temperature at standard test conditions.

$G(W/m^2)$ represents solar irradiance and $G_{STC}(W/m^2)$ is the incident irradiance under standard test conditions usually $1\ kW/m^2$

In the above equations: $I\ (A)$ is the PV module current, $I_0(A)$ is the diode reverse saturation current, $V\ (V)$ is the PV module voltage, $q(C)$ is the charge of an electron, Θ is the diode ideality factor $k(J/K)$ is Boltzmann's constant, $T_{Cell}(°C)$ is the cell temperature, N is the number of cells in series, $R_s(\Omega)$ is the series resistance and $R_{Sh}(\Omega)$ is the shunt resistance.

To use the single diode model five unknown parameters need to be calculated I_{pv}, I_0, Θ, R_s, R_{Sh} as they usually are not given in the datasheet [3, 7, 8, 9, 10].

The single-diode model has been used in many studies as it is a good compromise between simplicity and accuracy. More sophisticated models have been developed that produce greater accuracy, such as the two-diode model, which aims to simulate the effect of the recombination of carriers and a three-diode model that simulates the effect of grain boundaries and leakage current through the peripheries [8, 11].

B. Modeling Home Energy Usage

Gao, Liu, and Zhu [12] suggest that the two most commonly used approaches for modeling the load profile of a home are the bottom-up method and the statistical method. The bottom-up approach produces a very high prediction accuracy; however, it requires a consumption model to be made for each electrical appliance. A large amount of data must be collected in order for the model of each appliance to represent the energy consumption of the appliance accurately.

Acquiring consumption data has proved difficult in the past, and this has limited the use of the bottom-up approach. Recent advancements and continuing development of smart home technology have created a path for more accurate forecasting of the load profile using the bottom-up approach. Smart Sockets, for example, could be used to collect the energy consumption data for the appliance and upload this to the data center over Wi-Fi; this would make the collection more efficient and accurate.

While Gao, Liu, and Zhu discuss using the models developed for forecasting the load profile of a home, it could be reasoned that a model able to predict the load profile accurately may also be used as a simulation of the same.

In [12], the statistical method of load modeling is also discussed. This approach attempts to analyze the characteristics of the load profile to produce a forecasting model. Applying statistical methods trends can be identified based upon the cause under consideration; these could include socio-economic factors, seasonality, the day of the week, et cetera.

In [13], Tsagarakis, Collin, and Kiprakis propose electrical load models based upon the resident's demand profile. The approach taken by the authors begins with creating user profiles using data from the UK Time Use Survey (TUS) and the Markov Chain Monty Carlo modeling (MCMC) Technique. The authors use the MCMC to produce activity profiles for single-person households as well as time-based occupancy patters for each house. In order to convert the activity profiles into an electrical model, an appliance load profile database was created along with statistical data describing appliance ownership and usage patterns. The model checks what activities are performed at each time step. If an electrical appliance is used, the appropriate appliance model and characteristics are used to determine the power used during that period; in this way, a load profile is created. The authors then go on to describe how this model can be used for power systems analysis by considering the electrical characteristics of the load with respect to the supply conditions.

It is also possible to model the load profile of a home from raw data that has been collected previously. One such source is the IEEE European Low Voltage Test Feeder (IELVTF) model [14], which is supplied with 100 load profiles each 24 hours long and with a time interval of 1 minute. The Load profiles contain a series of 1440 multipliers which, when applied to a base value (kW) to give the load (kW) at that time. There is no information as to how these load shapes were generated, and since the base value may be selected, these load shapes could be considered to be synthetic.

The IELVTF has been used in several research projects; in [15], the model is used to verify the operation of a proposed Peer-To-Peer energy trading platform. Morstyn and McCulloch elected to use the load profiles supplied with the IELVTF described above. Hayes, Thakur, and Breslin [16] use the model to assess the impact of a peer-to-peer energy trading market utilizing a double auction mechanism on the distribution network. In [17], Morstyn, Teytelboym, and McCulloch propose a peer-to-peer scalable energy trading market based upon bilateral contract networks. Case study simulations were performed in order to evaluate the operation of the proposed energy market in an islanded microgrid. In these simulations, the load profiles from the IELVTF were used to represent the inflexible load profile of each prosumer.

The Commission for Energy Regulation collected real-world energy consumption data for their investigation of the performance of smart meters and their impact on the energy consumption of consumers in order to evaluate the economic case for a more comprehensive national rollout. In total, 4225 residential smart meters were installed; data collection began at midnight on 15/07/2009 and ran until midnight on 02/01/2011. The smart meters measure and record the power used in each half-hour interval.

In [18], Al Khafaf, Jalili, and Sokolowski propose a method to find the optimal grouping of electrical consumers with similar consumption features in order to make the analysis of data collected from smart meters easier to analyze and understand. A genetic algorithm is first employed to discover the most significant features in the dataset; this is then clustered into groups using Self-Organizing Maps. The optimal number of clusters is found by finding the grouping where the information held in each cluster is as dissimilar as possible. The authors tested their clustering method using two datasets; the first is from a study performed by a Power Distribution Network Authority in Australia where residential smart meters captured the energy consumption profiles of 609 households in Victoria for a full year. The second dataset was the Irish study coducted by the Commission for Energy Regulation described above.

The data gathered from such a study can be used directly to model individual customers with the following limitations: the number of customers that can be simulated must be less than or equal to the number of customers in the original data set, in order to preserve the individuality of customers. The maximum simulation time for the model of the house is the time that the study was carried out for as it cannot be known if the customer's behavior is cyclical and, the amount of detail in the load profile is determined by the sampling time of the original data.

III. SIMULATING PEER-TO-PEER TRADING SYSTEMS

The simulation of the energy trading system depends upon the method employed to match prosumers with an energy deficit to those who have excess production. In [15], Morstyn and McCulloch propose that energy may be traded based on prosumer's values, such as the source/destination of the traded energy and the generation method. In this way, the energy available to the prosumers can be divided up into different classes, three energy classes were chosen green energy, subsidized energy, and grid energy. Consumers were placed into three categories: low-income households, green prosumers, and philanthropic prosumers. Green prosumers are willing to pay a premium to obtain green energy, philanthropic prosumers sell their unused production to low-income households, and low-income households seek only to minimize their energy cost. A platform agent regulates the trading between, and the wholesale energy market acts as an auctioneer between trading parties and sets the price of each class.

During each market trading interval, the prosumers solve the local optimization problem utilizing a distributed price-directed optimization method in order to schedule their renewable energy sources and storage, taking into consideration: the power generated, load prediction, and price of each energy class. The market platform sets the price of each energy class based upon the wholesale energy price, prosumer demand, and expected losses. The platform Agent and prosumers work to schedule power flows that maximize the social welfare of the participants.

The operation of the proposed market trading scheme was tested using the IEEE European Low Voltage Test Feeder Model; this can be simulated on many different simulation platforms, including MATLAB, OpenDSS, and GridLAB-D. The authors do not indicate which simulation platform was used in this paper. They do state, however, that MATLAB was used to solve the local optimization and platform agent problems.

In [19], Long et al. investigate bill sharing, mid-market rate, and auction-based methods for trading energy between prosumers. Bill sharing describes a market where the power use of all the participants in a community microgrid is amalgamated by a meter installed at the grid connection point. A bill for the whole community is generated, and each participant then pays their share based upon their total consumption and export during the billing cycle. Every customer in the microgrid has the same charge for each kilowatt hour of energy consumed and receives the same price for every kilowatt hour of energy exported.

The participants of the scheme benefit by having a reduced kilowatt hour price; however, the selling price of each kilowatt hour produced is also reduced. The results show that the majority of the participants would benefit from the scheme, one customer would have broken-even, and one customer (who had the highest excess production) saw a loss. A drawback with this system appears to be that those who are being the most conscious of their energy consumption are the ones who see the least benefit as cost and benefits are averaged out between all members.

The second market strategy investigated was the mid-market rate, this sets the price of the energy traded within the microgrid midway between the cost of purchasing power from, and the price given for selling energy back to the National grid when the power in the microgrid is balanced. If the power generated in the microgrid is higher than the consumed power, the buying price will be the halfway value; however, the sale price will be lower as some power will have to be sold at a price set by the National grid. Likewise, if the energy consumed in the microgrid is higher than the production, the sale price will be the halfway value, but the purchase price will be higher as some power must be bought from the National grid. The test results from the author's journal show that every customer saw a reduction in their bills using this method.

In the auction-based pricing system proposed by Long et al. at the start of each trading period, each household announces its estimated clearing price. This price is based upon the bidding, offering, and clearing prices during the previous trading period and calculated using the recursive least square method. Each household is then classified as a buyer if their power consumption exceeds their generation, or seller if their generation is higher than their consumption. The buyer provides bids in an attempt to purchase the extra energy required to meet their need; likewise, the seller provides offers for the excess production they have for sale. After all the bids and offers have been sorted into ascending order, the clearing price is calculated.

Where the distributed generation is higher than the demand, the clearing price will be the purchase price set by the national grid. When demand is equal to generation, the clearing price is the highest offer amongst all the buyers, and when generation is lower than demand, the cleating price is the sale price set by the national grid. The absolute value of the difference between the customers bidding price and the clearing price determines their priority in obtaining the lowest price; the lower the value, the higher their priority is. The prices for the current period for each customer are determined, and the cycle repeats. The author's results showed that this scheme provided savings for all customers though those customers who had the highest disparity in generation and consumption tended to see the smallest benefit.

The method used to simulate the marketplaces was not discussed in the paper; however, mathematical formulas were given for each market method.

Sabounchi and Wei [20] propose a peer to peer trading mechanism where sellers form a coalition with one representative during each round of trading. The buyers, on the other hand, act independently, each making a bid for electricity; the highest bidder wins the round purchasing the electricity. Multiple rounds of bidding occur until all available generation is sold, or until all the demand has been met, any unmet demand or unused generation is traded with the national grid by the coalition's representative. The proposed market system is implemented on the Ethereum Network in smart contacts, the terms of the contract are, in this way, implemented with the minimum of human intervention.

In [21], Rodrigues, Moreira, and Strbac suggest an intra-neighborhood peer-to-peer trading system which allows the homeowners to pool their photovoltaic production and energy storage systems. The pooled resources can be used to provide frequency response and energy reserve services to the Systems Operator, and peak demand reduction to the distribution network operator in order to reduce the energy supply cost to the whole community.

The system was modeled mathematically and tested using the FICO Xpress Optimization software. The authors simulated a neighborhood with 100 homes, 50 of which are equipped with rooftop solar PV and an energy storage system. Their study found that when the community coordinated their resources, they benefitted from reduced supply costs. When providing balancing services in addition to the coordinated approach, there is a slight increase in network costs compared to the coordinated approach alone. The total costs are still less than uncoordinated trading using this approach, and there is a much higher income from balancing services than these additional costs. The coordinated approach with balancing services also increased the amount of energy being traded between households; the authors explain this is due to Energy Storage Devices being reserved for balancing purposes instead of the homeowner saving the energy for their evening demand. The provision of balancing services caused an increase in the peak demand at the primary substation; this is due to the financial benefit of providing balancing services outweighing that of peak demand reduction; however, the volume of energy across the primary substation was reduced.

IV. SIMULATING THE DISTRIBUTION NETWORK

In [22] Yi, Pages, Allahham, Giaouris, and Patsios develop a model of the 132kV and 33kV Isle of Wight distribution network in Interactive Power System Analysis 2 (IPSA2) and MATPOWER. The model was used to; establish baselines for scenarios with different load and generation profiles, identify potential constraints caused by increases in electrical load and distributed generation. Carry out simulations to identify any network limit violation which may be caused by real-world trials and to explore the effects of new scenarios, and unfeasible trials Interactive Power System Analysis on a refined version of the model. The developed model could then be generalized so that it may be used to identify the effects of smart grids and the proposed cross-functional modular platform on other networks.

Four test cases considered were; The first simulated demand with no distributed generation, the second demand, and distributed generation. The third and fourth both simulated demand, distributed generation, and five energy storage systems, however in the third simulation, the energy storage systems acted as voltage control. In contrast, in the fourth test case, they were used to avoid reverse power flow to mainland Britain. The factors considered in evaluating the effect of distributed generation and energy storage systems were; network losses, voltage headroom, the daily number of tap changes, and the power flow headroom.

Yi, Pages, Allahham, Giaouris, and Patsios [22], concluded that in their simulations, adding distributed generation to the network reduced the network losses, and they were further reduced when energy storage systems were used to preventing reverse power flow to the mainland. When distributed generation is introduced, both the maximum and minimum voltage increased, causing a reduction in headroom, however by adding energy storage systems, the maximum voltage was reduced, creating additional capacity for more distributed generation. The introduction of distributed generation also caused an increased the required number of tap changes, adding energy storage did not affect the number of changes, this was due to the location and size of the storage systems employed in the study. The total power imported the network when distributed resources where added; however, reverse power flow occurred during peak solar production hours. The reverse power flow was eliminated with test case 4 when the energy storage systems were set to this purpose; this also had the effect of increasing the utilization of the locally generated renewable energy.

In [23], Pakka and Rylatt present their framework for the design and simulation of UK electrical distribution systems and short term energy markets. The authors adopted an object-oriented approach to distributed network analysis and created an agent-based model of a short-term electricity market. These models could work independently to solve problems specific to their domain or work together to solve cross-domain challenges. Java was used to develop the distribution system analysis module, while the Java-based Recursive Porous Agent Simulation Toolkit was used to create the electricity market module.

Pakka and Rylatt [23], employ an algorithm based upon the backward/forward sweep strategy to perform the power flow calculations in their distribution system module. The module was used to implement the IEEE 123 bus test feeder set for radial configuration, a 4.16kV predominantly radial network, and tested by addressing the issue of voltage regulation in this network the genetic algorithm. The Genetic algorithm altered the tap-positions of the voltage regulators, the status of the capacitors, and reactive power generated by the distributed resources in order to minimize the voltage imbalance at each node and to reduce the power losses in the entire network.

The short term market module was utilized to investigate the effect of intermittent energy sources, such as wind turbines, on the ability of the balancing mechanism to balance the network. The authors explored two scenarios, the first where wind generation was at around its 2016 level of 3%, the second where the generation capacity of wind power had increased to 60%.

The authors also tested the operation of both modules in combination; they implemented a framework where demand could alter their consumption based upon price signals from the market. Equally, generators were given the flexibility to alter their bids in a dynamic market and constrained by the operating cost of their generation technology.

Pakka and Rylatt [23] conclude that the developed distribution system module and genetic algorithm based solver produced a very well balanced voltage profile with a high degree of controllability over each phase. The developed short term market module needed further work to give it greater flexibility and the capacity to capture complex system effects. When using both of the developed modules in combination, it was possible to assess the effects of varying the proportions of energy generation technology on the response of demand aggregators allowing for the best mix of technologies to be selected to maintain the required level of demand response.

In [24] A. Aithal, G. Li, J. Wu, and J. Yu model a test network consisting of two radial feeders connected by a 6MVA soft open point in order to evaluate the performance of a medium voltage distribution grid with a soft open point under grid side AC Faults. The network was modeled in PSCAD/EMTDC, and line to ground, line to line, and three-phase faults were introduced to observe their effects. The authors created equivalent sequence networks for each of the fault conditions; these were validated using a generic distribution network with a soft open point connection. The voltages at the soft open point connection point were found to be consistent and predictable for the different operating scenarios when operating within the physical limits of the soft open point. The proposed fault index, which utilizes the positive, negative, and zero sequence components at the grid connection point, was found to be useful for AC fault detection, however, the fault index alone is not sufficient in determining the type of fault.

V. Conclusions

The research carried out for this paper shows there are many options for the simulation of each element of a grid-connected Peer to Peer energy trading microgrid. As the most popular and widely available technology for home energy production is photovoltaic panels, this paper focused exclusively on this. The single diode model is the most widely used in simulations of PV panel and can produce accurate simulations of home energy production when combined with measured irradiance and temperature data for the simulated home. Modeling home energy consumption can be achieved by the modeling of each appliance in the home individually, create a household model from sampled data, or use the sampled data as a model. The choice of model will depend upon its application and the available software.

Peer to Peer energy is a popular area of research, and so many different market structures are currently being considered. Many different simulation platforms exist, and the decision as to which platform will be employed will largely depend upon the individual's competence with the available software. Distributed computing technologies are being investigated to make the markets more secure and to increase automation. The main factor that must be considered with choosing the simulation software is its ability to send and receive data from the other simulation platforms.

A wide choice of free and commercial distribution network simulation software exists; however, there is not a purpose-built simulation platform that simulates the power and communications networks simultaneously. A combined software package would be useful for the simulation of smart peer-to-peer power networks.

If the software is to operate as a real-time simulation, then it must be able to receive and send data from and to the other simulation platforms in real-time. When choosing the simulation platform, consideration must also be given to the testing being carried out.

This paper serves to provide a brief overview of some of the simulation software and techniques available for simulating grid-connected peer-to-peer networks. Many other simulation packages available, and it would be impossible to discuss all of these. The literature discussed in this paper highlights some of the available software it uses, a few limitations of available software, and the work being done to mitigate these.

REFERENCES

[1] G. Hartley, "The present and future of UK solar power," energysavingtrust, 08th July 2019. [Online]. Available: https://www.energysavingtrust.org.uk/blog/present-and-future-uk-solar-power.. [Accessed 11 May 2020].

[2] L. Ingham, "UK solar capacity growth stalls as heatwave rocks the UK," Verdict, 25th July 2019. [Online]. Available: https://www.verdict.co.uk/uk-solar-capacity/. [Accessed 11th May 2020].

[3] Y. Cui, J. Zhu, F. Meng, S. Zoras, J. McKechnie and J. Chu, "Energy assessment and economic sensitivity analysis of a grid-connected photovoltaic system," *Renewable Energy,* vol. 150, pp. 101-115, 2020.

[4] V. Aggarwal, "Are Solar Panels a Sustainable Product?," Ogden Publications, Inc, 06th September 2016. [Online]. Available: https://www.motherearthnews.com/renewable-energy/are-solar-panels-a-sustainable-product-zbcz1609. [Accessed 11th May 2020].

[5] Ofgem, "Feed-in Tariff Installation Report 31 March 2020," 07 April 2020. [Online]. Available: https://www.ofgem.gov.uk/publications-and-updates/feed-tariff-installation-report-31-march-2020. [Accessed 12 May 2020].

[6] T. Nacer, A. Hamidat, O. Nadjemi and M. Bey, "Feasibility study of grid connected photovoltaic system in family farms for electricity generation in rural areas," *Renewable Energy,* vol. 96, pp. 305-318, 2016.

[7] P. G. McCormick and H. Suehrcke, "The effect of intermittent solar radiation on the performance of PV systems," *Solar Energy,* vol. 171, pp. 667-674, 2018.

[8] M. G. Villalva, J. R. Gazoli and E. R. Filho, "Comprehensive Approach to Modeling and Simulation of Photovoltaic Arrays," *IEEE Transactions on Power Electronics,* vol. 24, no. 5, pp. 1198 - 1208, 2009.

[9] D. Sera, R. Teodorescu and P. Rodriguez, "PV panel model based on datasheet values," in *IEEE International Symposium on Industrial Electronics*, Vigo, Spain, 2007.

[10] N. Pandiarajan and R. Muthu, "Mathematical modeling of photovoltaic module with Simulink," in *1st International Conference on Electrical Energy Systems*, Newport Beach, CA, USA, 2011.

[11] K. Nishioka, N. Sakitani, Y. Uraoka and T. Fuyuki, "Analysis of multicrystalline silicon solar cells by modified 3-diode equivalent circuit model taking leakage current through periphery into consideration," *Solar Energy Materials and Solar Cells,* vol. 91, no. 13, pp. 1222-1227, 2007.

[12] B. Gao, X. Liu and Z. Zhu, "A Bottom-Up Model for Household Load Profile Based on the Consumption Behavior of Residents," *Energies,* vol. 11, no. 8, p. 2112, 2018.

[13] G. Tsagarakis, A. J. Collin and A. E. Kiprakis, "Modelling the Electrical Loads of UK Residential Energy Users," in *47th International Universities Power Engineering Conference (UPEC)*, London, 2010.

[14] IEEE Power & Energy Society, "The IEEE European Low Voltage Test Feeder," 19th May 2015. [Online]. Available: https://site.ieee.org/pes-testfeeders/resources/. [Accessed 14th May 2020].

[15] T. Morstyn and M. D. McCulloch, "Multiclass Energy Management for Peer-to-Peer Energy Trading Driven by Prosumer Preferences," *IEEE Transactions on Power Systems,* vol. 34, no. 5, pp. 4005 - 4014, 2019.

[16] B. P. Hayes, S. Thakur and J. G. Breslinb, "Co-simulation of electricity distribution networks and peer to peer energy trading platforms," *Electrical Power and Energy Systems,* vol. 115, p. 105419, 2020.

[17] T. Morstyn, A. Teytelboy and M. D. McCulloch, "Bilateral Contract Networks for Peer-to-Peer Energy Trading," *IEEE Transactions on Smart Grid,* vol. 10, no. 2, pp. 2026 - 2035, March 2019.

[18] N. Al Khafaf, M. Jalili and P. Sokolowski, "Optimal Clustering of Energy Consumers based on Entropy of the Correlation Matrix between Clusters," Unpublished, Australia, 2019. "Unpublished."

[19] C. Long, J. Wu, C. Zhang, L. Thomas, M. Cheng and N. Jenkins, "Peer-to-peer energy trading in a community microgrid," in *IEEE Power & Energy Society General Meeting*, Chicago, 2017.

[20] M. Sabounchi and J. Wei, "Towards resilient networked microgrids: Blockchain-enabled peer-to-peer electricity trading mechanism," in *IEEE Conference on Energy Internet and Energy System Integration*, Beijing, 2017.

[21] T. Rodrigues, R. Moreira, and G. Strbac, "Coordinated operation of distributed energy storage in low carbon networks," in *2017 IEEE Power & Energy Society General Meeting*, Chicago, 2017.

[22] J. Yi, C. Pages, A. Allahham, D. Giaouris, and C. Patsios, "Modelling and simulation of a smartgrid architecture for a real distribution network in the UK," *The Journal of Engineering,* vol. 2019, no. 8, pp. 5415 - 5418, 2019.

[23] V. H. Pakka and R. M. Rylatt, "Design and Analysis of Electrical Distribution Networks and Balancing Markets in the UK: A New Framework with Applications," *Energies,* vol. 9, no. 2, p. 101, 2016.

[24] A. Aithal, G. Li, J. Wu and J. Yu, "Performance of an electrical distribution network with Soft Open Point during a grid side AC fault," *Applied Energy,* vol. 227, pp. 262-272, 2018.