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Adaptive Stochastic Energy Flow Balancing in Smart Grid

Hassan Shirzeh
University of Wollongong, hs920@uowmail.edu.au

Fazel Naghdy
University of Wollongong, fazel@uow.edu.au

Philip Ciufo
University of Wollongong, ciufo@uow.edu.au

Montserrat Ros
University of Wollongong, montse@uow.edu.au

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Abstract

A smart grid can be considered as an unstructured network of distributed interacting nodes represented by renewable energy sources, storage and loads. The nodes emerge or disappear in a stochastic manner due to the intermittent nature of natural sources such as wind speed and solar irradiation. Prediction and stochastic modelling of electrical energy flow is a critical characteristic in such a network to achieve load balancing and/or peak shaving in order to minimise the fluctuation between off peak and peak demand by power consumers. Before contributing energy to the network, a node acquires information about other nodes in the grid and the state of the grid in order to adjust its power injection to or consumption from the grid. The unpredictable behaviour of nodes in a smart grid is modelled and administered through a scheduling strategy control and learning algorithm using the historical data collected from the system. The stochastic model predicts future power consumption/injection to determine the power required for storage components. In the proposed stochastic model and the deployed learning and adaptation processes, two indicators, based on moving averages of different subsets of the time series are implemented to satisfy two objectives. The first objective is to predict the most efficient state of electrical energy flow between a distribution network and nodes. Whereas the second objective is to minimise the peak demand and off peak consumption of acquiring electrical energy from the main grid by using ant colony search algorithm (ACSA). The performance of the indicators is validated against limited autoregressive integrated moving average (LARIMA) and second order Markov Chain model. It is shown that proposed method outperforms both LARIMA and Markov Chain model.

Keywords

smart, stochastic, grid, energy, flow, balancing, adaptive

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Hassan Shirzeh, Fazel Naghdy, Philip Ciufo, and Montserrat Ros
School of Electrical, Computer and Telecommunications Engineering,
University of Wollongong, Australia

***Abstract*—A smart grid can be considered as an unstructured network of distributed interacting nodes represented by renewable energy sources, storage and loads. The nodes emerge or disappear in a stochastic manner due to the intermittent nature of natural sources such as wind speed and solar irradiation. Prediction and stochastic modelling of electrical energy flow is a critical characteristic in such a network to achieve load balancing and/or peak shaving in order to minimise the fluctuation between off peak and peak demand by power consumers. Before contributing energy to the network, a node acquires information about other nodes in the grid and the state of the grid in order to adjust its power injection to or consumption from the grid. The unpredictable behaviour of nodes in a smart grid is modelled and administered through a scheduling strategy control and learning algorithm using the historical data collected from the system. The stochastic model predicts future power consumption/injection to determine the power required for storage components. In the proposed stochastic model and the deployed learning and adaptation processes, two indicators, based on moving averages of different subsets of the time series are implemented to satisfy two objectives. The first objective is to predict the most efficient state of electrical energy flow between a distribution network and nodes. Whereas the second objective is to minimise the peak demand and off peak consumption of acquiring electrical energy from the main grid by using ant colony search algorithm (ACSA). The performance of the indicators is validated against limited autoregressive integrated moving average (LARIMA) and second order Markov Chain model. It is shown that proposed method outperforms both LARIMA and Markov Chain model.**

I. Introduction

Distributed electrical power production using renewable energy sources is growing rapidly due to electricity price increases and environmental policies [1]. This phenomenon has led to highly geographical distributed power generation with its consequence of operational uncertainty due to stochastic and uncontrollable nature of primary power generation resources [2]. Management of electrical energy flow (hereafter simply referred to as energy flow) faces difficulties brought about by the unpredictable nature of renewable energy sources such as solar and wind. The unpredictable characteristics lead to fluctuation and disturbance in energy flow of distribution power grid [3].

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Moreover, high fluctuation of power demand between peak hour and off-peak hour can result in further disturbance in energy flow. This challenge can be dealt with by reducing peak consumption and valley filling to guarantee smooth energy consumption/injection on load and demand sides [4] [5]. Flat and balanced energy consumption assists the energy distribution network service providers (DNSP) to save cost due to electrical components maintenance, strategy management and other unpredicted problems resulted from stochastic behaviour of the environment [6].

Based on the report from Industry & Investment NSW Minerals and Energy Division [7] in the state of New South Wales in Australia, the number of photovoltaic (PV) systems connected to the radial distribution grid has increased from 2,900 in 2008 to 50,000 in 2010. This significant increase in the number of renewable energy sources causes fluctuation on the supply side of the distribution grid due to the intermittent nature of resources. Leveraging multi-timescale dispatch and prediction accuracy for scheduling of power generation is an important issue to coordinate between energy demand and supply [8].

A smart grid is an unstructured network of a large number of independent energy nodes represented by renewable energy sources, storages and loads, distributed across the grid. In the current research, the proposed solution is designed for the highest level of management of energy flow by achieving two objectives: i) prediction accuracy ii) the necessary storage to minimise the fluctuation between peak hour demand and off-peak hour demand. In an ideal network, nodes should continuously predict the parameters that govern their behaviour [9] [10]. After prediction, a set of parameters is exchanged amongst nodes to share information about the abilities of the nodes [11].

After prediction of energy flow, the learning and adaptation process taking place determines not only which nodes to activate/deactivate but also how much energy to inject/consume. An energy storage system (ESS) plays an important role in scheduling algorithms and load matching during peak demand hours [12]. In the learning process, the power acquired from the main grid and states of charge (SOC) of the batteries are estimated to determine the total power consumption in the main grid at any given period of time.

The proposed stochastic model is validated using real solar and wind speed data recorded every five minutes from a weather station in Cleveland, Queensland, Australia [13].

Using ant colony search algorithm (ACSA), the maximum and minimum energy exchanged between the batteries and the main grid is calculated. The structure of the paper is organised a follows. Section II provides a review of literature related to this work. Sections III and IV describe the work on stochastic modelling and development of the leaning and adaptive algorithm. Section V provides the results of the simulation and validation of the proposed algorithm. Finally, Section VI draws some conclusions and describes the future work.

II. Background and related work

A number of methods have been proposed for stochastic modelling of the behaviour of renewable energy sources including (i)artificial neural networks [14];combined hybrid genetic algorithm and neural network methods to use energy storage units to shift energy consumption models [15], (ii) Markov chain decision model in a multi-timescale [16] (iii) multi-layer scenario tree in each time period based on the observed values of uncertain events [17]. Research on these methods has achieved acceptable results in terms of prediction accuracy but in most of the cases, the selected timeframe for sampling and validation is either daily or more than an hour. The energy flow produced by PV or a small size wind turbine can show completely different behaviour when sampled every five minutes. For example, with a small cloud in the sky, the injected power from a PV can drop from maximum to minimum value in much less than five minutes. Furthermore, the methods developed are justified just for integration of one type of renewable energy source.

Using limited autoregressive integrated moving average (LARIMA); Chen [18] shows that LARIMA outperforms the ten-state first-order discrete Markov model in terms of probability distribution and the number of model parameters. The research illustrates that using a different method of time series analysis, such as LARIMA (0,1,1) as outlined by Box-Jenkins [19], can be more efficient in terms of prediction accuracy compared to that of Markov Chain models. In the current study, different methods of times series analysis based on moving average are developed and shown that they outperform LARIMA (0,1,1) and Markov chain modelling based on climate and consumer power consumption patterns in Australia.

The moving averages of different subsets of time-series are used as indicators in [20] [21] to stochastically model economic data to forecast future trends and large price fluctuations. The deployed indicators are short-term (5-10 minutes) and can be applied effectively to the modelling of small sized, natural energy resources used in a dwelling. Small power sources are sensitive to any minor change in the wind speed or solar irradiation. It is possible to predict such short term variations based on the recent behaviour of the energy source and a series of indicators reflecting its dynamic behaviour. This approach forecasts at a faster speed with smaller memory requirements. For example, the short-term behaviour of the energy source can be predicted by considering 10 to 20 latest samples produced by the system.

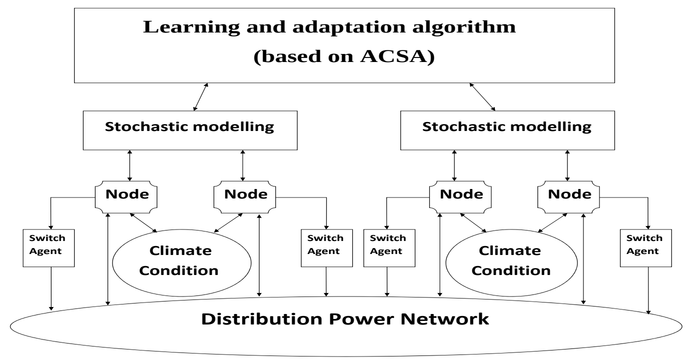

Fig. 1. Exchange of information between different layers of information system.

A. Learning and adaptation

There are heuristic methods reported in the literatures for learning and adaptation that offer a satisfactory outcome based on empirical testing and evaluation [22]. There are different approaches for learning, adaptation, and optimisation such as genetic algorithm (GA), simulated annealing (SA), reinforcement learning (q-learning) and ACSA [23]. For implementation of the reinforcement learning method in Micro-grids; Dimeas et al. [24] use Q-Learning method as a distributed algorithm that allows the agent to learn and adapt to the environment. On the other hand, Lee and El-Sharkawi [23] show that Q-Learning is less efficient than ACSA due to its higher iteration number. Chang [25] uses ACSA to outperform GA and SA to solve optimal feeder reconfiguration and the optimal capacitor placement problems. ACSA is a probabilistic technique implemented for various optimisation problems, such as the short-term generation scheduling problem, optimal switch relocation, network-constrained optimization problems, and power system restoration. ACSA is also a suitable method for large-scale distributed systems.

III. Stochastic model of Sub-Grid

The information model proposed in this system is illustrated in Figure 1. The overall system consists of three levels. The climate condition and current situation of distribution power network are recorded by nodes in the first layer. The focus of the second layer is on stochastic modelling of renewable energy sources and power consumption nodes. In the third layer, a learning and adaptation algorithm uses ACSA to calculate the charge states of Store (battery) to minimise the gap in energy consumption between peak and off-peak demands. The results of the analysis set appropriate commands switch agents to activate/deactivate the energy sources.

The stochastic model of energy flow in the network is developed based on two selected indicators as proposed in [20] and [21]. Two indicators are selected based on the highest prediction accuracy for short term forecasting, which are: i)

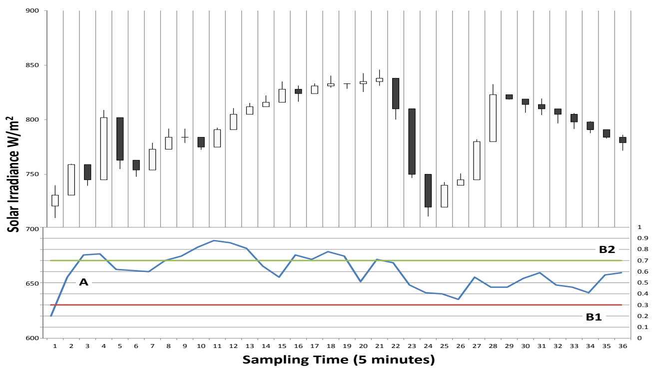

Fig. 2. Example of Reference lines and oscillating line in DeMarker indicator.

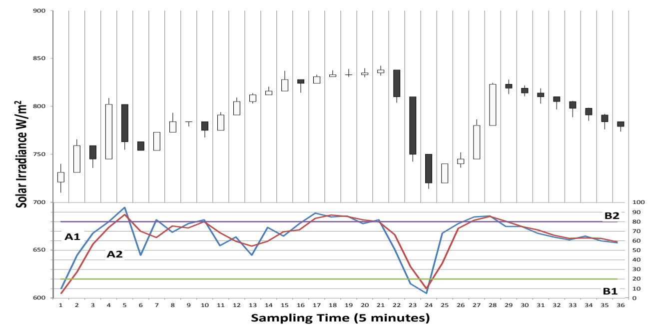

Fig. 3. Example of Reference lines and oscillating line in K%D indicator.

DeMarker, ii) K%D indicator. The indicators are primarily used to estimate the one step ahead forecast based on previous values. In the following sections, the nature and role of these indicators are illustrated by applying them to solar irradiation that has ad-hoc behaviour.

A. DeMarker

DeMarker indicator as described by (1) and illustrated in Figure 2, consists of one oscillating line (A) and two reference lines ($B1, B2$). This indicator is the result of a comparison between two maximum values of the latest subset of time series against a previous one. If the current subset is higher, the difference is recorded otherwise a zero is registered. Two reference lines in this method are used to find the inverse point. For example, if line A falls below line $B1$ then a downturn is expected whereas if line A rises above line $B2$ then an upward movement is expected for the one step ahead forecast. The following algorithm shows the process used to calculate DeMarker indicator. The value of the DeMarker for the "i" interval is calculated as follows: If $high(i) > high(i-1)$, then $DeMax(i) = high(i) - high(i-1)$, otherwise $DeMax(i) = 0$ and If $low(i) < low(i-1)$, then $DeMin(i) = low(i-1) - low(i)$, otherwise $DeMin(i) = 0$. Where SMA is Simple Moving Average and N is the number of subset used in the calculation.

$$DeMarker(i) = \frac{SMA(DeMax, N)}{(SMA(DeMax, N) + SMA(DeMin, N))} \quad (\underline{LineA}) \tag{1}$$

B. K%D Oscillator

K%D indicator, illustrated in Figure 3 includes two oscillator lines ($A1, A2$) and two reference lines ($B1, B2$). Line $A2$ is the moving average of line $A1$. When both $A1$ and $A2$ are below line $B1$ and $A1$ rises above $A2$ then an upward movement is predicted. When both $A1$ and $A2$ are above $B2$ and $A1$ falls below $A2$, then a downward movement is expected. Equation (2) is based on α subset of time series. Equation (3) calculates moving average of the resulted value

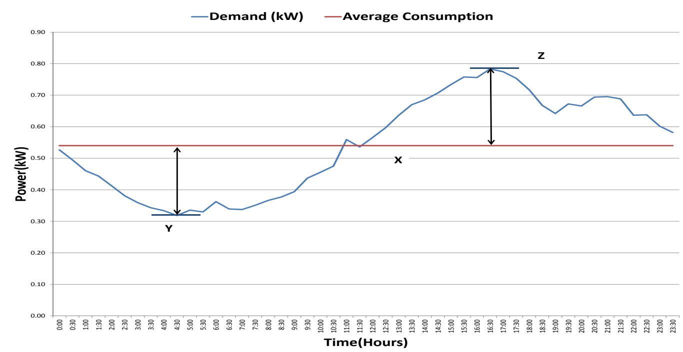

Fig. 4. Valley Filling /Peak Shaving to minimise the pulling power from main grid.

from (2) for N subsets, where $Low(\alpha)$ is the lowest low in α subset and $High(\alpha)$ is the highest high in α period.

$$\beta = \frac{(Close(\alpha) - Low(\alpha))}{(High(\alpha) - Low(\alpha))} * 100 \quad (\underline{LineA1}) \tag{2}$$

$$\gamma = SMA(\beta, N) \qquad (\underline{LineA2}) \tag{3}$$

IV. Predictive Learning modelling

The context of the current research is valley filling/peak shaving to design control modelling. Figure 4 shows the typical daily energy consumption by one dwelling. The gap between point Y and Z with line X should be minimised to guarantee smooth acquisition of power from the main grid. Line X shows the average power consumption in the next 24 hours. The reason behind selecting the timeframe of 24 hours is to ensure that both peak demand and off-peak demands are included. The average line provides estimation of power consumption every 5 minutes based on 24 hours power consumption.

A. Learning and adaptation formulation

The behaviour of the smart grid is formulated for minimising (4), in which P_w and P_p are the power produced by wind turbine and PV respectively, in the next five minutes. $Load$ is the average power consumption in the next 24 hours. M_1 is the acquired power from the main grid and M_2 is the state of the charge of batteries in the next five minutes, SOC_{t+1}. Equation (5) shows that M_2 is equal to the current battery state of charge, SOC_t, plus the required power in the next 5 minutes, P_{batt}.

$$P_w + P_p + M_1 + M_2 - Load \tag{4}$$

$$M_2 = SOC_{t+1} = SOC_t + P_{batt} \tag{5}$$

Due to the limitation of the charge state of the battery, $-C_{max} < SOC_t < C_{max}$, a typical battery has a maximum state of charge, C_{max}. When the SOC_t is negative, it means that the battery is consuming power. When the SOC_t is positive, it means the battery is an energy source. C_{max} can be different based on required storage. In this work, it is considered between 1 and 1.5 kW. The maximum acquired power from the main grid depends on the DNSPs standard which is considered 7 kW in this work.

ACSA method plays the main role in the learning and adaptation process. The potential of each node to inject/consume power is calculated to determine the best state for nodes. Each charge state of battery is considered for potential state for ant to move from one to another. Ant by moving in a tour from state *m* to state *n* at each iteration minimises equation (6). For ant *k*, the probability P^k_{mn} of moving from state *m* to state *n* depends on the combination of two values: i) the state of charge in next state (C_n) which is new potential charge state of battery, ii) trail level, τ_{mn}, which is the pheromone strength between state *m* and *n* calculated in equation (7).

$$P^k_{mn} = \frac{\tau^a_{mn}/C^b_n}{\sum_q \tau^a_{mq}/C^b_q} \tag{6}$$

$$\tau_{mn} = (1-\xi)\tau_{mn} + \varepsilon\tau^{elite}_{mn} \tag{7}$$

Where, *a* is pheromone weighting and *b* is capacitance weighting for all charge states. C_q is the charge state of battery on tour between state *m* and *n*. τ_{mq} is the pheromone strength between charge states *m* and *q*. ξ is the pheromone evaporation constant . ε is $elite$ path weighting constant which is between zero and one. τ^{elite}_{mn} is the pheromone strength of best tour found by the algorithm between *m* and *n*.

V. Simulation and Validation

In the current research, two types of stochastic behaviours are considered for validation: i) systems with regular oscillation pattern such as solar radiation and power consumption in a dwelling, and ii) systems that do not have a regular oscillation pattern such as wind. The desired operation of a smart grid can be achieved if the network topology and the power flow states are accurately modelled and estimated. The gap between peak and off peak hour energy demand from the main grid is reduced by estimating stored energy during off peak hours and consumption of that energy during peak hours.

TABLE I
ASSIGNING THE STATE NUMBER FOR EVERY VALUE OF WIND SPEED.

Wind Speed (m/s)	States	Output power (W)
0-6	1	0-200
6-7.5	2	200-300
7.5-8.7	3	300-400
8.7-9.5	4	400-500
9.5-10.5	5	500-600
10.5-11.5	6	600-700
11.5-12.5	7	700-800
12.5-40	8	800-900

Each node collects the environmental data and exchanges information with other nodes to calculate the final state of a node in terms of consumption/injection of power. The state of nodes shows the rate of consumption/injection of power by that node. The result of the predicted value and learning algorithm is estimated and applied to the power flow storage switches. The input data is based on actual data from a typical household and the environmental conditions in Cleveland, QLD, Australia. The maximum output of the Battery, PV, and the wind turbine are 1 kW, 2.5 kW, and 900 W, respectively. The climatic conditions are recorded every five minutes due to selection of short-term timescale for stochastic modelling. MATLAB is used as the simulation platform. From the group of regular patterns, solar irradiation is selected and from the group of irregular patterns, wind speed is selected for validation of the stochastic model.

In the first step, the stochastic model of wind speed is validated. Based on the injection of power, eight exclusive states for power injection are considered to capture all the dynamic behaviour of the wind turbine caused by different wind speeds. Table I shows assigned states for different wind speeds. Due to 900 W maximum output for wind turbine, every state is considered to provide an extra 100 W by wind turbine. Figure 5 shows the comparison between actual states and predicted states by K%D stochastic modelling in three hours. It shows that there is a close gap between actual data and the one step ahead forecast.

In the next step, a comparison is made between the performances of two technical indicators, LARIMA (0,1,1), and Markov chain based on their standard deviations for one step ahead forecast error. Using the sum of difference in actual value and forecasted value for every five minutes, the standard deviation of one step ahead forecast error is calculated for every day. The climate data for the last six months, which has been recorded every five minutes, is used to calculate the transition matrix of Markov chain. Based on heuristic method of trial and error for more accurate prediction, the final value for the length of time period for each indicator is selected as $B1 = 0.3, B2 = 0.7, N = 7$ in DeMarker indicator and $B1 = 20, B2 = 80, \alpha = 7, N = 28$ in K%D indicator. Figure

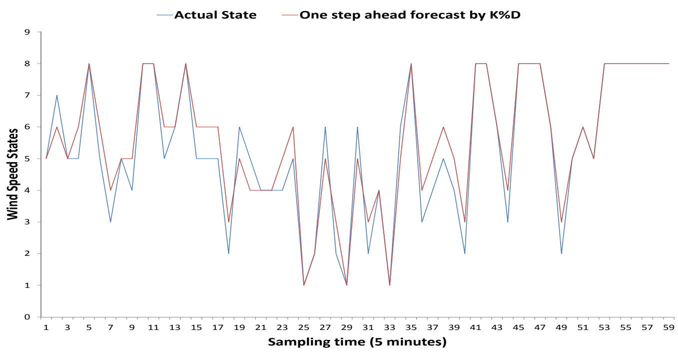

Fig. 5. The comparison of actual wind speed and predicted value.

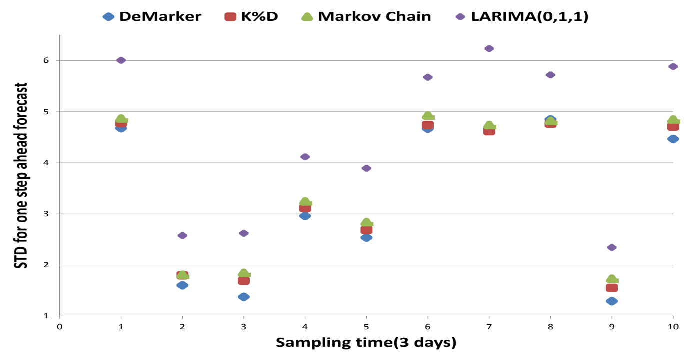

Fig. 7. Comparison of two indicators with Markov Chain and LARIMA(0,1,1).

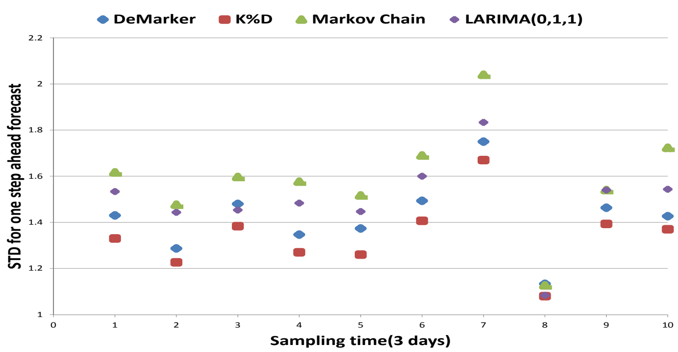

Fig. 6. Comparison of two indicators with Markov Chain and LARIMA(0,1,1).

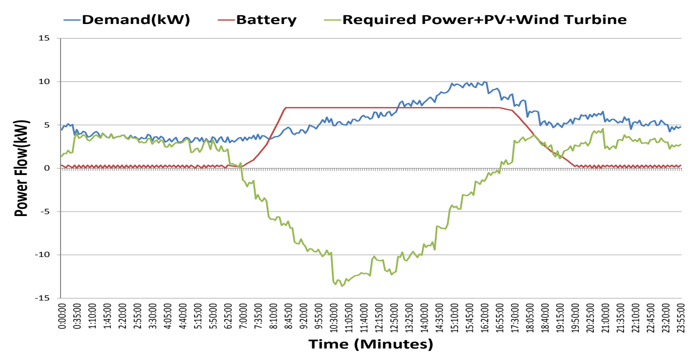

Fig. 8. Power flow before using predictive control algorithm.

6 shows the comparison of indicators with the second order Markov chain and LARIMA (0,1,1) during one month. K%D indicator shows less error in standard deviation compared to other methods by an average of 1.35 for one month. This indicator calculates the maximum and minimum values of the previous 35 minutes. All the results in this step prove that considering the most recent history is the best option for stochastic modelling in terms of prediction accuracy.

In the third step, solar irradiation is selected from the group with the regular pattern. There are 65 states due to the need to cover all behaviours of solar irradiation and high power output from PV. Based on heuristic method of trial and error for more accurate prediction, the final value for the length of time period for each indicator is selected as $B1 = 0.3, B2 = 0.7, N = 6$ in DeMarker indicator and $B1 = 20, B2 = 80, \alpha = 14, N = 28$ in K%D indicator. Figure 7 shows the comparison of standard deviation of one step ahead forecast errors by two indicators, Marko chain model, and LARIMA(0,1,1) for all days in one month. In this experiment, the Markov chain method shows less error in prediction compared to LARIMA (0,1,1). However, it is still outperformed by DeMarker by 3.33 average during one month. It shows that considering long history data could be suitable for this group but recent history still produces more accurate data for prediction of values in the future. DeMarker considers the last 35 minutes history which is enough to cope with any uncertainties such as small cloud in the sky. The high fluctuation in the standard deviation error is due to the large number of states for PV.

Predictive learning algorithm is validated by considering the acquired energy from the main grid by seven dwellings in one day before and after using the learning algorithm. The size of the battery in this example is 1 kW for all dwellers. In the first part, acquired power from the main grid is calculated when there is no strategy on energy flow. Figure 8 shows the lack of a strategy to store or consume energy when there is a considerable amount of power produced by PVs and wind turbines. The big valley causes the reverse energy flow on the main grid due to the absence of predictive control method.

In the second part, predictive learning algorithm is used with the same size battery. Minimising the size of battery is evaluated based on ACSA and stochastic modelling. In every learning step, a storage node selects one of the five states: 0.2, 0.4, 0.6, 0.8, and 1 kW. Based on heuristic method of trial and error for less iteration number, the final value for parameters in equation (6) are selected as $a = 2, b = 6, \xi = 5$, and $\varepsilon = 0.5$. The node tries to minimise equation (4) by implementing the learning steps. Figure 9 shows the necessary

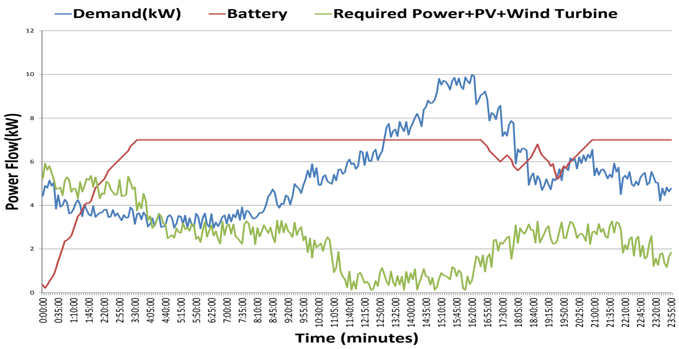

Fig. 9. Power flow after implementing predictive control algorithm.

required size of a battery to deal with valley filling/peak shaving for every day during one whole week. It shows that the minimum battery size of 1 kW is required in each dwelling for valley filling/peak shaving without facing any problem. By selecting a 1 kW battery, the seven households can maintain injection/consumption of power around the same level almost during 24 hours. It shows an acceptable smoothing movement of the average line with no gap between peak demand hour and off peak hours.

VI. Conclusion and Future Work

The reported research is a step towards the scheduling strategy control algorithm of a smart grid with stochastic modelling of renewable energy sources. The architecture of this stochastic model stems from smoothing moving average techniques. The proposed algorithm allows the network elements to minimise the fluctuation of the acquired power from the main grid between off peak hours and peak demand hours. In the current work, the research is focused on the stochastic modelling of the unpredictable behaviour of renewable energy source with or without daily pattern. Predictive learning algorithm allows nodes to predict the value of injected/consumed energy flow to measure the required power to store in storage components such as batteries.

Simulation has been carried out using MATLAB based on the ongoing situation in the environment, and in terms of prediction accuracy. The performance of the technical indicators is compared with LARIMA and Markov chain modelling techniques. By using ACSA, the amount of power required to be stored in battery is calculated to match demand and supply for future. Future work will focus on adding more functionality to virtual power systems. Other issues that can be considered include developing a framework for information system, message exchanging standards, and team work strategies for collaboration of nodes. The stored energy in the number of dwellers can be optimised by using team work among them.

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