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Balancing energy in the smart grid using distributed value function (DVF)

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Abstract

As the penetration of renewable energy resources increases in distribution networks, so does the need to manage these resources in an effective manner. Since these resources are installed to displace carbon-based generation and to provide an income stream to the resource owner, it is important that both installation objectives (as a minimum) can be met. With all of these renewable energy resources available, the opportunity also exists to assist with the energy management of this resource-rich distribution network. However, the renewable energy resources do not produce power in a deterministic manner. The available production depends on the time of day and many other environmental factors. Accordingly, a system that is able to program and coordinate the production and storage of power in a distribution network would be of benefit to the network operator. This paper presents a multiagent system (MAS) that is responsible for the management of renewable energy resources and power storage systems connected to the distribution network of a zone substation. The MAS manages the orderly connection and disconnection of resources using a plug and play algorithm in order to minimize disturbances to the supply-and-demand balance within the distribution network. The proposed MAS design is validated using a network based on the IEEE 34-bus test feeder. The results obtained through computer simulation show that with the MAS, it is possible to manage the power resources so that there is minimal power drawn from the upstream network during periods of high demand.

Keywords

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Balancing Energy in the Smart Grid using Distributed Value Function (DVF)

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***Abstract*—As the penetration of renewable energy resources increases in distribution networks, so does the need to manage these resources in an effective manner. Since these resources are installed to displace carbon-based generation and to provide an income stream to the resource owner, it is important that both installation objectives (as a minimum) can be met. With all of these renewable energy resources available, the opportunity also exists to assist with the energy management of this resource-rich distribution network. However, the renewable energy resources do not produce power in a deterministic manner. The available production depends on the time of day and many other environmental factors. Accordingly, a system that is able to program and co-ordinate the production and storage of power in a distribution network would be of benefit to the network operator. This paper presents a multi-agent system (MAS) that is responsible for the management of renewable energy resources and power storage systems connected to the distribution network of a zone substation. The MAS manages the orderly connection and disconnection of resources using a Plug and Play algorithm in order to minimise disturbances to the supply-and-demand balance within the distribution network. The proposed MAS design is validated using a network based on the IEEE 34-bus test feeder. The results obtained through computer simulation show that with the MAS, it is possible to manage the power resources so that there is minimal power drawn from the upstream network during periods of high demand.**

***Index Terms*—Smart Grid, Plug and Play, Reinforcement Learning, Team Formation, Energy Management.**

I. Introduction

THE term ‘smart grid’ has, in recent times, been used to describe a power network that extensively leverages communication technologies as part of the control and management of the network. In the context of the present research, a smart grid is an unstructured network consisting of a large number of independent energy nodes represented by renewable energy sources, storage systems and loads distributed across the grid [1]. In an ideal network, nodes constantly communicate to exchange parameters that govern their performance and that of the network. The nodes emerge or disappear from the smart grid in an *ad hoc* manner, which can be interpreted as a node becoming active or inactive, respectively. Interoperability is therefore a critical characteristic in such a network and an effective strategy for managing the *ad hoc* activity of the nodes is required [2]. In an interoperable network, a node can autonomously plug into the network, exchange information with other nodes and function effectively without centralised supervision.

In the work presented in this paper, the *ad hoc* behaviour of the nodes in a smart grid is modelled and managed by a plug and play (PnP) algorithm. The aim is to establish an interoperable model and information system that allows the orderly connection and disconnection of renewable energy resources to/from a distribution substation in order to minimise disturbances to the supply-and-demand balance within the distribution substation. The PnP algorithm is implemented through a multi-agent system (MAS) that is responsible for the management of renewable energy resources and power storage systems connected to the distribution network of a zone substation.

In the proposed approach, the disturbance to the power balance of the substation is continuously minimised by adjusting the power contribution (injection or consumption) of each node by applying a reinforcement learning method known as ‘distributed value function’ (DVF) [3]. The PnP algorithm determines the nodes that should become active (connect) or inactive (disconnect). If the nodes become active, then the DVF will calculate the value of injection/consumption power flow by the nodes in order to minimise the deviation between the power flow in the main power line before and after the activation of the nodes. Each agent then switches its node to be active or inactive according to the command received from the PnP algorithm.

The proposed algorithm is validated using a network based on the IEEE 34-bus test feeder. The results obtained through computer simulation show that with the MAS, it is possible to manage the power resources so that there is minimal power drawn from the upstream network during periods of high demand. The learning ability of PnP process with DVF algorithm is compared against ant colony search algorithm (ACSA) [4], and genetic algorithm (GA) [5]. According to the results, the collaboration in DVF method provides less iteration compared to GA and it is more competitive with ACSA.

The remaining part of the paper is structured as follows. A review of the literature to further highlight the contribution of the work is provided in Section III. Section IV provides an overview of the proposed approach in smart grids. The modelling of the network using multi-agents is described in Section V. The results produced in the simulation and validation of the method are provided in Section VI. Conclusions are drawn and future work proposed in Section VII.

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II. Background

A. Plug and Play in a Smart Grid

The co-ordination of an increasing number of renewable energy sources in energy networks requires a higher level of interoperability compared to the networks of today [6]. If the nodes involved are designed with standards compliance as a criterion, then that enables the connection of nodes and facilitates their co-operation, which is the objective of interoperability. In a PnP environment, the same communication protocols and standards must be applied to both new and existing components without re-engineering the information system of the nodes. This approach ensures that a node can join any other node in the network within the required time. Hence, PnP can play a significant role in the intelligent grid by responding to the *ad hoc* behaviour of a node and decentralising the real-time communication of a large-scale complex network [7].

The number of renewable energy sources in electrical power networks is increasing. Based on a report from the Clean Energy Regulator in Australia, the number of photovoltaic (PV) systems connected to the radial distribution grid has increased from 20,000 in 2008 to 1,011,000 in March 2013 [8]. In 2011-2012, PV penetration was accounted as 1.1% of Australia's annual electricity energy production ($\sim$3 in $\sim$260 terawatt hours) and 5.3% of Australia's annual total residential electricity consumption ($\sim$3 in $\sim$56 terawatt hours) [9] [10]. At present, about 11% of the Australian population use solar power in their homes. The Climate Commission predicts that the solar PV sector will provide around 5% of total electricity production in Australia by 2020 and a third of Australia's total energy needs by 2050 [11].

This clearly shows the popularity of renewable energy sources among home-owners but it also highlights the potential adverse effects of distributed energy sources. Any real power system is a combination of residential, commercial and industrial customers. Hence, the average power demand can fall dramatically over some days of the week, such as weekends. In order to meet such non-uniform power consumption and avoid the worst-case scenario to the radial distribution feeder, the operation of such a large number of PV systems must be regulated. In addition, strong solar irradiance, high temperatures and low power consumption causes a power flow from the source nodes to the main grid. This reverse power flow causes various problems for the main grid such as voltage rise, voltage fluctuation, phase imbalance, and increased harmonic distortion. The PnP approach to managing the renewable energy sources in the network has the potential to deal with these problems.

The importance of PnP in smart grids has been recognised by many research groups. The National Institute of Standard Technology (NIST), for example, has proposed using the International Electrotechnical Commission (IEC) 61850 standard as a framework and roadmap for smart grid interoperability standards among intelligent electronic devices (IED) [12]. IEC 61850 accommodates the technical limitation of the networking technology by using basic functionality for the power systems automation such as (i) eliminating procurement ambiguity over expectation in the IED from various component suppliers, (ii) standardising configuration language (SCL) to simplify the configuration of a device and its role in the power systems, (iii) exchanging data by using a standard data format of data and messages for lowering communication cost, and (iv) by utilising the standard networking technology for wide area protection schemes for lowering maintenance cost [13].

B. Smart Agents and PnP

Agent technology is one of the approaches deployed to design PnP models in the smart grid. An agent behaves like a physical entity but with no physical presence in the environment [14]. The deployment of MAS to achieve PnP operation in smart grids is explored by McArthur et al. [15] and Liu et al. [16]. Multi-agent systems have been previously used to control power flow through the use of an auction algorithm [17]. An intelligent distributed autonomous power system (IDAPS) based on customer-owned resources to control critical loads at the distribution level through a standardised interoperability algorithm is proposed by Pipattanasomporn et al. [18].

In many of the methods proposed in the literature, the communication between the entrepreneur and the end-users may be established by standard interoperability in real time. For example, in the systems proposed by Dimeas et al. [17] and Pipattanasomporn et al. [18], there is an optimum association between the controllable load and distributed energy resource (DER) in order to design a framework for control of the power flow. However, the above mentioned studies do not consider co-operation of multiple energy sources by exchanging messages to optimise the energy delivered to load or collections of loads. Due to the unpredictable nature of renewable energy sources, a group of co-operating energy sources is necessary to provide the energy needed by loads. This makes a protocol for negotiation essential, especially in hybrid renewable energy generation systems.

In [19], a future renewable electric energy delivery and management (FREEDM) mechanism is proposed that deploys the PnP algorithm for decision making in power flow management. This is an architecture which utilises the interoperability of distributed renewable energy and energy storage devices. The method proposed in their research allows residential and industrial users to share and control energy through a standardised PnP interface. In a similar way, Logenthiran et al. [20] consider energy consumers to be responsible for finding the best offers from energy suppliers through a request/negotiation method. Chatzivasiliadis et al. [21] have identified other parameters for negotiation in a team such as the amount of power required, the duration of service, and the energy price.

In such models, each autonomous agent takes responsibility for making decisions and interacting with other agents. For example, contract net protocol (CNP) [22] is a model for dynamic task allocation via negotiation among multiple agents by constantly exchanging environmental information among themselves. In the strategy proposed in [23] and [24], a cooperative multi-agent framework is deployed to control a distributed power system for self-correction purposes by locating and isolating faults. In the majority of methods proposed in the literature, the lack of a standardised communication model between an increasing number of electric components in the power grid is a major challenge to the implementation of a PnP information model. A solution to this problem is explored in the work presented in the current research.

C. Learning and Adaptation in Cluster Formation

Learning and adaptation methods have been extensively used in smart grid applications. For example, a heuristic model presented in [25], based on an evolutionary algorithm for learning and adaptation, offers a satisfactory outcome based on empirical testing and evaluation. Automatic learning (AL) aims at extracting information from the environment about any excess or shortage of power caused by the activation/deactivation of a node. The learning algorithm determines the nodes to be activated/deactivated as well as the amount of power that should be injected/consumed by each node.

There are three categories of methods in AL: (i) statistical, (ii) machine learning, and (iii) artificial neural networks learning [26]. The aim of machine learning is to build rules inspired by human learning processes. There are different approaches to machine learning such as reinforcement learning, and genetic programming. Machine learning is implemented in the smart grid for protection against vulnerability, management of energy, and maintenance of infrastructure [27].

The Markov decision process (MDP) is the foundation of reinforcement learning (RL) in a single agent environment [28]. Dynamic stochastic optimal power flow (DSOPF) [29] control using adaptive critic design (ACD) outperforms traditional automatic generation control (AGC). ACD is proposed as a new, optimal method developed based on reinforcement learning and approximate dynamic programming. In another application, an innovative energy management system called 'consumer automated energy management system' (CAES) is developed based on reinforcement learning [30]. Reinforcement learning is also used in a distributed model for negotiating electric power between widely distributed sources [31] or with demand response [32].

Q-learning as a distributed algorithm for learning of the power flow adjustment is used in [33] to allow an agent to learn and adapt to the environment in a microgrid. Optimised learning algorithms are presented to study distribution system operation by using the ACSA [4] and the GA [5]. Q-learning is less efficient than ACSA due to the higher number of iterations required for convergence [34]. In Q-learning, each agent stores a Q-table that depends only on its own action. This makes Q-learning inefficient because it fails to consider the action of neighbour and non-neighbour agents action. ACSA achieves cluster formation among the agents by evaluating pheromone deposit in order to reduce the number of iterations. Both Q-learning and ACSA operate based on only one criterion, making them inappropriate for this study because multiple criteria must be considered concurrently. In this study , the DVF is deployed due to its ability to optimise multiple criteria and its fast convergence compared to other methods [35].

III. Problem formulation and the Proposed Approach

The PnP algorithm manages interoperability among various nodes and reduces the risk associated with network disruption caused by the unpredictable addition or removal of nodes, which may result in power flow fluctuations [36]. In the context of our research, a zone substation refers to an infrastructure consisting of a number of incoming high voltage (transmission line) connections and multiple outgoing and medium voltage (MV) distribution lines. The MV lines are further transformed to a low voltage (LV) for connection to customer equipment. In a dwelling, there are agents representing photovoltaic (PV) resources, small wind turbines, power storage systems and power consumers. All the agents associated with nodes perform three main tasks: (i) they monitor and communicate to exchange information about the state and parameters of the nodes, (ii) they form clusters to reduce the number of messages and optimise the PnP algorithm, and (iii) they learn and adapt to determine the states of nodes in terms of power flow estimation.

Each node in the grid is represented by a set of parameters defining its ability to inject power into the grid or draw power from it. These parameters are continuously exchanged between agents, providing a global awareness for each node about the characteristics of other nodes present in the substation. This information plays a critical role upon the emergence of a new node in a distribution substation in order to form clusters of power-consuming and power-generating nodes. The information is exchanged by transferring messages among agents.

A cluster of the selected agents operates the orderly connection and disconnection of resources in order to minimise disturbance to the supply-and-demand balance within the distribution substation. The *ad hoc* emergence/disappearance of a node can adversely affect the power balance in the substation. In this algorithm, the PnP algorithm determines the nodes that should be active or inactive and DVF calculates the value of power flow for minimising the deviation from the main power line.

In such a system, the large number of messages required to be exchanged among the nodes can be a challenge. Through two methods, the algorithm proposed in this study keeps the number of exchanged messages between the nodes to a minimum, even if the network consists of a large number of nodes. In the first method, an agent called 'multi agent systems management' (MASM) keeps a directory of the agents in the network. Hence, any enquiry about other agents is directed to this agent. In this manner, each agent only needs to update the MASM agent rather than directly contacting each individual agent in the network.

In the network, each MASM is responsible for communication among the nodes associated with a limited number of dwellings. This method can face the single point of failure (SPOF) [37] problem and can undermine the scalability of the large network. This is addressed by adding redundancy in all SPOFs. If the MASM fails to connect then a secondary MASM that has been mirrored with primary MASM is deployed to obtain the replacement. This duplication and redundancy prevents a total system failure in case of malfunction.

The communication protocol in multi agent systems deals with query, tracking, subscription, and approval of requests and agent status. In our PnP algorithm, further communication is required to transfer additional messages after cluster formation. Cluster formation makes the PnP algorithm manageable by lowering the number of nodes and messages as it eliminates the need to send messages to agents not involved in the PnP process.

The information available from the PnP algorithm, which includes the value of power flow in each node, is transferred by the MASM agent to the lower layers of the smart grid responsible for functions such as voltage or power quality control. The agents have their own local control and are able to report their status to the MASM agent located at the distribution substation. In this way, the low-level control of the nodes in terms of voltage and current adjustment is decoupled from energy management. This co-ordinated approach means that the zone substation has the autonomy to make decisions about peak demand requirements by just supervising the distribution substations.

The proposed PnP algorithm is applied to a network based on the IEEE 34-bus test feeder and using real data of a typical domestic dwelling. MATLAB/Simulink and JADE are deployed to explore the performance of the algorithm in terms of the number of messages exchanged, disturbances caused and power losses incurred. The performance of the DVF is compared against the ACSA, and GA techniques, with DVF outperforming both.

IV. Modelling of Nodes in the distribution substation

The smallest elements of the proposed system are nodes representing sources (such as renewable energy sources or generators), storage (such as batteries), and loads (such as home or business dwellings), communicating continuously by exchanging messages to manage the power demand of the distribution substation. Using multi-agent methodology, an agent is assigned to each type of node: A 'source agent' to a power source, a 'sink agent' to a load (or group of loads), and a 'storage agent' to storage systems. The sink and source terminologies represent consumption and injection of power, respectively. Storage can be a source or a sink depending on whether the power is in surplus or in deficit.

A. Model of a Node

We define a distribution substation (*D*) consisting of a set of *N* nodes connected by power lines:

$$D = \{N_i \parallel i = 1, \ldots, h\}.$$

The parameters associated with node N_i in conjunction with node N_j considered in cluster formation can be represented by a 5-tuple:

$$N_i =< N_i\_Sp_t, N_i\_Av_t, N_{i,j}\_Co, N_{i,j}\_Di, N_{i,j}\_Ca_t >$$

where $N_i\_Sp_t$ is the Set-point of N_i at time *t*, defined by three parameters: (i) the amount of power that the node exchanges with other nodes ($N_i\_P_t$, kW), (ii) the sampling time (N_i_ST, minutes), and (iii) the priority (N_i_Pr) of the node in the cluster formation. N_i_Pr is assigned 0 (low priority) or 1 (high priority) depending on the type of the node. If a node is a source, then N_i_Pr is set to 1 for renewable energy sources, and 0 for other types such as fuel power generator or batteries. If a node is a load, then N_i_Pr is set to 1 for batteries, and 0 for others. If a node is storage and operates as a load, then N_i_Pr is always set to 1, and set to 0 if it operates as a source. For example, $N_i\_Sp_t$ for a battery, which operates as a source, can be defined by a power rating of 0.8 kW, sampling time of five minutes with a priority of zero because the battery is given the lowest priority (zero) compared to other sources of power, such as a wind turbine, during cluster formation with load nodes.

The parameters $N_{i,j}\_Ca_t$, $N_{i,j}\_Co$ and $N_{i,j}\_Di$ define the characteristics of a node during cluster formation. $N_{i,j}\_Ca_t$ represents Capability of a node at time *t*, calculated based on the difference between the power required by node N_j and the amount of power that N_i can provide during cluster formation. For example, during cluster formation between two load nodes and two source nodes, if the total load power is 2.1 kW and total source power is 3.4 kW, then the Capability of each source node in the cluster is 1.3 kW.

$N_{i,j}\_Co$ is Cost and is defined as the cost of power exchanged between N_i and N_j. For example, the electricity pricing or electricity tariff which varies widely from locality to locality within a particular time, such as between peak demand hours and off-peak hour demand. $N_{i,j}\_Di$ is the physical distance between N_i and N_j which shows the power lost during power exchange between them. For example, the power losses in the power line, measured in kW, depends on the length of the power cable.

$N_i\_Av_t$ defined as the availability of a node at time *t*, provides an indication of how active or inactive the node is. When the power injected/consumed by a node surpasses a pre-defined threshold, it is considered as an active node in the network, otherwise it is an inactive node. The threshold is determined based on the size and characteristics of the renewable energy source. For example, for a wind turbine with maximum 900 W output power, the minimum output might be 300 W and so this is selected as the threshold value. Availability is usually considered within a specific timeframe and is measured as the probability of the node's availability within that timeframe. Availability is an indication of the node's potential for cluster formation.

Availability of a source node within a timeframe can be estimated based on the historical data accumulated over the operation of the node. This historical data represents the active (up) and inactive (down) states of the source node in the previous timeframes. In this study, $N_i\_Av_t$ for a source node over a timeframe of (*T*) is calculated based on the Time Decay Average [38] of the historical data as shown in (1). Availability of a sink node in timeframe (*T*) is the same as availability of a sink during timeframe (T-1).

$$A_i(T) = \frac{\sum_{i=0}^{n} f(t_i) g(T - t_i)}{\sum_{i=0}^{n} g(T - t_i)} \quad \text{, where,} \quad g(x) = \frac{1}{x^{\varphi}} \quad (1)$$

where $g(x)$ is a polynomial function and $\varphi > 0$. f(t_i)=0 if the node is inactive during a timeframe (T), otherwise, it is 1 if the node is active, and φ is the rate of decay that could vary over twenty four hours. For example, for a solar panel (source), the decay rate is identified based on the solar irradiance pattern. This means that at the beginning of the day, the decay rate is set close to 0 to start a new cycle independent from the previous day. At midday, the decay rate is set close to 1 because the pattern of the data recorded since sunrise determines Availability. At sunset, the decay rate is set close to 0 as the historical data loses its significance.

B. Plug and Play Algorithm

A distribution substation (D) consists of N_i nodes, controlled by a set of agents:

$$D_{\text{Agents}} = \{AN_i \parallel i = 1, \ldots, h\}.$$

The PnP algorithm is triggered when a node, N_{new} becomes active in the distribution substation due to a change in the amount of power within the node from $N_{\text{new}}\_P_{(t-1)}$ to $N_{\text{new}}\_P_t$, where $(N_{\text{new}}\_P_t - N_{\text{new}}\_P_{(t-1)}) \neq 0$. When $N_{\text{new}}\_P_t$ is positive, the node is consuming power whereas when $N_{\text{new}}\_P_t$ is negative, the node is an energy source. N_{new} becomes active within *D* through the following steps during the PnP algorithm.

I) In the first step, the agent associated with N_{new}, AN_{new} sends to and receives a message from the MASM agent, asking for the parameters of N_i.

II) AN_{new} analyses the received data and selects a set of nodes with the potential to form a cluster with N_{new}. This is carried out according to the following rules. A node N_i is selected:

1) If N_i has the opposite function of N_{new}, this means that if N_{new} is source, then N_i must be load, and vice versa.
2) In the first instance, if $\Sigma|N_i\_P_t| > |N_{\text{new}}\_P_t - N_{\text{new}}\_P_{(t-1)}|$ and N_i_Pr =1. In the absence of a high priority node, a node with N_i_Pr=0 will be selected.

If at least one potential node cannot be found, then AN_{new} becomes inactive and the next step is skipped.

III) After selecting the candidate nodes, AN_{new} evaluates the potential of different permutations of candidate nodes to determine the best cluster formation Cl_{opt}. This is carried out by calculating an index *U* (2) which is the sum of normalised Capability, Cost and Distance of N_{new} in connection with the candidate nodes over each permutation. If *p* is the number of candidate nodes in a permutation *P*, then

$$U_{\text{new,p}} = \sum_{k=1}^{p} NN_{\text{new},k}\_Co + \sum_{k=1}^{p} NN_{\text{new},k}\_Ca_t + \sum_{k=1}^{p} NN_{\text{new},k}\_Di + \sum_{k=1}^{p} N_k\_Av_t \quad (2)$$

The normalised values of $NN_{\text{new},k}\_Co$, $NN_{\text{new},k}\_Ca_t$, and $NN_{\text{new},k}\_Di$ for every node in the permutation are calculated as follows:

$$NN_{\text{new},k}\_Ca_t = \frac{1}{1 + e^{(N_{\text{new},k}\_Ca_t - l)}} \quad (3)$$

$$NN_{\text{new},k}\_Co = \frac{1}{1 + e^{(N_{\text{new},k}\_Co - m)}} \quad (4)$$

$$NN_{\text{new},k}\_Di = \frac{1}{1 + e^{(N_{\text{new},k}\_Di - n)}} \quad (5)$$

In (3), (4) and (5), the parameters *l*, *m* and *n* are the average values of Capability, Cost and Distance between N_{new} and the nodes considered in the permutation. The parameters are normalised using a sigmoid curve function to make it possible to combine them in one index. The permutation with highest $U_{\text{new,p}}$ is selected as the best cluster.

IV) AN_{new} broadcasts another messages to the agents of the formed cluster, asking for their confirmation and subscription to start the learning and adaptation process.

V) The excess or deficit power flow caused by cl_{opt} can disturb the power balance within the distribution substation. Hence, in this step the amount of power injected/consumed by each node in cl_{opt} is adjusted globally by D_{Agents} using a learning algorithm, DVF [3]. The process is illustrated in Fig. 1 in which AN_{new} (assigned as AN_1) starts the learning process within cl_{opt} to minimise an objective function called the 'power deviation index' (6) before and after the addition of the nodes in cl_{opt} to the distribution substation. The power deviation index is defined as follows:

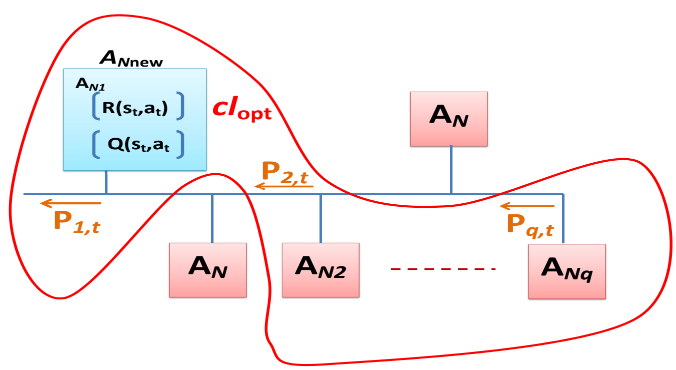

Fig. 1. The formed cluster.

$$\text{Power deviation index} = \sum_{i=1}^{q} (P_{i,t} - P_{i,t-1})^2 \quad (6)$$

where q is the number of nodes in cl_{opt}, $P_{i,t}$ is the power in the distribution substation after adding node N_i into cl_{opt}, and $P_{i,t-1}$ is the power in the distribution substation before adding node N_i into cl_{opt}.

The DVF is an iterative leaning algorithm that estimates the values of the state-action pair through a process of trial and error. In the state-action pair, state s_t represents the amount of power flow in each agent within cl_{opt} in terms of the injection or consumption of power. The action a_t is defined as the change of power in each agent during the transition between states.

When there are q nodes with a power P_q within cl_{opt}, each agent will have a state of ($|$ ROUNDUP$(P_q, 0)$ $|$) state and action of ($|$ ROUNDUP$(P_q, 0)$ $| +1$). Consequently, there will be ($\prod_{i=1}^{q}$ $|$ ROUNDUP$(P_i, 0)$ $|$) states and ($\prod_{i=1}^{q}(|$ ROUNDUP$(P_i, 0)$ $| +1)$) actions in cl_{opt}. For example, if a_t is defined as the change of 1 kW and there are 2 sources which inject 2.8 kW and 4 kW respectively, then there are 3 states ($0 \leq P < 1$, $1 \leq P < 2$, $2 \leq P \leq 2.8$) and 4 actions ($A = 0, 1, 2, 2.8$) for the first agent and there are 4 states ($0 \leq P < 1$, $1 \leq P < 2$, $2 \leq P < 3$, $3 \leq P \leq 4$) and 5 actions ($A = 0, 1, 2, 3, 4, 5$) for the second agent. This will result in 12 states and 20 actions for cl_{opt} in overall. The DVF operates based on two matrices , $Q(s_t, a_t)$ and $R(s_t, a_t)$, as illustrated in Fig. 1.

In every learning step in DVF, $Q(s_t, a_t)$ is updated according to (7) in which α is the learning factor. $R(s_t, a_t)$ is calculated based on (6). In every learning step in DVF, AN_{new} observes the current state s_t of the cl_{opt} and accordingly selects an action a_t for each agent and consequently, all agents enter a new state s_{t+1}. Each new state update the estimated $Q(s_t, a_t)$ value associated with AN_{new}. Updating the $Q(s_t, a_t)$ will result in an optimum path and a set of state-action pairs minimising the power deviation index.

$$Q_{\text{new}}(s_t, a_t) = (1 - \alpha)Q_{\text{new}}(s_t, a_t) + \alpha[R_{\text{new}}(s_t, a_t) + \sum_{i \in \text{Neigh(new)}} f(\text{new}, i)V_i(s'_i)], \text{where}, V_i(s'_i) = \max_{a \in A_i} Q_i(s'_i, a) \tag{7}$$

Forming the cluster has two advantages for the learning algorithm: (i) it helps to reduce iteration number and the size of $Q(s_t, a_t)$ and $R(s_t, a_t)$ matrix which results in reducing the complexity as well, and (ii) Equations (8) and (2) will be used to calculate $f(\text{new}, i)$ in (7) to assign different weights for the distrbution value function which will result in faster updating of $Q(s_t, a_t)$ matrix. A weight function $f(\text{new}, i)$ shows how much AN_i contributes towards updating the Q-value of agent AN_{new}. According to (8), pair of nodes, N_{new} and N_i, may receive non-zero weight based on ratio of $U_{\text{new,i}}$ to the all $\sum_{j=1}^{q} U_{\text{new},j}$ in cl_{opt}.

$$f(\text{new}, i) = \frac{U_{\text{new},i}}{\sum_{j=1}^{q} U_{\text{new},j}} \tag{8}$$

V. Validation of Plug and Play algorithm by MAS in a power network

For validation of the proposed methodology, the agents are simulated using the JADE platform. Agents exchange a set of parameters by sending messages to each other using 'semantic language' (SL) [39]. There are three types of agents defined in the current research: source, storage, and sink, each assigned to each node within the dwelling. The message type and information model for each agent is shown in Fig. 2. The result of the learning and adaptation is used by agents to determine the state of the switches.

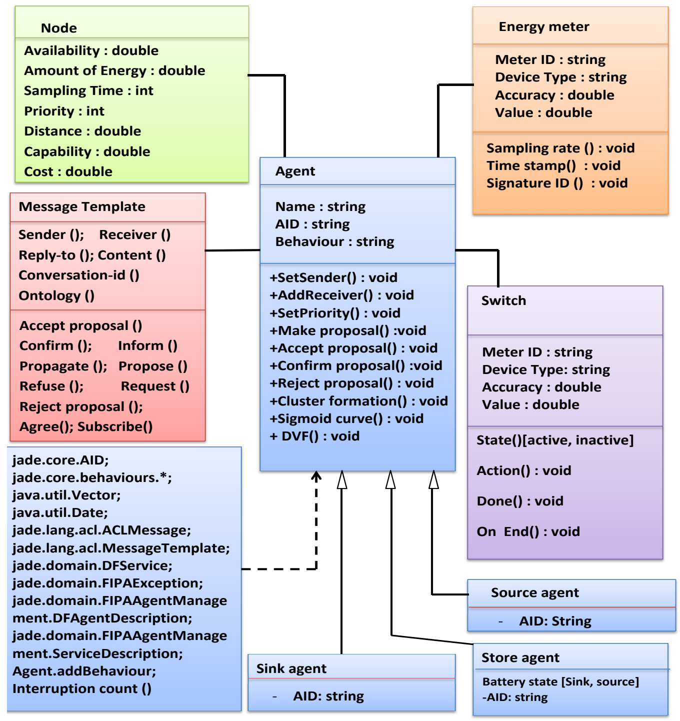

Fig. 2. Information model of each agent.

A. Computer Simulation Set up

In the computer simulation, seven dwellings including different levels of occupancy are assigned to the dwellings that are connected to the distribution substation. Inside each dwelling, there is one PV (maximum output: 2.5 kW), one wind turbine with the maximum output of 900 W, one battery with maximum capacity of 1500 W and a load with average consumption of [0-1.5 kW] per hour. The environmental data used in the source agent consisting of solar irradiance and wind speed were recorded in Cleveland, QLD, Australia [40] at a time interval of five minutes. The typical load consumption in a dwelling was provided by Endeavour Energy Pty Ltd. [41]. The environmental data used in the simulation and their sources are summarised in Table I. The power components of a dwelling including PV, wind turbine, load, and battery are simulated in MATLAB/Simulink (Fig. 3). As demonstrated in Fig. 3, the variables and dynamics of this network are sent to the JADE platform by an S-function, MACSimJX [42] which acts as a gateway to pass data between MATLAB/Simulink and JADE.

The IEEE 34-bus test feeder was chosen for simulating the distribution power network because of its simplicity in monitoring the network parameters. The IEEE 34-bus test feeder (Fig. 4) is simulated in PSCAD that is linked to MATLAB/Simulink. The dwelling substation is connected to each of the buses 846, 844, 848, and 842. The values of the power flow are imported from MATLAB/Simulink after calculation by agents in the JADE platform. In Table I, $N_{i,j}\_Co$ is the electricity tariff that for simplicity is considered to be the same from one locality to another within a particular period. After calculation and exchange of messages in JADE, the data is

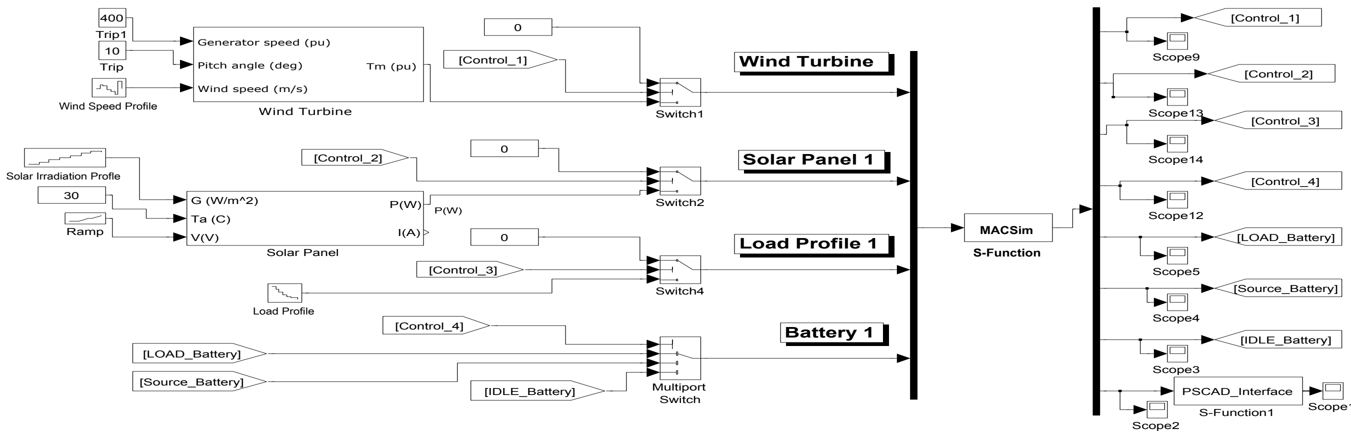

Fig. 3. Modelling of one dwelling and wind turbine in MATLAB/Simulink.

TABLE I
THE PARAMETERS OF ENVIRONMENTAL CHARACTERISTICS.

Parameter	**The methods of obtaining**
Solar irradiance	Cleveland, QLD, Australia (http://www.clevelandweather.net/misc/archive.php)
Wind speed	Cleveland, QLD, Australia (http://www.clevelandweather.net/misc/archive.php)
Load consumption	Endeavour Energy Pty Ltd. (http://www.endeavourenergy.com.au/)
$N_{i,j}\_Di$	The interval between buses in IEEE 34 bus test feeder
$N_{i,j}\_Co$	Electricity tariff which considered same for all agents
$N_{i,j}\_Ca_t$	The current active power inside node minus requested power

sent back to MATLAB/Simulink (Fig. 3) and consequently to the PSCAD platform.

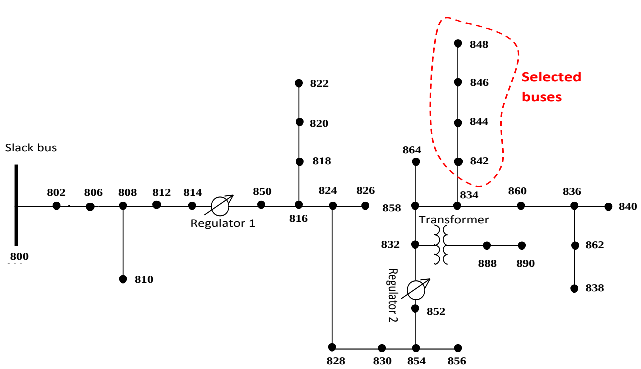

Fig. 4. IEEE 34-bus Test Feeder.

The internal connection between JADE and the MATLAB/Simulink is achieved by MACSimJX, an open source software tool. MACSimJX provides the means, utilising JADE, to receive data from Simulink and pass it on to agents for further processing. The reverse functionality is also possible [43].

B. Results

The main focus of the computer simulation was to study the power balance within the distribution substation network, the number of messages exchanged, and the comparison of the computational cost of the learning methods in terms of iteration and processing time. In the first step, there is no PnP algorithm. Each dwelling has its own 1.5 kW battery. The solar irradiance is the input for the PV units and wind speed is the input for the wind turbines. Fig. 5 shows the active power in two selected bus test feeders (846 and 848) over a 24 hour period. It shows that the power has high fluctuations, especially, at noon when PVs inject power into the main grid. When the power flow is negative, there is reverse power to bus feeders from the dwellings. In Fig. 5, the demand line shows the required power by sink and home consumption excluding batteries. The maximum and minimum power required by the selected bus test feeder (846 and 848) is 5.85 kW and -6.44 kW respectively which result in 12.29 kW magnitude of fluctuation.

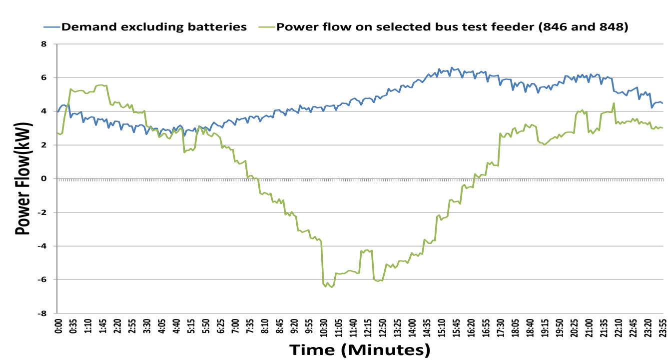

Fig. 5. Power flow on distribution substation bus with 1.5 kW batteries in each house; no PnP algorithm.

In the next step, the PnP process is started and agents on each bus communicate to each other within the distribution substation. Fig. 6 shows the resultant power flow in the selected bus test feeders (846 and 848). Due to the controlling action of the MAS, whenever the source agent cannot form a cluster with the sink agent then the power will not be injected to the distribution substation bus. Based on the network structure, the surplus of power may be used by another sink in other bus feeders. The maximum and minimum of required power by selected bus test feeder (846 and 848) is 2.02 kW and 0.1 kW respectively which result in 2.01 kW magnitude of fluctuation. The results show 81% less fluctuation than the non-PnP operation, which is quite significant. The batteries in this scenario were the source for 3 hours and 20 minutes and the demand for 4 hours and 10 minutes. Consequently, batteries were active on average for 7 hours and 30 minutes during the day.

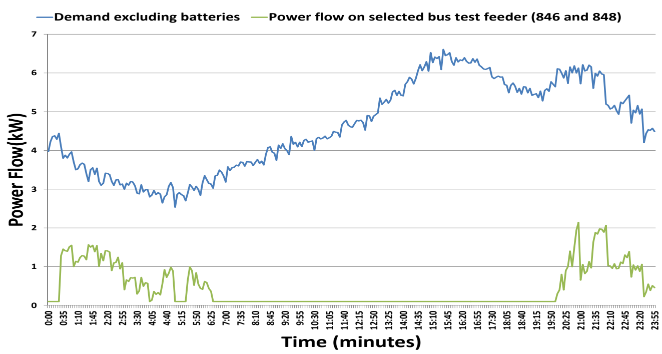

Fig. 6. Power flow on distribution substation bus with 1.5 kW batteries in each house with the PnP algorithm enabled.

Table II compares different results by different capacities of a storage node. In Table II, the size of the battery was changed to find the minimum fluctuation of power based on the size of the storage node. These results illustrate the critical role a storage node has in decreasing power fluctuations. However, the cost and environmental impact of batteries should be also considered because batteries may contain toxic material.

TABLE II
COMPARING THE RESULTS FROM DIFFERENT SIZE OF BATTERY.

Size of battery (kW)	Average of fluctuation (kW)	Maximum value of fluctuation (kW)	The time that battery was sink (minutes)	The time that battery was source (minutes)
0.5	1.52	2.17	150	100
1	1.38	2.10	200	175
1.5	1.24	2.02	250	200
2	1.1	1.81	300	245

Fig. 7 shows the number of messages that are transmitted by one source agent assigned to the wind turbine during a typical day. The result demonstrates the efficiency of the number of generated messages by selecting two appropriate sink agents. There are three possible scenarios in this process: (i) when the source agent does not communicate with the other sink agents and sends message just inside the dwellings (scenario A), (ii) when the source agent communicates with other sink agents inside the other dwellings but selects agents randomly (scenario B), and (iii) when the source agent communicates with sink agents inside other dwellings and selects agents based on the PnP algorithm (scenario C). Fig. 7 shows that a lower number of messages are generated in the first scenario when the agents are isolated without agent selection, but it is less efficient in terms of power saving and minimising disturbances. The second scenario is compared to the third scenario in which an agent selects sink agents with or without considering the parameters of the nodes. In scenario B, 67% more messages are exchanged during a typical day as there is the possibility for an agent to select an agent that does not have adequate potential for cluster formation.

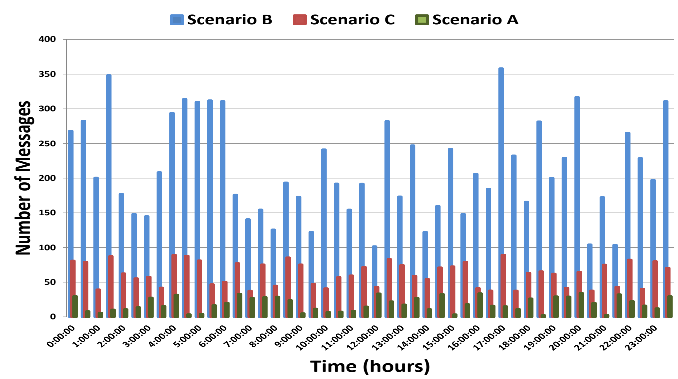

Fig. 7. The number of messages exchanged for each load agent daily.

The number of messages exchanged across the network is changed with an increase or decrease in the number of dwellings. In this experiment, the number of messages generated by the PnP algorithm is validated for different numbers of dwellings. Table III shows the maximum and the minimum and the average number of messages in every hour by all the agents associated with the dwellings. The result shows that the number of messages is doubled if the number of dwellings is increased by two-fold. The reason for this efficiency is the deployment of an MASM agent which has control over all the messages and consequently, the agents transfer their messages to the MASM agent system instead of contacting each other directly.

TABLE III
COMPARISON OF THE NUMBER OF MESSAGES IN DIFFERENT NUMBER OF DWELLINGS.

Number of dwellings	Minimum number of messages in an hour	Maximum number of messages in an hour	Average number of messages in an hour
3	288	480	384
7	745	1176	9610
14	1354	2256	1805

Fig. 8 shows the comparison of learning steps between ACSA, GA, and DVF. All three of these learning algorithm are simulated in the same environment with the same input data. In all of the learning algorithms, it is assumed that one sink agent creates a cluster with two source agents. The load consumes 3 kW that two source agents have collectively provided. In every learning step, an agent selects one of the six actions:

0, 1, 2, 3, 4 and 5. The sink agent tries to minimise (6) by implementing the learning steps. There are five states for each source agent with injection of 5 kW in our scenario as follows:

$$(0 \leq P < 1), (1 \leq P < 2), (2 \leq P < 3),$$
$$(3 \leq P < 4), (4 \leq P < 5).$$

In the GA method [5], a binary code is assigned to each state in each source agent. The cost and fitness function are based on (6). This method finds the best fitness states based on minimising the cost by using Parent Selection, Crossover and Mutation of the string. Parent Selection is a probabilistic process in which strings are selected to produce offspring based on their fitness value. The crossover rate has been changed from 0.6 to 1 and the mutation rate has been changed from 0.01 to 0.05 for the lowest learning rate. The iteration stops if (i) all the produced binary strings are the same, or (ii) the required number of iteration is achieved. The other parameters of the GA are as follows: population size = 8, crossover rate = 0.7, mutation rate = 0.03, and maximum iterations=450.

In the ACSA method [4], each ant finds the shortest path to food (the five states in each source agent) by laying a pheromone trail as they walk. An ant minimises (6) by updating the pheromone when moving in a tour from one state to another during each iteration. The probability of moving from one state to another state depends on the combination of two values: (i) the state of power flow in the next state which is a potential source to inject power, (ii) the trail level which is the pheromone strength between states. The algorithm is terminated if (i) all ants select the same path in their tours, or (ii) the maximum number of iteration is achieved. The following parameters are used for ACSA: Number of ants=6, maximum iterations=450, pheromone weighting=2, state weighting=6, pheromone evaporation constant =0.8, and elite path weighting constant =0.5.

In the proposed scenario and application, the problem of a high number of iterations, which is mentioned in [34] in comparison to Q-learning and ACSA, has been solved in the DVF (distributed learner) by collaboration on updating the Q-value. As illustrated in Fig. 8, the GA has the worst performance and the result for ACSA and DVF are roughly the same. In this paper, DVF has been selected because of its mathematical simplicity in modelling the collaboration between agents. The main disadvantage of the GA is that it is a stochastic algorithm and its solution cannot be guaranteed to be optimum.

The hardware for simulating has a central processing unit (CPU) with 3 GHz speed and each millisecond is defined as 1 per unit (p.u.). In this case, every learning step by DVF, ACSA, and the GA takes 11, 12, 42 p.u., respectively. Fig. 8 compares the learning rates for three nodes (one sink agent and two sources nodes). The real network has a lot of nodes which constantly run the learning algorithm every 5 minutes as well as having other PnP functionality. A low number of iterations is important, especially for an agent which does not have powerful computing hardware in terms of memory and processor.

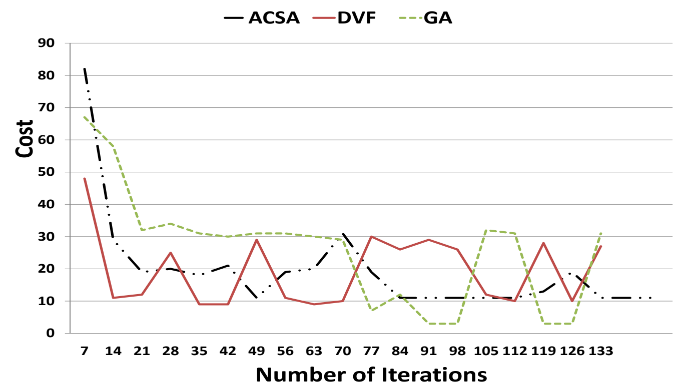

Fig. 8. comparison learning steps among ACSA, DVF, GA.

VI. Conclusion and Future Work

The reported research is one step towards the PnP techniques in a smart grid with distributed intelligent automation. The architecture of the proposed information model is hierarchical and stems from PnP techniques. The algorithm allows the network elements to be active or inactive with minimal fluctuations in power flow. In the current work, the research is focused on the control and collaboration of the intelligent components. This research aims at achieving management of the power resources so that there is minimal power drawn from the network via the distribution substation. Simulation has been carried out using MATLAB/Simulink and JADE platform. Based on the ongoing situation in the environment, MATLAB/Simulink sends data to JADE for processing and the agent makes a decision to open or close the power switches.

In terms of learning steps, the performance of the PnP process using the DVF algorithm is compared with ACSA, and GA techniques. According to the results, the collaboration in the DVF method provides fewer iterations compared to GA and it is more competitive with ACSA. It also shows that the battery has a critical role in the smart grid because it helps to minimise disturbances to the supply-and-demand balance within the distribution network. Future work will be in the direction of adding more intelligent functionalities in virtual power systems. The other issues can be considered such as developing a framework for learning algorithms for the scheduling of demand-side integration, optimising the size of storage capability and control and management of forecasting power flow by using stochastic models.

VII. Acknowledgement

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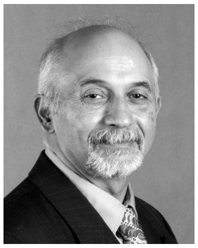

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