An IoT- Based Decision Support Tool for Improving the Performance of Smart Grids Connected with Distributed Energy Sources and Electric Vehicles

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***Abstract*— The growing penetration of distributed energy sources (DES) such as photovoltaic (PV) solar power, battery energy systems (BESs) and electric vehicles (EVs) into low voltage distribution networks is creating serious challenges for distribution network operators (DNOs). Uncertain nature of these DES and EV charging is a key factor to cause unbalance which degrade network performance in terms of energy loss, voltage unbalance and voltage profile of the distribution network, etc. Some methods were proposed to mitigate such negative impact of these uncertain DES and EV charging from both centralized and decentralized approaches by controlling charging or discharging power of EVs. However, these methods involve all active EVs to participate in coordination and this causes significant inconvenience to EV owners along with requirements of complex communication infrastructure and huge data processing overhead. This paper proposes an Internet of Things (IoT)-based centralized control strategy to coordinate EV and DES distribution by using the differential evolution (DE) optimization algorithm. The obtained results show that the proposed control strategy can improve network performance (voltage imbalance, neutral current, energy loss, and node voltage) significantly. In addition, the control strategy is less demanding on communication infrastructure and convenient for EV owners as well as having a lighter data processing overhead.**

***Index Terms*— electric vehicle, IoT, distributed generation, network reliability, smart grid.**

I. Introduction

THE growing penetration of distributed energy sources (DES) such as photovoltaic (PV) solar power, battery energy systems (BESs), and electric vehicles (EVs) in the residential distribution networks raises challenges for distribution network operators (DNOs). The increasing penetration of these DES and EVs into the low voltage (LV) distribution grid causes a higher degree of imbalance which violates voltage constraints, reduces network hosting capacity, increases energy losses and requires more power generation [1]. Network imbalance also increases the neutral current, which in turn increases the cost of the neutral conductor [2]. The centralized and decentralized control approaches were proposed to control the EV charging or discharging power at the service point of connection (SPOC) [3]–[15].

In the centralized control approach, a central controller communicates with all EVs to control their charging or discharging rate to achieve the desired objectives. The approach presented in [3]–[6], considered the minimization of EV charging cost or maximum energy delivered to EVs by optimizing EV charging or discharging power for an unbalanced distribution grid. The approach demonstrated in [7], optimized state of charge (SoC) level of each EVs to improve the voltage at each SPOC. A method of variable charging or discharging power for each EV to reduce the voltage unbalance factor (VUF) at each SPOC was discussed in [8]. The central controller manages the EV charging or discharging rate or disconnects EVs to obtain desired objective subject to network constraints. Though the network performance and constraints are well maintained, more complex intricate communication infrastructures and higher overhead of data processing causes concerns when the number of EV participants becomes large [9], [10].

To avoid the requirements of a complex communication infrastructure and high data processing overhead, several decentralized control approaches were also proposed [9], [10]. These approaches use distributed EV controllers (one controller per EV) to control the EV charging and discharging rate at the respective SPOCs to achieve the desired objective. In order to improve the voltage quality, each EVs' charging or discharging power was optimized by measuring the voltage at respective EV SPOC [11], [12]. The energy loss of the distribution network was optimized by controlling the EV's charging or discharging power at each EV's SPOC [13], [14]. Each EV controller decides the charging or discharging rate, which reduces communication overhead and computational

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complexity compared with the centralized control approach [9], [10]. But this approach becomes inefficient to maintain the network operating constraints when the number of EVs becomes high [9].

The contribution of EVs is uncertain because they serve both the power system and the transportation sector. Scheduled EV charging also can be affected. Furthermore, the EV contribution uncertainty either by failures of components such as charging facilities, or by human errors such as punctuality, rounding of time and errors in forecast of energy consumption may change the optimal condition at a scheduled time, e.g., EV SPOCs are not connected among phases according to the schedule so that there are more surplus or shortage of energy in the distribution network. The study [15] shows that EV uncertainties impact on generation scheduling. Most of proposed methods focus on reducing energy loss or energy cost and improving the voltage in an unbalanced distribution network. To the best of the authors' knowledge, how to mitigate network imbalance due to EV uncertainty and uncoordinated power dispatch per phase remains as a research gap.

This paper aims to bridge the aforementioned research gap, i.e. to propose an internet of things (IoT) enabled improved centralized control strategy to mitigate network imbalance considering four objectives including the neutral current, voltage unbalance, node voltage, and energy loss with a special consideration of EV uncertainty based on real-time network performance. The proposed control strategy does not require information from all active EVs (e.g., charging or discharging power, SoC rate) and this reduces the volume of data processed and simplifies the communication infrastructure. The key contributions of this paper are:

- Proposed an IoT enabled centralized control strategy to coordinate DESs and EVs, which reduces number of active EV participants which leads to less data storage capacity, a simple communication infrastructure.
- Proposed an idea of estimating the EV contribution uncertainty and its impact on the network performance.
- Presented a simulation tool based on the proposed control strategy, which will be triggered when the network performance is below the standard value. With this tool, minimization of the impact of EV and DES uncertainty can be achieved by jointly coordinating phases and DESs.
- Introduced sensitive nodes in a low voltage residential network in terms of reserve power integration.
- Established a reserve management strategy by allowing active participation of EV owners and BES owners to mitigate network imbalance (the voltage imbalance and neutral current) and to improve voltage.
- Provided a comprehensive comparison between the proposed control strategy and two competing control techniques, which are EV charging or discharging method [8], and Dynamic static compensator method [29].

II. Problem Formulation

In this section, an optimization problem with multi-objectives is mathematically formulated. DNOs optimize each objective (the energy loss, voltage, voltage unbalance, and the neutral current) based on real-time network performance. The EV charging and discharging constraint, PV and BES power delivery constraint, and the network constraints are formulated to limit the searching space to solve the optimization problem. The EV charging cost and network performance (energy loss) are not dependent on each other [16]. For this reason, the network performance is considered as an objective function assuming a suitable tariff time for EV charging.

A. Constraints

Each single-phase load and each EV is connected at its respective SPOC among any one of the phases of a node/measuring point [16]. The uncoordinated integration of DESs and EVs induce voltage imbalance [1]. The voltage sensitivity of a node can be expressed as:

$$\begin{aligned} V(t)^n &= V(t)_b^n + \sum_{\phi\in NEV_c} \frac{\partial V^n}{\partial P}(\phi,t)\times P(\phi,t)_{ch} + \\ &\sum_{\gamma\in NEV_d} \frac{\partial V^n}{\partial P}(\phi,t)\times P(\gamma,t)_{dch} + \sum_{\varphi\in NDES} \frac{\partial V}{\partial P}(\varphi,t)\times P(\varphi,t)_{DES} \end{aligned} \tag{1}$$

where $\forall \mathrm{t} \in \mathrm{T}$, $\forall \mathrm{n} \in \mathrm{NNode}$

where t is the time slot (usually each hour, T is the set of twenty-four hours a day), n is the node and *NNode* is the set of all nodes in a network. $V_b^{(n)}(t)$ is the initial voltage (with residential loads and generation) at each node at a time slot. $V^{(n)}(t)$ is the node voltage after connecting the DESs and EVs in either charging or discharging mode. ϕ,γ,φ is the set of charging EVs, discharging EVs, and DESs among three phases. $\partial V/\partial P^{(n)}$ is a three-dimensional matrix of $V^{(n)}(t)$ with respect to EV and DES SPOCs among phases at each node. P_{ch}, P_{dch}, and P_{DES} represents the active charging power consumption of the EVs, EV discharging dispatch, and the power delivered by DESs among phases in a timeslot t. EV owners are either charging or discharging their EVs. The power consumption/dispatch constraint of each EV depends on the efficiency of the EV converter as shown in (2)–(3).

$$P(\phi,t)_{ch} = \eta \times P(\phi,t)_{ch} \times \zeta \tag{2}$$

$$P(\gamma,t)_{dch} = \eta \times P(\gamma,t)_{dch} \times \xi \tag{3}$$

where $\forall\phi \in NEV_c$, $\forall\gamma \in NEV_d$ *and* $\forall t \in T$

where η is the EV converter efficiency, and ζ and ξ are the charging and discharging rates of each EV at the respective time slot. The SoC level limits EVs to charge/discharge fully to increase battery life. Equations (4) – (5) show the EV charging and discharging constraints. The suffix NEV_c and NEV_d presents EV charging and discharging power.

$$P(\phi,t)_{NEV_{c\_\min}} \le P(\phi,t)_{NEV_c} \le P(\phi,t)_{NEV_{c\_\max}} \tag{4}$$

$$P(\gamma,t)_{NEV_{d\_\min}} \le P(\gamma,t)_{NEV_d} \le P(\gamma,t)_{NEV_{d\_\max}} \tag{5}$$

where $\forall\phi \in NEVc$, $\forall\gamma \in NEV_d$ *and* $\forall t \in T$

The power delivered by PVs at respective SPOCs among phases depends on irradiance, panel efficiency, converter efficiency, and the ramp rate of PV power. In this paper, the converter output of respective PVs and BESs is considered as delivered power at each node. The delivered power of each PV and BES is limited within a boundary as shown in (6)-(7). The suffix *PV* and *BES* presents PV and Battery power. ψ is the set of all battery energy storage in a network.

$$P(\sigma,t)_{PV\_\min} \le P(\sigma,t)_{PV} \le P(\sigma,t)_{PV\_\max} \tag{6}$$

$$P(\psi,t)_{BES\_\min} \le P(\psi,t)_{BES} \le P(\psi,t)_{BES\_\max} \tag{7}$$

where $\forall \sigma \in NPV$, $\forall \Psi \in NBES$, *and* $\forall t \in T$

To increase the battery lifetime of BESs and EVs, manufacturers recommend the minimum depth of discharge (DOD). BES and EV owners set their minimum and maximum level of SoC (8) which is also a constraint for dispatched power.

$$SOC(t)_{\min}^{\gamma,\Psi} \le SOC(t)^{\gamma,\Psi} \le SOC(t)_{\max}^{\gamma,\Psi} \tag{8}$$

where $\forall \gamma \in NEV_d$, $\forall \Psi \in NBES$, *and* $\forall t \in T$

where the SOC value of each battery of EV and BES is constrained with a minimum and maximum value. The γ, v represents the set of discharging EVs and the set of dispatched BESs. The total active delivered power of DESs is the total power of PVs and BESs. The total delivered DES power per node should remain the same and the total power variation between phases should be within the allowable limit (DD), as given in (9). The network will not take support from the external grid during optimization but takes support during reserve managing if adequate generation is not available.

The balance between network demand and generation is maintained at each time slot as given in (10). The total energy loss is the summation of loss of all branches at that time slot as given in (11).

$$\sum \Delta P(t)_{\Phi=a}^{DES,n} \sim \sum \Delta P(t)_{\Phi=b}^{DES,n} \sim \sum \Delta P(t)_{\Phi=c}^{DES,n} \le DD\% \tag{9}$$

$$\begin{aligned} &\sum_{\sigma\in NPV} P(\sigma,t)_{PV} + \sum_{\psi\in NBES} P(\psi,t)_{BES} + \sum_{\gamma\in NEV_d} P(\gamma,t) + P_{ext} \\ &= \sum_{\alpha\in NRES} P(\alpha,t)_{res} + \sum_{\phi\in NEV_c} P(\phi,t)_{ch} + \sum_{br\in Nbranch} P(br,t)_{loss} \end{aligned} \tag{10}$$

$$P(br,t)_{loss} = \sum_{br\in Nbranch} R(br,t)\times\left|I(br,t)\right|^2 \tag{11}$$

where $\forall br \in Nbranch$, $\forall t \in T$

In this paper, EVs charging/discharging constraints (2)–(5), PV and BES constraints (6)–(7), battery SoC constraint (8), and power flow constraints are maintained to solve the optimization problem. The node voltage obtained in (1) should not be reduced and the grid energy loss obtained in (11) should not be increased more than the initial network performance (prior to the start of optimization) due to the proposed optimization.

B. Proposed multi-objective optimization problem

This study investigates the scenario when EVs (charging or discharging) and DESs integration makes the distribution network unbalance even though the scheduled amount of DES power is maintained. It is noted that optimizing EV SPOCs among phases cannot guarantee that the network power quality will improve. Therefore, it is necessary to coordinate both EVs and DESs to obtain the optimum result to improve the neutral current, voltage unbalance, node voltage, and energy loss.

For this reason, a multi-objective optimization problem is formulated in (12). The neutral current at the supporting feeder is the lump sum of three phase currents as shown in the first part of the objective function (12). The numerical value of $\mathbf{\Omega}_1$ increases with increasing unbalanced power flows. Though the neutral current represents the imbalance problem at the feeder, control of voltage unbalance at every node is another objective $\mathbf{\Omega}_2$ to mitigate the network imbalance. The VUF is defined as the ratio between negative sequence voltage components $/V_{neg}/$ and positive sequence voltage components $/V_{pos}/$ as shown in the second part of (12). The voltage $\mathbf{\Omega}_3$ is measured at each node and calculated using (1). The objective of this study is to improve the node voltage to be nearer to the slack bus voltage (1.05 p.u) by minimizing the node voltage deviation compared to the slack bus voltage V_s as shown in the third part of (12). The fourth part of multi-objective function (12) is to minimise the energy loss $\mathbf{\Omega}_4$ of the network. Energy loss is calculated using (11) at a time slot. The sum of weighting factors must be equal to 1.

$$MOF = \omega_1\times\Omega_1 + \omega_2\times\Omega_2 + \omega_3\times\Omega_3 + \omega_4\times\Omega_4 \tag{12}$$

where $\omega_1+\omega_2+\omega_3+\omega_4 = 1$, $\Omega_1 = I_a + I_b + I_c$,

$$\Omega_2 = \frac{\left|V(t)_{neg}\right|^n}{\left|V(t)_{pos}\right|^n},\ \Omega_3 = \sum_{n\in NNode}\left|V_s - V(t)^n\right|,\ \Omega_4 = P(t)_{loss},$$

$\forall n \in \mathrm{NNode}$, *and* $\forall t \in T$

In this study, the fuzziffication method as addressed in [19] is employed to convert each objective into the same scale [0, 1] as given in (13). Therefore, it is necessary to convert the values of the individual objectives $\Omega_1, \Omega_2, \Omega_3, \Omega_4$ to a fuzzy variable.

$$\mu_k = \begin{cases} 0 & \mu_j \leq 0 \\ \mu_j & 0 \angle\ \mu_j \angle 1 \\ 1 & \mu_j \geq 1 \end{cases} \tag{13}$$

where $\mu_j = \dfrac{\Omega_l - \Omega_l^{nadir}}{\Omega_l^{ideal} - \Omega_l^{nadir}}$ and j,k,l=1,2,3,4.

The multi-objective is converted from (12) to (14) by using fuzzy membership (μ_k) condition as given in (13).

$$MOF_{proposed} = \min(\omega_1 \times \mu_1 + \omega_2 \times \mu_2 + \omega_3 \times \mu_3 + \omega_4 \times \mu_4) \tag{14}$$

Since the proposed multi-objective function (14) has no nonlinear term, the optimization problem using stochastic based search methods can be solved efficiently. To achieve a global optimal solution for the optimization problem (14), the differential evolution (DE) optimization algorithm is employed in this article.

III. Proposed IoT Decision Support Tool

The proposed IoT tool monitors the power quality indices (the neutral current, VUF, and voltage) at different measurement points or nodes. If the network performance is below the standard value, the IoT tool decides to optimize the distribution network by managing demand, generation, and resources of the distribution network. If the distribution network still does not achieve the standard power quality indices due to a shortage of production, the IoT tool manages the optimum generation resources or controls EV charging power among phases. The proposed control approach and communication strategy used in the IoT tool is described here.

A. Proposed Control Approach

Previous research work [11], [17] recommends that EV users install a special controller which can measure voltage or voltage unbalance at respective SPOCs. These EV controllers manage the charging or discharging power (SoC rate) of an EV to achieve the desired objective. Centralized and decentralized control strategies have been employed to control the SoC of an EV to improve network performance. But the SoC control strategy inconvenient for the EV users [18], [19]. On the other hand, the complexity of the communication infrastructure increases with an increase in EV penetration because communication with each EV is required. To ensure the comfort level of the EV user, the proposed control approach in this paper allows less number of EVs as participants.

The proposed control approach jointly coordinates EV and DES SPOCs among phases of a distribution network to improve network performance. The proposed IoT tool performs the optimization task and reserve managing control task, which is described in the flow chart, as shown in Fig. 1.

The proposed IoT tool collects network information e.g. node information ($D^{n,\,t}$), line configuration ($D^{l,\,t}$), and real-time phase configuration ($D^{\Phi,\,n,\,t}$) at each time slot *(t)*. The IoT tool gathers measurement information e.g. the total power consumption ($P^{load,\,\Phi,\,n,\,t}$) including EV charging, delivered PV power ($P^{PV,\Phi,n,t}$) and dispatched BES power ($P^{BES,\Phi,n}$) at each phase of the corresponding node at each time slot t.

The proposed tool monitors the power quality indices e.g., VUF, the neutral current, and the node voltage. Each network has an allowable threshold for the neutral current and a preventive relay is employed there if the neutral current exceeds the allowable threshold. In Australia, the voltage unbalance factor (VUF) should be less than 2% and the bus voltage is maintained within 0.95 p.u. to 1.05 p.u. [20], [21]. If the value of the power quality indices are below the control criteria (*TC, NU, NV* are the threshold values of neutral current, VUF, and node voltage respectively), the decision support tool performs the optimization control approach.

The proposed control method consists double stages. In the first layer, phases are re-sequenced at each node of the distribution network to minimize the optimization problem (14) using the DE optimization algorithm subject to the constraint (2)–(10). The iteration number (*it*), crossover (*CR*) and mutation probability (*F*) of the DE optimization algorithm are initialized prior to optimization. The value of the weighting or importance factor (ω) is also defined in the objective function (14). In the proposed control approach, the network constraints (e.g., the total power consumption, EV charging or discharging rate, and total power generation) are maintained to obtain the minimum value of objective (14).

The optimum power dispatch is managed by considering constraint *DD*. The *DD* is the allowable maximum power variation between phases. The lower percent value of *DD* means that a smaller number of DESs are required to re-phase among phases. In this way, the proposed tool coordinates the phases and DESs in a distribution network.

When demand is higher than generation, the network requires support from EV and BES owners. The optimal location and sizing of the generation is necessary to improve network performance [22]–[24]. An arbitrary size of BES generation is connected to every node and the power quality indices (neutral current and energy loss) are recorded to find the sensitive node to integrate dispatchable generation sources. As the aim of this study is to reduce network imbalance and improve voltage, the sensitive node is selected based on the normalized sensitive fitness value (the magnitude of the neutral current and the energy loss) of the network, Nodes are ranked based on the minimum value of sensitive fitness. The IoT tool undertakes the reserve control task to calculate the required optimum generation.

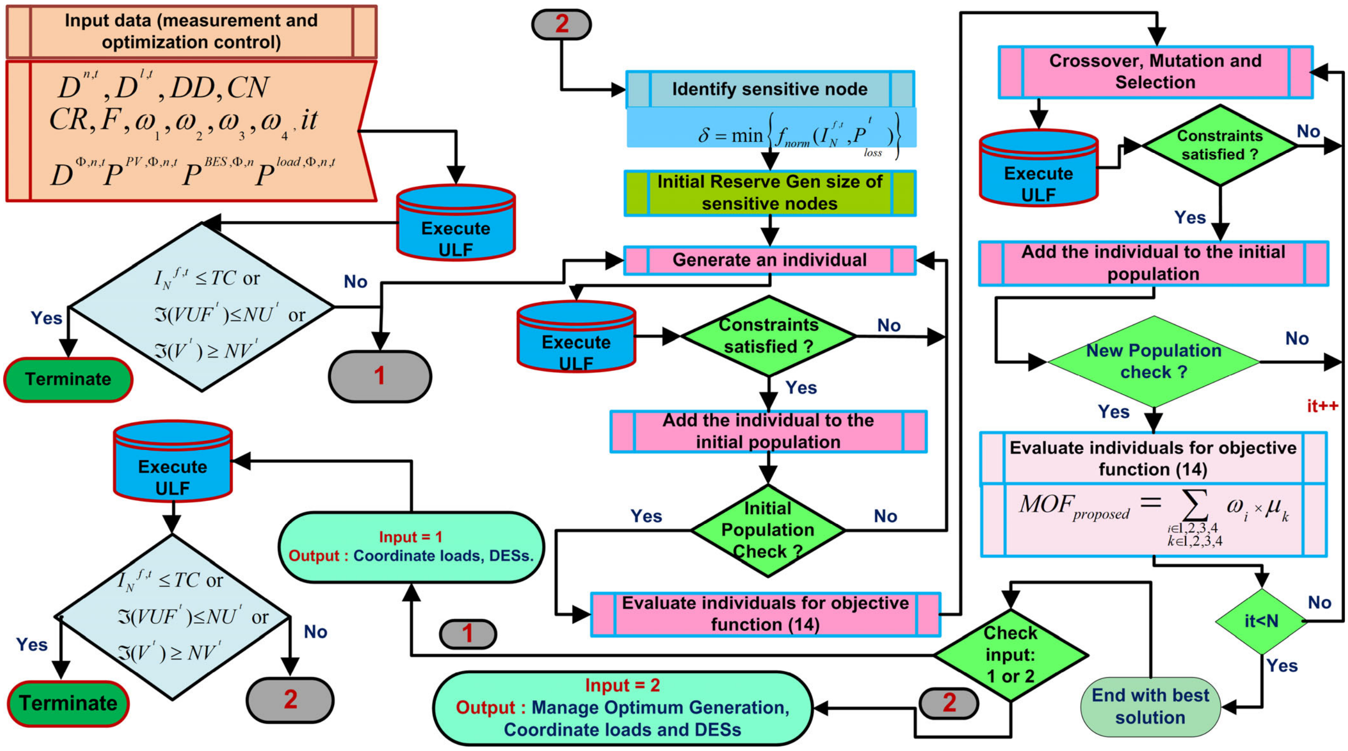

Fig. 1. Proposed control method

The number of participating nodes depends on the demand-generation gap and generation availability. If there is not adequate generation, the IoT tool can ask EV or BES owners, controls EV charging, or the external grid for the required generation. In this way, the proposed IoT tool improves network performance by managing reserve generation.

Fig. 1 summarizes the hierarchical control approach of the proposed IoT tool. A centralized controller collects information, e.g., total demand and generation, EV and DES uncertainty error, the location of the node, participating PV and BES SPOCs, BES SoCs, and DE optimization control parameters (CR, F, iteration number, importance factor, etc.). Therefore, the IoT tool calculates network performance (VUF, voltage, energy loss, and the neutral current) and checks the control criteria. Based on the control criteria, the IoT tool performs the task (optimization or the reserve control) using the DE optimization algorithm. In the DE optimization algorithm, each individual are maintain constraints (2-10) and follows the crossover, mutation, and selection process to obtain the optimum values for fitness (14) as shown in Fig.1.

B. Proposed Implementation Infrastructure

Each PV, BES, and EV user make registers and DNOs store each PV, BES, and EV identification information (ID) [25]. DNOs record several pieces of information e.g., the SPOC information (location), SoC, and the contact information for each EV ID [25]. It is assumed that EVs and DESs are connected according to the recommendation of DNO to maintain the power quality indices.

The proposed control approach requires a controller in each node or measurement point with a measuring meter, and a switch box to re-sequence phases. In the switch box, the re-phasing switches have three states to connect each phase. This study only considers positive and negative phase sequences to avoid the reverse operation of three-phase inductive loads such as motor loads. If the existing phasing sequence is {A, B, C, N} for three phases of the network, the positive phase sequence would be {B, C, A, N} and the negative sequence would be {C, A, B, N}. In this paper, the {A, B, C, N}, {B, C, A, N}, and {C, A, B, N} is represented correspondingly by 0, 1, and 2. DESs (PV and BES) which are participating in the control task require a controller with a switch box in each dispatch point at the respective SPOC {A, N} or {B, N} or {C, N}. For example, PV35 is connected at phase A and proposed control approach recommends that it re-phases to phase B. The switch connected to PV 35 is able to select either phase A or phase B or phase C. The design of such switches consists of a ZigBee wireless receiver to obtain control information, a snubber circuit, TRIAC, and over-voltage protection. These switches can enable or disable power flow based on the control command received by the ZigBee receivers [26].

The measurement devices consisting of various types of sensors which are installed at every node, feeder, and connection point at the substation. The measurement information is sent to the central controller using the ZigBee transceiver through the message queuing and elementary transport (MQQT) communication protocol. The IoT tool executes ULF, calculates the network performance, and checks the control criteria. If network performance is below the control criteria, the IoT tool implements the DE optimization algorithm to obtain the optimize phase sequence per node and DES SPOCs among phases. The implementation of the phase re-sequence per node and DESs re-phasing is done in two layers. The implementation architecture of the proposed control approach is shown in Fig. 2.

In the first layer, the ZigBee receiver at the switch box receives control information from the central controller and controls the switch-breaker status. In this way, the proposed control algorithm is implemented by controlling the switch-breaker status to re-sequence phases of a distribution network. In the second layer, the control information (re-phasing) for the respective DESs is sent to be implemented by maintaining the constraint. In this way, the proposed IoT tool performs the optimization task.

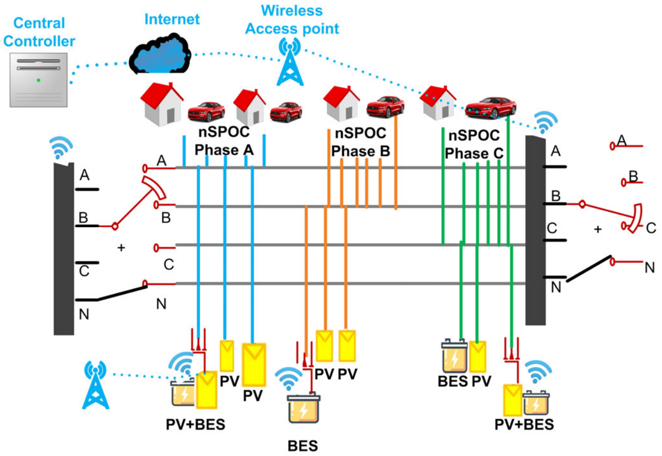

Fig. 2. Proposed implementation architecture.

If the control criteria are violated due to a shortage of generation, the IoT tool decides to perform the reserve control task. The optimum node and optimum generation size are determined according to the proposed strategy. The IoT tool asks for generation support to EV and BES owners of a particular location (sensitive node) or controls EV charging to manage the demand-generation.

IV. Test System

Three types of single-phase EVs were considered and the power consumption depends on the type of EV charger at each time slot. EVs are connected at each SPOC in a distribution network. DNOs and EV owners come to an agreement regarding SoC values during EV registration based on several criteria e.g., the location of the EV, EV penetration, and seasonal demand in a distribution system. A single-phase photovoltaic solar plant with or without battery energy storage (BES), and a single-phase energy storage system (battery storage) are connected to the LV distribution grid to deliver power at the respective SPOCs. The intermittent nature of solar energy (e.g., irradiance, cloud movement, and soling effect) makes PV power as a non-dispatchable source and PV power varies with time.

It is assumed that the amount of delivered PV power variability is less than 30% at a time slot. BESs and EVs (in discharging mode) are considered as controlled dispatchable power as well as considered as reserve generation. The Newton-Raphson load flow method is employed to execute the ULF of the distribution network. The analysed LV distribution network under the Newmarket zone substation area, Brisbane, Australia is modelled in this paper as shown in Fig. 3 (distribution network I) and the distribution network II was modelled in [27].

The distribution network is usually a three phase-four wire system. The distribution network is connected to the MV network through the transformer. In this study, the power quality enhancer equipment such as voltage regulators, dynamic voltage restorer (DVR), distribution static compensator (D-STATCOM) and shunt capacitors is not considered in the investigation of the efficacy of the proposed method.

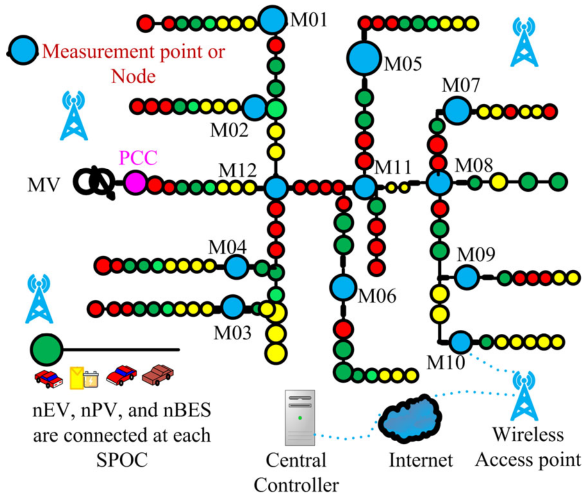

Fig. 3. Network model of a distribution grid in Brisbane, Australia

V. Results and Discussions

The proposed method considers demand and generation data of one year to investigate the performance. DNOs forecast the residential demand, EV charging power demand, and EV discharging power dispatch per phase per node after analyzing the historical data. The phase power consumption or dispatch per phase of the network is predicted based on historical data. EVs consume or dispatch much more power than residential loads. Therefore, the impact of EV charging or discharging forecasting error at a time (t) affects the distribution network severely. The effect of EV uncertainty is investigated in this study by assuming that EVs are not connected at the respective SPOC by following the scheduled time, but the total demand and generation follows the schedule. It is assumed that EV charging loads are increasing at a phase which makes phase imbalance. The degree of EV uncertainty (ε) gradually increases from 0% to 100% by sharing EV SPOCs to one of the phases (say, phase A) from the rest of two-phases (e.g., phase B and phase C). The power demand for different phases due to EV uncertainty is shown in (15).

$$\begin{aligned} P_{\Phi=A} &= P_{\Phi=A} + 2\times\varepsilon \\ P_{\Phi=B} &= P_{\Phi=B} - \varepsilon \\ P_{\Phi=C} &= P_{\Phi=C} - \varepsilon \end{aligned} \tag{15}$$

$$[\,\varepsilon = \%of\,\frac{P_t}{3},\; P_t = \sum_{\Phi=A,B,C} P_\Phi\,]$$

When there is no EV uncertainty, phases are equally balanced. The network is entirely unbalanced when the value of ε is 100%.

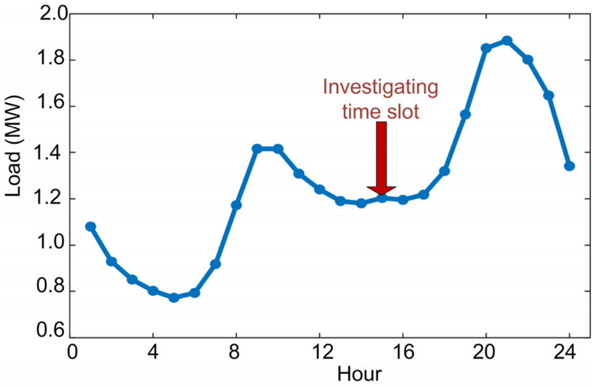

Fig. 4. The hourly load curve of a day

In this paper, EV uncertainty ε = 35% is considered and calculated the demand of each phase per node by keeping the schedule demand-generation at 15:00 h of a day. The hourly demand of a day is shown in Fig. 4. The efficacy of the proposed method is investigated by applying to the test distribution networks described in section IV assuming two scenarios –

i) Case I: with EV charging uncertainty ε = 35%, and without generation uncertainty. Where, the IoT tool performs optimization, and

ii) Case II: with EV charging uncertainty ε = 35%, with generation uncertainty 23%. Where, the IoT tool performs reserve control task.

In this paper, the voltage, voltage imbalance sensitivity, and the energy loss sensitivity are calculated after executing the ULF using the DIgSILENT PowerFactory software package. The ratio of negative sequence voltage to positive sequence voltage magnitude is increased, which results in the VUF value increasing up to 14.57% due to EV uncertainty despite the scheduled generation, as shown in Fig. 6 of the test distribution network I considering case I. The unequal EV charging demand at different phases produces a large amount of the neutral current 189.96 A at the supporting feeder. The minimum voltage at each node is reduced to below 0.95 p.u. as shown in Fig. 5. The energy loss at 15:00 h is 101.37 kW. Therefore, the voltage and VUF value at each node are below the standard value, which violates the control criteria at that time slot though there have not generation uncertainty (case I).

In this paper, the main goal is to mitigate network imbalance (voltage unbalance and the neutral current). It is not guaranteed that the reduction in network imbalance improves the bus voltage to the standard value [28]. For this reason, higher importance to the network imbalance *(ω_1=0.36, ω_2=0.36)*, voltage *(ω_3=0.18)*, and energy loss (*ω_4=0.1*) is considered. The proposed multi-objective is optimized using the DE optimization algorithm. The optimization problem (14) in this paper is solved using the DIgSILENT PowerFactory language capability of the DIgSILENT PowerFactory package.

After executing the proposed multi-objective optimization (14) with individual importance factors, the optimum phase sequence per node and DESs distribution is obtained. Table I shows the phase sequence at each node. It is also observed that the phase sequence is not changed at every node, which reduces implementation time. The allowable DES power variation per phase is set to 10%, which is also a constraint. The proposed solution recommends that an additional 7.28% of power is required in phase A and 0.15% of power in phase B than the existing power dispatch. The surplus amount of power in phase C is equal to the required power in phase A and B. So, it is observed that the power variation is within the search space and the participation of 10% of DES owners per phase can improve network performance.

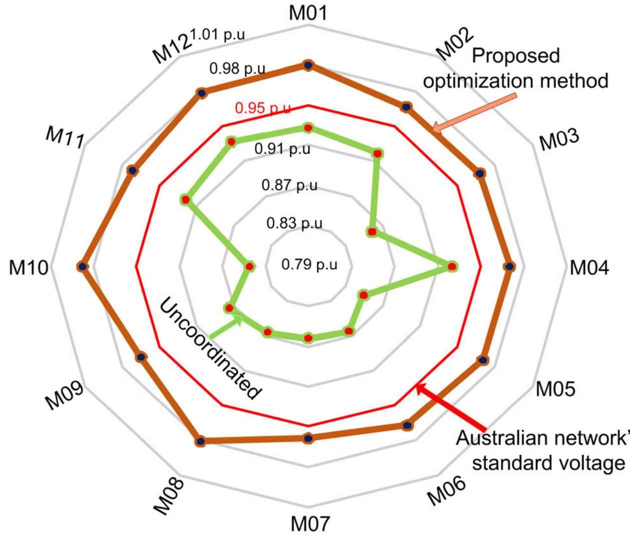

Fig. 5. Voltage at different node (case I) of distribution network I.

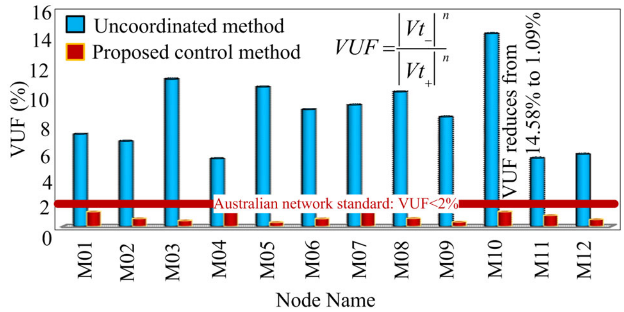

Fig. 6. Voltage unbalance factor at different node (case I) of distribution network I.

TABLE I
PROPOSED PHASE SEQUENCE (CASE I)

Node name	Proposed phase sequence	Node name	Proposed phase sequence
M10	1	M08	2
M12	0	M09	0
M04	2	M03	2
M11	0	M06	1
M01	2	M05	1
M02	0	M07	2

The recommended EV and DES SPOCs movement per phase is implemented using the proposed control approach. The ULF is executed with an optimized configuration, and it is observed that the voltage and VUF at each node are improved as shown in Fig. 5 and Fig. 6. In Fig. 6, it is observed that the VUF is reduced to below 2% at each node of the distribution network. The voltage imbalance (VUF) is reduced from 14.57% to 1.09% at node M10. The proposed method improves the minimum voltage at each node and is above 0.95 p.u. as shown in Fig. 5. The node voltage is improved up to 18.35% whereas the neutral current is reduced from 189.96 A to 17.42 A. The energy loss is reduced from 101.37 kW to 64.49 kW after implementing the proposed control algorithm.

On the other hand, the uncertain PV solar energy and SoC limitation of BESs can produce generation uncertainty. Both EV, PV, and BES can induce forecasting error in scheduled generation. DNOs manage reserve generation or shed load to meet demand to maintain the power quality indices of a distribution network.

In this paper, the reserve control approach is tested in the distribution network when there is a generation shortage due to PV and EV uncertainty (case II). It is assumed that the EV charging uncertainty is 35% whereas DESs uncertainty is 23% for both distribution network. The proposed IoT tool manages the reserve generation by following the proposed control approach. A BES with an arbitrary size (in this study, 7 kW) is integrated to a node. The energy loss and the neutral current is recorded after integrating to every node (one by one). Fig. 7 shows the normalized value of the sensitive fitness (the neutral current with weighting factor 0.6 and the energy loss with weighting factor 0.4) per node. Nodes are ranked based on the value of minimum fitness to select the sensitive node for dispatch generation integration.

The optimum size of BES and EV dispatch at the respective sensitive node is calculated using the DE optimization algorithm. The IoT tool asks EV owners to support the grid by offering a suitable tariff through text messages and the reserve storage (BESs) is made online to meet the gap of demand-generation. If the adequate generation is not managed, the IoT tool controls active EVs charging of the sensitive location.

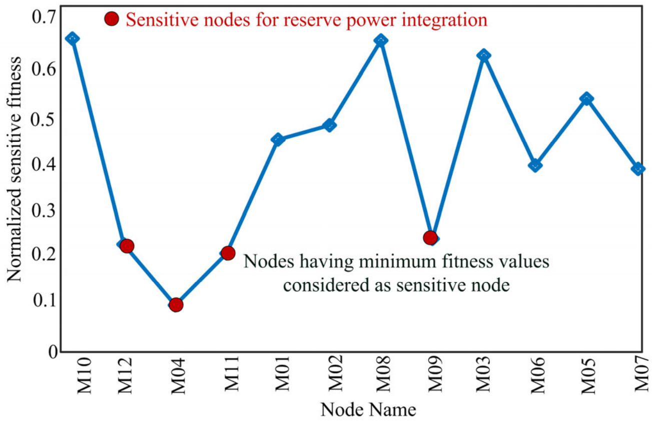

Fig. 7. Normalized sensitive fitness at different node of distribution network I.

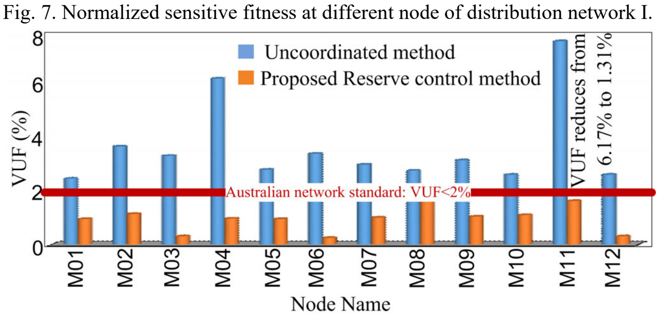

Fig. 8. Voltage unbalance factor at different node (case II) of distribution network I.

In this paper, it is assumed that EVs at the top four nodes (#M12, #M04, #M11, and #M09) is participated to meet the reserve generation. EV charging or discharging power is controlled of these sensitive nodes to improve the network performance. EV charging power of these EVs are optimized to improve the network performance. The improved network performance is shown in Fig. 8 and Fig. 9.

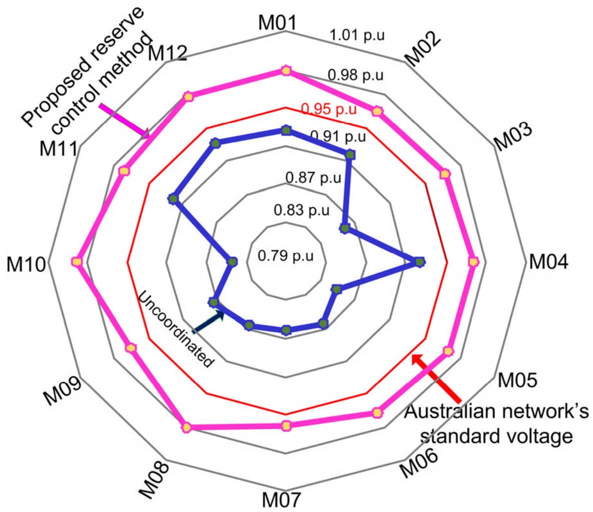

Fig. 9. Voltage at different node (case II) of distribution network I.

TABLE II
PROPOSED PHASE SEQUENCE (CASE II)

NODE NAME	PROPOSED PHASE SEQUENCE	NODE NAME	PROPOSED PHASE SEQUENCE
M10	0	M08	1
M12	2	M09	2
M04	0	M03	0
M11	2	M06	1
M01	0	M05	2
M02	1	M07	0

It is observed that the voltage unbalance is below 2% at each node and the minimum voltage at each node is above 0.95. The new generation is integrated into the sensitive node, which also re-sequence phases at each node of the network, as shown in Table II. From Table I and Table II, it is observed that the proposed phase sequence is not the same and alters the additional DES SPOCs among phases.

The proposed centralized control method is implemented in a distribution network II considering case II. The IoT tool performs optimization task. The improved performance is shown in Fig. 10 and Fig. 11. It is observed that voltage at each node is above 0.95 p.u after optimization.

From Fig.11, it is observed that the optimization approach reduces the voltage imbalance significantly (from 6.77% to 1.68% at node #M626) but the value of VUF is not less than 2% at all nodes. For this reason, the IoT tool performs reserve control task. EV charging method is controlled at sensitive nodes as shown in Fig. 11. From Fig. 11, it is observed that the voltage imbalance reduces from 3.46% to 0.26% at the node #M624 after optimization as well as below 2% at all nodes. The proposed control method regulates voltage within 0.95 p.u to 1.05 p.u and voltage unbalance below 2% at all nodes of distribution network II.

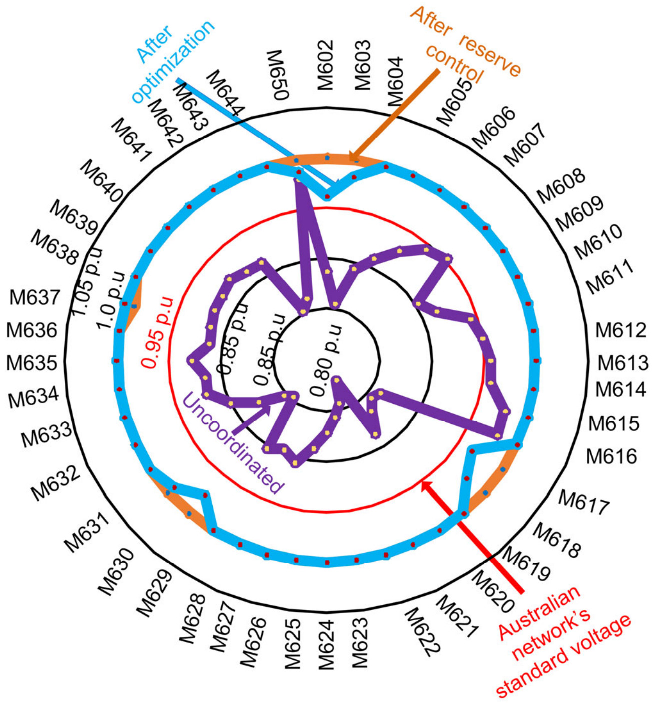

Fig. 10. Voltage at different node of distribution network II.

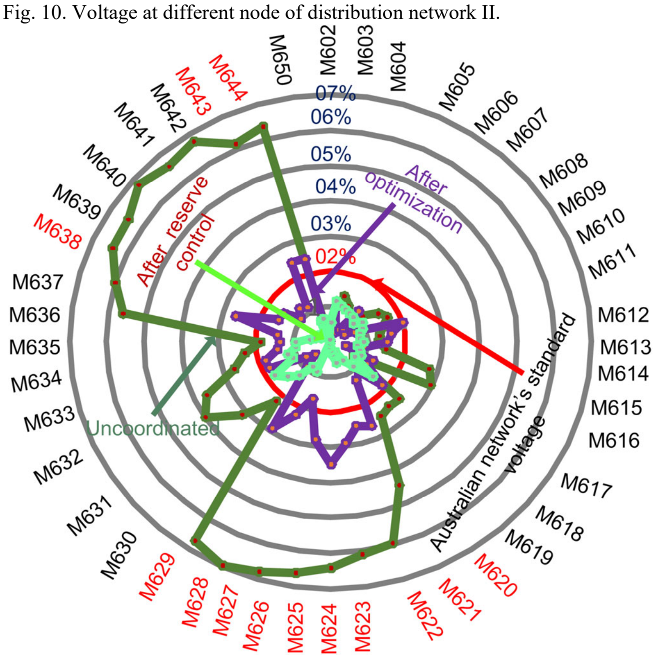

Fig. 11. Voltage unbalance factor at different node of distribution network II.

From the above discussion, it is observed that the IoT tool can decide which task (optimization or reserve control) to undertake. The first layer of the proposed control method jointly re-sequences phases and DESs which can mitigate network imbalance due to EV charging uncertainty if there have no generation shortage. But EV charging or discharging power coordination is required if there have generation uncertainty. Therefore, the proposed control method by using double layer strategy can completely mitigate the impact of EV and DES uncertainty.

The performance of the proposed control method is compared with recent methodologies for mitigating voltage imbalance. This study compares the performance with recent methods:

1) EV charging or discharging method [8], and

2) D-STATCOM method [29].

1) EV charging method

For minimizing voltage unbalance factor (VUF), different EV charging methods are discussed in [8]. It is observed that variable EV charging or discharging method can minimize the VUF value and perform better than the constant EV charging or discharging method [8]. The variable EV charging or discharging method is applied to distribution network I assuming both cases (case I and case II) for solving the optimization problem (14). For case I, the variable EV charging or discharging method improves the network performance to the standard value (node voltage above 0.95 p.u, VUF less than 2%, and the neutral current reduces to 10.24 A). Though the performance is improved, it is observed that individual EV charging power is reduced up to 32% for case I. The variable charging or discharging method reduces EV charging power as [8] and all connected EVs act as participants in the optimization. On the contrary, the proposed centralized approach in this study does not reduce EV charging power as well as include EVs as a participant at any node in case I. The proposed control method is compared with the variable charging and discharging method considering both cases and summarized in Table III.

Table III shows that the proposed control method requires less number of EV participants to improve the network performance. In variable EV charging or discharging method, each EV participates to maintain the network performance [8] which compromises with the satisfaction level of EV owners. The proposed method reduces the number EV participants. In this way, the proposed control method increases the level of comfort of EV owners.

TABLE III
PROPOSED METHOD VS VARIABLE EV CHARGING METHOD
(NUMBER OF PARTICIPATED EVS)

DISTRIBUTION NETWORK	CASE	VARIABLE EV CHARGING METHOD	PROPOSED METHOD
NETWORK I	CASE I	ALL CONNECTED EVS	NONE OF EVS
	CASE II	ALL CONNECTED EVS	38.91% EVS
NETWORK II	CASE I	ALL CONNECTED EVS	NONE OF EVS
	CASE II	ALL CONNECTED EVS	53.46% EVS

The developed control method does not require various pieces of information from EV users, or grid performance at respective SPOCs of the whole network at each time slot. In this way, the centralized control method reduces the data storage capacity, and communication complexity by maintaining network constraints.

2) D-STATCOM method

The D-STATCOM is used to regulate voltage by controlling active power (P) and reactive power (Q). For mitigating voltage unbalance and regulate voltage, the amount of required power (S) is quantified in [29].

In this section, it is assumed that PV owners installed STATCOM devices to maintain power quality of the distribution grid and delivering power at rated converter capacity with a unity power factor. EV charging or discharging power would be remained the same. The performance of D-STATCOM is investigated to improve voltage unbalance, voltage, and energy loss with a tuned value of P and Q. The tuned P and Q value is determined by using the DE optimization algorithm subject to constraint (16) considering case II. The D-STATCOM performance is compared with the proposed control method as shown in Fig. 12 and Fig.13.

$$S = \sqrt{\left(P^2 + Q^2\right)} \tag{16}$$

It is observed that voltage is improved at all nodes above 0.95 p.u. as shown in Fig. 12 by controlling P and Q of a PV converter. The tuned value of P and Q is dispatched subject to converter capacity (S). It is observed that the value of VUF is higher than 2% at three measurement point out of twelve measurement point. It is also investigated that the VUF value can be minimized in these three nodes by increasing converter capacity (S) as like [29]. Increasing capacity also induce additional cost to PV owners. Moreover, suitable policies and price based incentives are required for PV owners to maintain power quality for dispatching reactive power. Therefore, the proposed control method is a cost-efficient solution to maintain power quality of the distribution network.

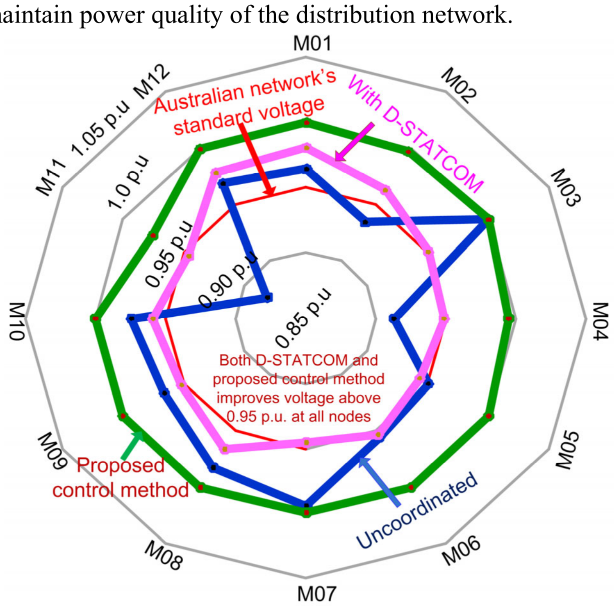

Fig. 12. Comparison of voltage at different node of distribution network I.

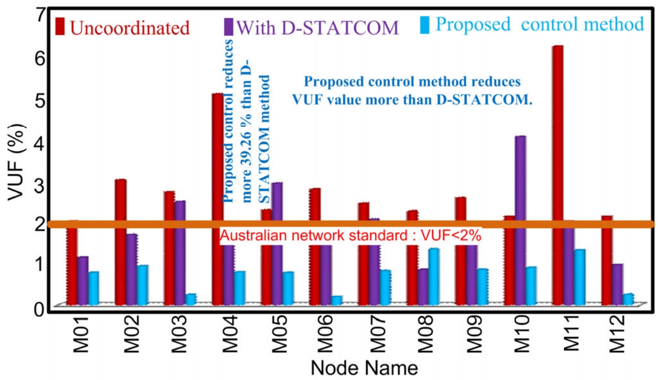

Fig. 13. Comparison of voltage unbalance at different node of distribution network I.

To demonstrate the robustness of the proposed control method, a new meta-heuristic algorithm named the whale optimization algorithm (WOA) is applied to distribution network I. The DE and WOA optimization algorithm have been successfully convergent for all timeslot (24 hour), representing the robustness of the proposed control method. The convergence characteristic plot of both optimization algorithms for the proposed method is shown in Fig. 14.

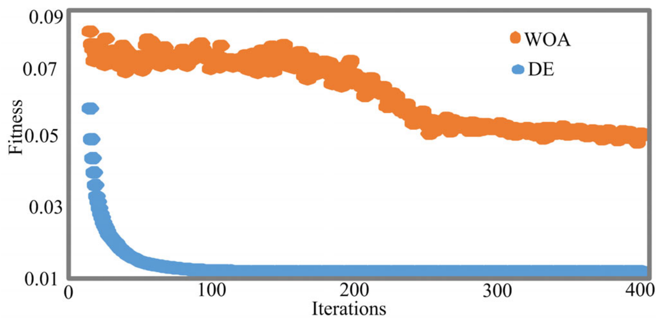

Fig. 14. Convergence characteristics of WOA and DE for the proposed control method.

Fig. 14 demonstrates the mean value of fitness function with 400 generations. It is observed that the fitness value is not improved after 120 generations for DE optimization, supporting higher efficiency. WAO requires higher number of generation to solve the optimization problem. Therefore, the DE optimization algorithm shows better exploration ability over WOA. In this analysis, the computing time for solving the optimization problem by using the DE optimization algorithm is 320s which is implemented on a computer with Intel Core i7 processor @ 2.80 GHz. Therefore, the proposed control method using DE optimization algorithm showed efficacy of the IoT tool.

VI. Conclusion

This paper proposed an IoT enabled centralized control strategy, which consists of two stages. The first stage is to jointly coordinate phases and DESs dispatch among phases per node. If necessary, the second stage is trigged to coordinate EV charging or discharging at sensitive nodes (having higher voltage unbalance and poor voltage profiles). The performance is evaluated on an Australian unbalanced distribution grid. The proposed control method improved voltage up to 18.35%, while voltage imbalance reduced below

2% at all nodes and the neutral current reduced from 189.96 A to 17.42 A. The proposed strategy shows superior performance over D-STATCOM and EV charging method. The obtained results showed that an optimal coordination of phases and DESs can involve much less number of EV participants to satisfy the expected network performance whereas keep the rest of EVs unaffected in a distribution network. This in term leads to a less complex communication infrastructure and lower data processing overhead and more convenience to EV owners. Based on the findings from this research, it can be recommended to optimize coordination phases and DESs prior to optimize controlling of EV charging or discharging power for mitigating voltage unbalance, neutral current, and regulating voltage in a distribution network.

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