Two-Stage Optimization Method for Energy Loss Minimization in Microgrid Based on Smart Power Management Scheme of PHEVs

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***Abstract*—Utilizing plug-in hybrid electric vehicles (PHEVs) is growing fast and booming nowadays. These vehicles, as portable loads and energy sources, may be connected to standard sockets at home. As a result, those extra electrical loads, grid to vehicle, generations, and vehicle to grid, have several impacts on distribution networks, e.g., network energy loss. This paper presents a two-stage optimization method to minimize the energy loss of microgrid with different penetration levels of PHEVs. In the first stage, a novel convex quadratic objective function for active power management of PHEVs is proposed, and daily required energy of PHEVs is calculated based on stochastic model of PHEV owners' behavior. It is supposed that PHEVs can be employed as distributed capacitors. Therefore, reactive power of PHEVs is specified in the second stage. Afterward, the proposed methodology is applied to a realistic distribution network. It will be illustrated that network energy loss is likely to rise considerably in the case of increasing penetration level of PHEVs without smart charging strategy; in order to minimize network energy loss, a smart management scheme will have to be considered. Also, the significant impact of PHEVs' active and reactive power management on energy loss reduction will be demonstrated.**

***Index Terms*—Active and reactive power management, energy loss reduction, microgrid, plug-in hybrid electric vehicle (PHEV), smart charging.**

NOMENCLATURE

R_i	Resistance of ith feeder.
I_i^t	Current of ith feeder at time t.
L	Set of lines of the power system.
T	Time period.
X, Y, Z	Decision parameter matrices.
N	Set of nodes of the power system.
V	Number of plug-in hybrid electric vehicles (PHEVs).
TS	Number of time steps over a day.
p_n^t	Net injected active power at the nth node at time t.
q_n^t	Net injected reactive power at the nth node at time t.
V_n^t	Amplitude of voltage at nth node at time t.
V_m^t	Amplitude of voltage at mth node at time t.
δ_n^t	Angle of voltage at nth node at time t.
δ_m^t	Angle of voltage at mth node at time t.
Y_{nm}	Amplitude of admittance between nth and mth nodes.
θ_{nm}	Angle of admittance between nth and mth nodes.
S_{customer}^t	Demand of customer load connected to node n at time t.
$P_{\text{PHEV},v}^t$	Active power of vth PHEV at time t.
$Q_{\text{PHEV},v}^t$	Reactive power of vth PHEV at time t.
$S_{\text{PHEV},v}^t$	Apparent power of vth PHEV at time t.
$S_{\text{Rated},v}$	Nominal rating of vth PHEV.
B_v	Battery capacity of vth vehicle.
$V_{\min}$	Minimum permissible bus voltage.
$V_{\max}$	Maximum permissible bus voltage.
$I_{\max,i}$	Current carrying capacity of ith line.
APL_i^t	Active power loss of ith feeder at time t.
P_i^t	Active power flow in the ith line at time t.
Q_i^t	Reactive power flow in the ith line at time t.
c_1, c_2, c_3	Constant values.
V_N	Nominal voltage of power system.
EL_i^T	Energy loss of ith branch over period T.
TE_n^T	Total required energy of nth node during period T.
CEL_n^T	Co-energy loss of nth node during period T.
$X_{C,v}$	Reactance of vth PHEV coupling inductor.
$V_{\text{PHEV},v}^t$	Inverter output voltage.
P_{Loss}	Inverter loss.

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I. INTRODUCTION

THE SWIFT technological advances in automotive sector, along with the increase in oil price as well as growing environmental concerns, have caused the rapid appearance of electric vehicles (EVs) with expanded energy sources [1]. There are basically two types of EVs: 1) pure battery electric vehicles, which solely work with batteries as electric power source; and 2) PHEVs, which essentially work with a combination of two power sources, i.e., batteries and gasoline [2]. The latter are an extended version of current hybrid electric vehicles including a battery with larger autonomy and able to be charged from a standard outlet at home [3].

PHEVs consume a large amount of electricity, so energy consumption will experience several possible significant peak values [4]. Consequently, charging these vehicles from home outlets dramatically affects the distribution system. The charging impacts of PHEVs on the power distribution networks have been introduced in the literatures and have been widely investigated [2], [3], [5], [6]. These impacts are generally categorized into two classes: 1) the impact on distribution system equipment including transformers [7], cables [8], circuit breakers, and fuses [8]; and 2) general effects on distribution system characteristics including harmonics [8], load profile [9], and power loss [5].

In the recent papers, significant effort has been devoted to reduce PHEV battery charging impacts through managing these loads [2], [5], [10]. On the other hand, many researches have focused on the infrastructures and architectures of smart charging [11]. However, the focus lies on both of them in this paper.

Besides, modeling PHEVs charging is of utmost importance. Modeling PHEV owners' behavior and forecasting battery state of charge (SOC), in any time, are proposed in [9]. Recently, in 2013, Grahn *et al.* [12] have proposed a new PHEV home-charging pattern.

Modeling PHEV, reducing distribution system loss, and designing infrastructure network for smart charging concepts have been independently introduced in [9], [11], and [12]. Nevertheless, there is little research on minimizing power loss using power management of PHEVs [13]–[15]. Mentioned studies point out that distribution loss can be reduced through managing PHEV charging pattern. However, they have not been involved in several overriding concerns such as uncertain nature of customer load, stochastic model of PHEV, and PHEV operation as reactive power compensator and vehicle to grid (V2G) operation mode, specially. Optimal PHEVs power management for minimizing energy loss in a large-scale penetration of PHEVs is a nontrivial task due to the large number of control variables. Therefore, some unrealistic assumptions (i.e., the size of power system and number of PHEVs are assumed to be small) are made in order to simplify the problem in all previous studies. This is the main drawback of previous studies.

Furthermore, none of the previous studies on minimizing power loss has considered the viability of the communication network architecture for smart charging scheme in a large-scale penetration of PHEVs. Consequently, we believe that considerable work is still required on the simultaneously managing PHEV active and reactive power for energy loss minimization, which have not been addressed.

This paper introduces a novel two-stage optimization method aimed at minimizing microgrid energy loss in a large-scale penetration of PHEVs based on smart power management of PHEVs while assuming the following features.

1) Monte Carlo simulation (MCS) is applied to take into account the uncertainties coming to the picture from customer load and PHEV owners' behavior.
2) A two-stage optimization method is proposed and investigated for fast computation of loss minimization problem in a large-scale penetration of PHEVs.
3) Reactive power supplied by PHEVs as distributed capacitors.

In this paper, a convex quadratic solution is proposed for the purpose of minimizing energy loss using active and reactive power allocation of PHEVs. At each time step over a day, the active power and reactive power of PHEVs are considered as control variables. In the first stage, a novel local convex quadratic approach is proposed for optimal active power management of PHEVs which is topology-independent. In the second stage, a time-independent global optimal reactive power management solution is introduced. One of the advantages of the proposed methodology is that it can be generalized to all power systems, i.e., radial or interconnected networks. Furthermore, this approach is applicable to any size of power systems with high level of PHEV penetration. Moreover, the convexity of the proposed method leads to fast and efficient solution which is fundamental and vital requirement of real-time dispatch.

This paper is organized in four sections. In the next section, problem statement and conventional energy loss minimization problem is presented. In Section III, the proposed methodology is discussed and each stage of optimization solution is separately explained in detail. PHEVs parameters required for modeling are explained in Section IV. In this section, part A is devoted to modeling customer load, and part B is devoted to stochastic forecasted amount of PHEVs energy required for typical day. In addition, modeling PHEV operating curves is presented in part C. To justify the proposed algorithm, a real distribution network is considered as a case study and several simulations are conducted in Section V.

II. Problem Statement

So far, different methods, i.e., optimal conductor selection, capacitor placement, distributed generation placement, and reconfiguration, have been proposed to reduce losses in distribution systems. In recent years, with PHEV technology development, power loss minimization has been shifted from the conventional methods to modern ones. One of these approaches is to use PHEVs as controllable load and dispatchable distributed energy resource. Under this circumstance, the active power and reactive power of PHEVs at each time step are considered as control variables. Therefore, the energy loss minimization formula for a distribution network over time period T is given by

$$\text{Minimize } F(X) = \left(\sum_{i \in L} \sum_{t \in T} R_i \left(I_i^t\right)^2 \right) \tag{1}$$

$$X = \begin{bmatrix} P_{\text{PHEV},1}^{1} & Q_{\text{PHEV},1}^{1} & P_{\text{PHEV},1}^{2} & Q_{\text{PHEV},1}^{2} & \cdots & P_{\text{PHEV},1}^{\text{TS}} & Q_{\text{PHEV},1}^{\text{TS}} \\ P_{\text{PHEV},2}^{1} & Q_{\text{PHEV},2}^{1} & P_{\text{PHEV},2}^{2} & Q_{\text{PHEV},2}^{2} & \cdots & P_{\text{PHEV},2}^{\text{TS}} & Q_{\text{PHEV},2}^{\text{TS}} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ P_{\text{PHEV},V}^{1} & Q_{\text{PHEV},V}^{1} & P_{\text{PHEV},V}^{2} & Q_{\text{PHEV},V}^{2} & \cdots & P_{\text{PHEV},V}^{\text{TS}} & Q_{\text{PHEV},V}^{\text{TS}} \end{bmatrix}$$

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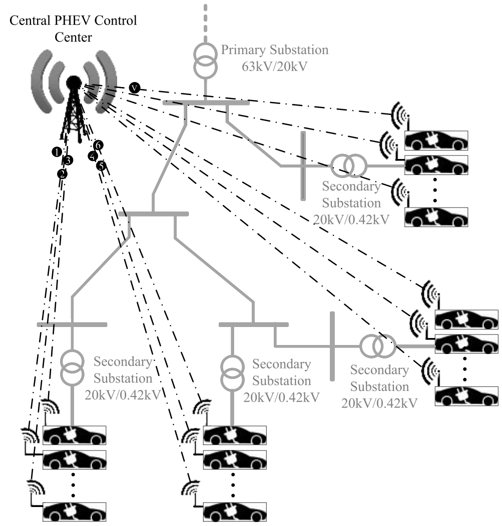

Fig. 1. Communication network architecture for common energy loss minimization.

Subject to

$$p_n^t = \sum_{m \in N} V_n^t V_m^t Y_{nm} \cos\left(\theta_{nm} - \delta_n^t + \delta_m^t\right) \quad \forall n \in N \tag{2}$$

$$q_n^t = \sum_{m \in N} V_n^t V_m^t Y_{nm} \sin\left(\theta_{nm} - \delta_n^t + \delta_m^t\right) \quad \forall n \in N \tag{3}$$

$$p_n^t + jq_n^t = S_{\text{customer}}^t + S_{\text{PHEV}}^t \quad \forall n \in N \tag{4}$$

$$\sum_{t \in T} P_{\text{PHEV},v}^t = B_v \quad \forall v \in V \tag{5}$$

$$P_{\text{PHEV},v}^{t2} + Q_{\text{PHEV},v}^{t2} \le S_{\text{Rated},v}^2 \quad \forall v \in V \tag{6}$$

$$V_{\min} \le \left|V_n^t\right| \le V_{\max} \quad \forall n \in N \tag{7}$$

$$\left|I_i^t\right| \le I_{\max,i} \quad \forall i \in L. \tag{8}$$

In the above equations, (2) and (3) are non-convex constraints which are load flow equations, (5) stems from this fact that PHEV battery should be fully charged during charging period, and (6), operating curve of PHEV, is explained in Section IV-C. The limits on terminal voltages and current carrying capacity of conductors are considered as (7) and (8).

It is very clear from decision parameter matrix that the number of control variables is equal to the number of matrix elements or $2 \times V \times \text{TS}$. Solving aforementioned energy loss minimization problem in a large-scale penetration of PHEVs needs too large calculation amount due to great number of optimization variables and in some cases may not yield the optimum network energy loss. Moreover, energy loss minimization solution through this approach needs such a communication network in which all PHEVs should be connected to central PHEV control center (CPCC), as shown in Fig. 1.

This scheme is not applicable due to technical and economic reasons. Therefore, it is critical to develop an effective and feasible method for energy loss minimization in the large-scale penetration of PHEVs. In the next section, a novel two-stage optimization approach, decoupled local active and global reactive power optimization solution, is introduced which does not require huge calculation burden.

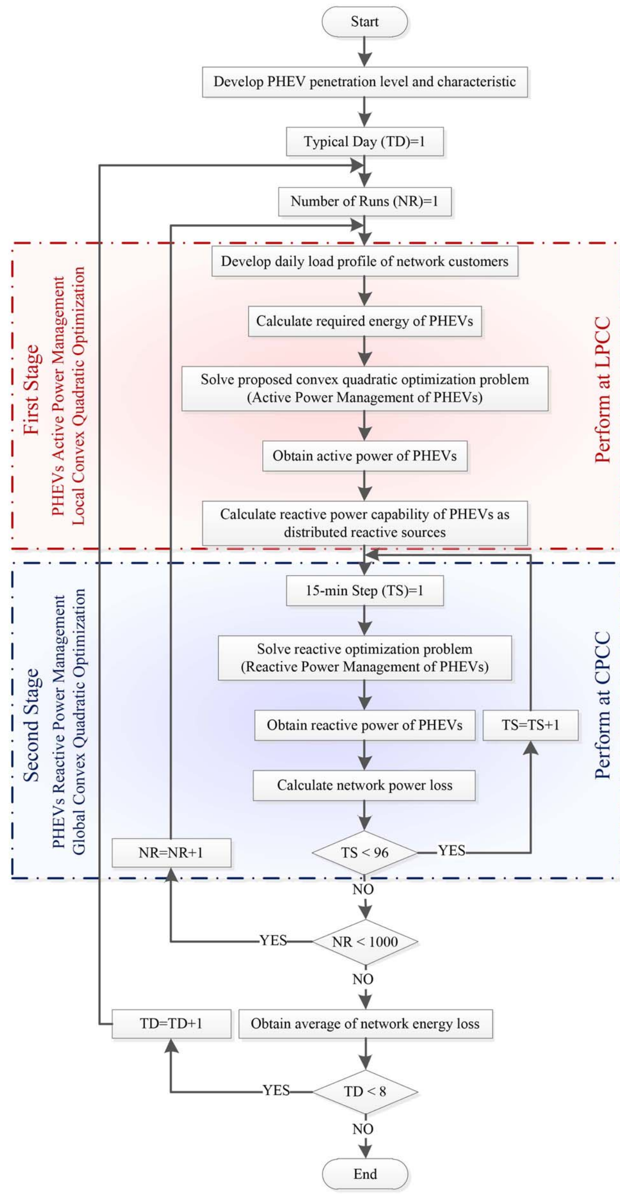

Fig. 2. Flowchart of the proposed methodology.

III. Proposed Two-Stage Optimization Method

The proposed methodology for optimal power management of PHEVs will be described in this section, comprehensively. Fig. 2 shows the flowchart of the proposed methodology. By following the step-by-step procedure of Fig. 2, it is possible to minimize network energy loss by managing active and reactive power of PHEVs.

First of all, a general description of active and reactive power decoupling is provided in Section III-A. Then, active power management, the first-stage control variable, as well as reactive power management, the second-stage control variable, are discussed in Sections III-B and III-C, respectively.

A. General Description

Active power loss of ith feeder at time t is proportional to the square of apparent power flow in the ith line, provided that the voltage in all points of the line is equal to nominal voltage [16]. It can mathematically be expressed as follows:

$$\mathrm{APL}_i^t = \frac{R_i\left(\left(P_i^t\right)^2 + \left(Q_i^t\right)^2\right)}{V_N^2} = c_1 R_i\left(\left(P_i^t\right)^2 + \left(Q_i^t\right)^2\right). \quad (9)$$

The energy loss relating to ith branch over an interval of time is the integral of apparent power loss over a period of time, e.g., 24 h, and it can be written as

$$\mathrm{EL}_i^T = \sum_{t\in T} \mathrm{APL}_i^t = c_1 R_i \sum_{t\in T}\left(\left(P_i^t\right)^2 + \left(Q_i^t\right)^2\right). \quad (10)$$

According to (10), it can be mathematically proven that energy loss minimization problem, simultaneous active and reactive power management of PHEVs, can be segregated into two separate optimization problems: 1) active power management of PHEVs as first stage; and 2) reactive power management of PHEVs as second stage, due to the following reasons.

1) Active power of loads is greater than the corresponding reactive ones at any given time (active and reactive power of loads have the same patterns in conjunction with the power factor of loads in distribution networks is generally greater than 0.8).
2) PHEV battery should be fully charged, refer to (5).

B. First Stage: Active Power Management

According to (4), the load of the each node may consist of customer and PHEV loads. Daily load profile of customers can be determined clearly using load forecasting techniques [17], [18]. In this way, active power of customer loads at any time can be estimated accurately. In similar fashion, daily required energy of PHEVs can be predicted precisely. As a result, the value of daily energy for each node is predictable and can be calculated accordingly by integration of loads power over 24 h

$$\mathrm{TE}_n^T = \sum_{t=0}^{T} P_n^t = c_2. \quad (11)$$

PHEVs as interruptible and controllable loads in grid to vehicle (G2V) operation mode and as dispatchable local dispersed generation in V2G operation mode are likely to change the shape of this curve. Therefore, with the presence of PHEVs a great number of demand curves can be found that satisfy (11). However, among these curves, one which guarantees the minimum energy loss should be chosen. The most optimum curve for this problem is a horizontal line. In other words, complete demand response (DR) leads to energy loss minimization in power system. It can be proved as follows. First, let define co-energy loss function

$$\mathrm{CEL}_n^T = \sum_{t\in T}\left(P_n^t - c_3\right)^2. \quad (12)$$

By expanding (12), it can be obtained that

$$\mathrm{CEL}_n^T = \sum_{t\in T}\left(P_n^t\right)^2 + \sum_{t\in T}\left(c_3\right)^2 - 2c_3\sum_{t\in T} P_n^t. \quad (13)$$

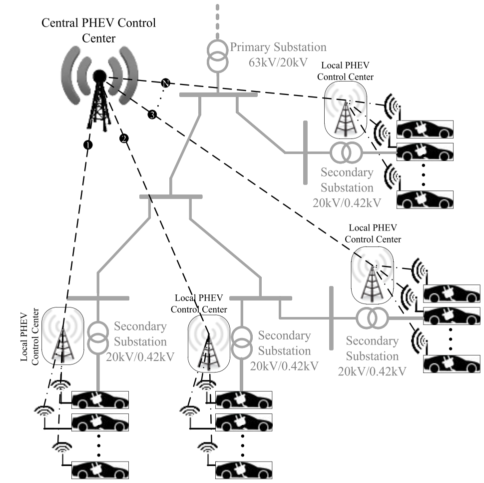

Fig. 3. Communication network architecture of the proposed method.

Then by substituting (11) in (13)

$$\mathrm{CEL}_n^T = \mathrm{EL}_i^T + T(c_3)^2 - 2c_3c_2. \quad (14)$$

It is obvious from (14) that minimization the branch energy loss by managing active power of PHEVs, EL_i^T, leads to minimization of co-energy loss function CEL_n^T. According to (12), CEL_n^T becomes minimized in case

$$P_n^t = c_3. \quad (15)$$

By substituting (15) in (11)

$$c_3 = \frac{\mathrm{TE}_n^T}{T}. \quad (16)$$

It means that if load profile is constant (equal to the mean of the daily energy), the energy loss will be minimized which cannot be attained in reality.

Therefore, the active power management of PHEVs formulation, first-stage optimization problem, over time period T can be written as

$$\text{Minimize } G(Y) = \sum_{t\in T}\left(P_n^t - \frac{\mathrm{TE}_n^T}{T}\right)^2 \forall n \in N \quad (17)$$

$$Y = \begin{bmatrix} P^1_{\mathrm{PHEV},1} & P^2_{\mathrm{PHEV},1} & \cdots & P^{TI}_{\mathrm{PHEV},1} \\ P^1_{\mathrm{PHEV},2} & P^2_{\mathrm{PHEV},2} & \cdots & P^{TI}_{\mathrm{PHEV},2} \\ \vdots & \vdots & \ddots & \vdots \\ P^1_{\mathrm{PHEV},V} & P^2_{\mathrm{PHEV},V} & \cdots & P^{TI}_{\mathrm{PHEV},V} \end{bmatrix}$$

Subject to: (4)–(6).

It can be inferred from (17) that the active power of PHEVs can be locally managed in local PHEV control centers (LPCCs) to achieve minimization of network energy loss without sending of PHEVs data to CPCC. It means that running time for solving optimization is reduced by converting large optimization problem to several parallel optimization problems. Fig. 3 shows architecture of local active power management of PHEVs. Moreover, first-stage optimization problem is topology-independent and can be solved faster at each of LPCCs. This is due to the fact that there is no need

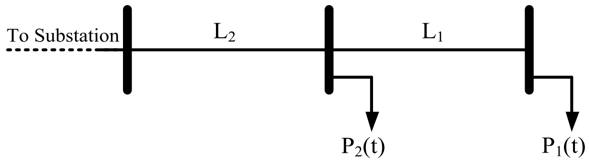

Fig. 4. Two-bus sample network under study.

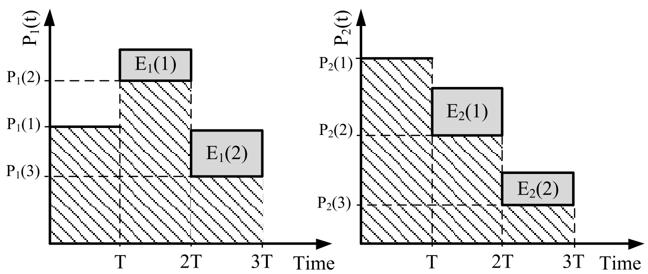

Fig. 5. Load profiles of two-bus sample network.

to solve the load flow equations. Furthermore, the proposed objective function is a convex quadratic function with convex constraints compared to common convex objective function with none-convex constraints.

To verify the proposed objective function and proving topology independency, energy loss minimization problem with two objective functions, common and proposed objective functions, in a simple two-bus network are solved analytically by means of the Lagrangian method. The single line diagram of two-bus sample system is shown in Fig. 4.

The load profiles of the network are presented in Fig. 5. As shown in Fig. 5, each load contains constant load, which are denoted by $P(1)$, $P(2)$, and $P(3)$; and controllable load, which are denoted by $E(1)$ and $E(2)$. Subscripts 1 and 2 refer, respectively, to the loads which are connected to buses 1 and 2. For simplicity, the power factor for loads is assumed to equal 1.

As mentioned earlier, active power loss of the feeder is proportional to the square of apparent power flow in the line. Therefore, the conventional objective function for energy loss minimization problem over period T (1) can be written as follows:

$$\begin{aligned} F(X) = R_1\Bigg[& P_1(1)^2 \times T + \left(P_1(2) + \frac{E_1(1)}{T}\right)^2 \times T \\ & + \left(P_1(3) + \frac{E_1(2)}{T}\right)^2 \times T \Bigg] \\ + R_2\Bigg[& (P_1(1) + P_2(1))^2 \times T \\ & + \left(P_1(2) + \frac{E_1(1)}{T} + P_2(2) + \frac{E_2(1)}{T}\right)^2 \times T \\ & + \left(P_1(3) + \frac{E_1(2)}{T} + P_2(3) + \frac{E_2(2)}{T}\right)^2 \times T \Bigg] \end{aligned} \tag{18}$$

$$\text{Subject to: } \begin{aligned} E_1(1) + E_1(2) &= \mathrm{BC}_1 \\ E_2(1) + E_2(2) &= \mathrm{BC}_2 \end{aligned} \tag{19}$$

where BC_1 and BC_2 are battery capacity of PHEV 1 and PHEV 2, respectively, R_1 and R_2 are the resistance of L1 and L2 feeders, respectively.

By solving the above optimization problem by means of the Lagrangian method, $E(1)$ and $E(2)$ for each load are found

$$\begin{aligned} P_1(2) + \frac{E_1(1)}{T} &= P_1(3) + \frac{E_1(2)}{T} \\ P_2(2) + \frac{E_2(1)}{T} &= P_2(3) + \frac{E_2(2)}{T}. \end{aligned} \tag{20}$$

In like manner, the energy loss minimization formulation with the proposed objective function can be written as

$$\begin{aligned} G(Y) = {} & (P_1(1) - M_1)^2 \times T + \left(P_1(2) + \frac{E_1(1)}{T} - M_1\right)^2 \times T \\ & + \left(P_1(3) + \frac{E_1(2)}{T} - M_1\right)^2 \times T + (P_2(1) - M_2)^2 \times T \\ & + \left(P_2(2) + \frac{E_2(1)}{T} - M_2\right)^2 \times T \\ & + \left(P_2(3) + \frac{E_2(2)}{T} - M_2\right)^2 \times T \end{aligned} \tag{21}$$

Subject to: (19).

$E(1)$ and $E(2)$ for each load can be obtained by solving the above optimization problem

$$\begin{aligned} P_1(2) + \frac{E_1(1)}{T} &= P_1(3) + \frac{E_1(2)}{T} \\ P_2(2) + \frac{E_2(1)}{T} &= P_2(3) + \frac{E_2(2)}{T}. \end{aligned} \tag{22}$$

As it is clear from (20) and (22), the results are the same for both the optimization problems with the conventional and proposed objective functions.

C. *Second Stage: Reactive Power Management*

To reduce energy loss in the network, schemes for reactive power compensation can be utilized [19]. Reactive power can be supplied through PHEVs [20], i.e., PHEVs can act as distributed capacitor and reduce the energy loss. Therefore, the proposed objective function for energy loss minimization in the second stage can be written as common capacitor placement problem for loss reduction in distribution networks

$$\begin{aligned} \text{Minimize } H(Z) &= \left(\sum_{i \in L} R_i \left(I_i^t\right)^2\right) \quad \forall t \in T \\ Z &= \left[Q^t_{\mathrm{PHEV},1} \; Q^t_{\mathrm{PHEV},2} \; \cdots \; Q^t_{\mathrm{PHEV},V} \right] \end{aligned} \tag{23}$$

Subject to: (2)–(4) and (6).

As inferred from (23), solving second-stage optimization problem depends on topology of the network. Consequently, reactive power should be globally managed at CPCC. On the other hand, this optimization stage is time independent and should be resolved to attain minimum power loss for each time interval. Subsequently, huge calculation burden can be avoided. Architecture of global reactive power management of PHEVs is shown in Fig. 3.

The proposed methodology can be used in practice. In this way, to attain minimum power loss, it is required to provide CPCC at primary substation and LPCCs at secondary substations. After PHEVs demand prognostication, local daily optimal active power management of PHEVs should be carried out at LPCCs. Afterward, reactive power of PHEVs should be managed globally at CPCC.

IV. Modeling

In this section, to investigate the issue of minimizing loss through simulation, model of loads including PHEVs and ordinary load is studied. Relevant explanation is divided into three sections: 1) customer loads (Section IV-A); 2) PHEVs stochastic demand (Section IV-B); and 3) PHEVs operating curves (Section IV-C).

A. Customer Load

Customer loads are implemented in simulation based on the provided data by an available database of load models that contains the results of statistical surveys performed in public residential areas in Iran [21]. The collected data from the distribution network are adopted to develop empirical cumulative density function (ECDF) of customer demands. Provided data represents weekly and seasonal variations of residential customer loads together with their power factor based on 15-min measurement intervals in eight typical days (weekdays and weekends in different seasons of the year). Subsequent to the adoption of the recorded load data, inverse ECDF was applied to develop simulated variables having the same uncertain nature as the recorded load. For more details, please refer to [21].

B. PHEVs Stochastic Demand

In this part, a comprehensive and flawless model is developed to forecast the energy demand of any vehicle based on the stochastic expected behavior of driving.

To calculate the effect of PHEVs penetrations on network energy loss, based on stochastic modeling, firstly it is necessary to generate random parameters. To do so, the battery capacity, electric usage per km, and location of any vehicle in each hour are probabilistically produced at 15-min interval of the typical days. Moreover, extra parameters such as number of trips and amount of distance in each trip shall be determined.

In this paper, it is assumed that this forecasting approach is randomly generated based on the MCS method. Moreover, all vehicles are assumed to be driven twice per day. The range of daily trips is simulated based on [22] that is, well, similar to the behavior of customers in the system under study. The characteristic of PHEVs is according to [23]. The efficiency of all vehicle chargers is supposed to be 90% [20]. The SOC of batteries at the beginning of the day is calculated by running 500 MCSs.

C. PHEVs Operating Curves

Different structures for bidirectional battery charger have been proposed so far. For the modeling required for this investigation, a common structure has been utilized.

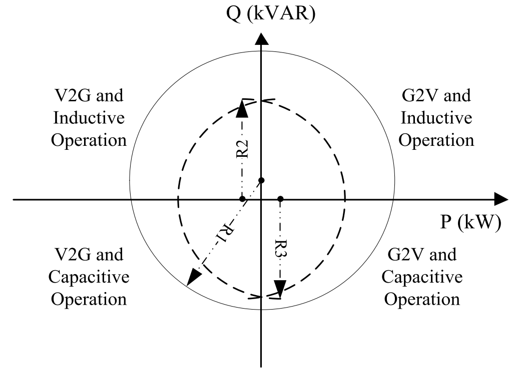

Fig. 6. Operating curve of PHEV.

The operating curve with bidirectional battery charger is confined by two limitations: 1) transferable power; and 2) equipment ratings. Transferable power can be written as following:

$$P^{t2}_{\text{PHEV},v} + \left(Q^{t}_{\text{PHEV},v} - \frac{|V^{t}_{n}|^{2}}{X_{C,v}}\right)^{2} = \left(\frac{\left|V^{t}_{\text{PHEV},v}\right|\left|V^{t}_{n}\right|}{X_{C,v}}\right)^{2}. \tag{24}$$

Therefore, transferable power limit can be plotted in the P–Q plane as a circle with radius $R1$ centered at $|V^t_n|^2/X_{C,v}$ on Q-axis and with radius $|V^t_{\text{PHEV},v}||V^t_n/X_{C,v}|$, as represented in Fig. 6. The other limitation curve is specified with regard to equipment ratings, i.e., nominal current of outlet and converter switches. Assuming the equipment to be lossless, these limitations are drawn as concentric circles centered at the origin in P–Q plane and mathematically written as (6).

However, transferring of electrical energy through the equipment is always accompanying with some losses. Therefore, (6) shall be written as follows:

$$\left(P^{t}_{\text{PHEV},v} \pm P_{\text{Loss}}\right)^{2} + Q^{t2}_{\text{PHEV},v} \le S^{2}_{\text{Rated},v} \tag{25}$$

where positive sign is used for G2V operation mode and negative sign is applied for V2G operation mode. These two equations appear as two semicircles that are denoted as $R2$ and $R3$ in Fig. 6.

The operating curve of PHEV is depicted in Fig. 6, represents all different operation modes of PHEV. In quadrants I and IV, PHEV is in G2V mode and draws power from the grid. In quadrants II and III, PHEV is in V2G mode and injects power into the grid. PHEV can acts as an inductor and provide reactive power in case it operates at quadrants I and II and acts like a capacitor if it operates at quadrants III and IV. Thus, PHEV can operate in all four quadrants provided that operating point should be inside the limiting curve.

V. Simulation Results

The proposed methodology is examined here on a realistic test case. The network under study is 20 kV distribution network of Sirjan city center. Refer to [16] for more details on the network structure and data.

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The proposed methodology is scrutinized for a typical summer weekday. In this way, the network under study is analyzed according to the flowchart as shown in Fig. 2, investigating the impact of different penetration levels of PHEVs, from 10% to 90% in 10% steps, on the distribution system energy loss by running 1000 MCSs. It is noted that, in these analyses, PHEV penetration is defined as the ratio of network customers with PHEV to the total number of customers.

Three proposed scenarios are considered for simulations conducted in this investigation corresponding to different charging strategies of PHEVs, along with an extra reference scenario without PHEV.

A. Reference Scenario

No PHEV connected to the network.

Scenario 1: The scenario with unmanaged charging of PHEVs.

Scenario 2: The scenario with PHEVs operating both in G2V and in V2G modes and no reactive compensation is presumed through PHEVs.

Scenario 3: The scenario with PHEVs operating both in G2V and in V2G modes and being able to compensate reactive power.

To investigate how energy loss quantities may be affected depending on charging of PHEVs, the calculation is further performed for 10%–90% penetration levels of PHEVs under the proposed scenarios. In this way, the load profiles of the network at each loading point are obtained by integrating the loads of customer and the connected PHEVs using MATLAB software. Then, general algebraic modeling system tool is used for solving the first- and second-stage optimization problems. Afterward, for average energy loss computation, simulations are performed by using DIgSILENT software.

To calculate energy loss more precisely, load flow study is conducted at all 15-min intervals of summer weekday of the year. The network energy loss for summer weekday without presence of PHEV is equal to 1.089 MWh.

Fig. 7 shows the average active, reactive, and apparent power of primary substation for the proposed scenarios during typical weekdays in summer with 90% PHEV penetration. For comparison, the load profile of the reference scenario (0% PHEV penetration) is added to the figure.

From Fig. 7(a) and (c), it can be observed that by imposing PHEVs charging load on distribution substation without any management on charging of PHEVs, load profile belonging to scenario 1 hits the greatest peak as compared to the other scenarios and can leads to the greater evening peak. It stems from the fact that people connect PHEVs when they arrive home. As PHEVs can operate both in G2V and in V2G modes in scenarios 2 and 3, active power value during peak hours is lower as compared to reference scenario [Fig. 7(a)]. Since in scenario 3, it is supposed that PHEVs can compensate reactive power, the apparent power of primary substation is lower as shown in Fig. 7(b), compared to the other scenarios.

According to Fig. 7(c), considering smart charging strategies leads to a decrease in apparent power demand in peak hours. It accompanies with an increase in demand in off-peak hours.

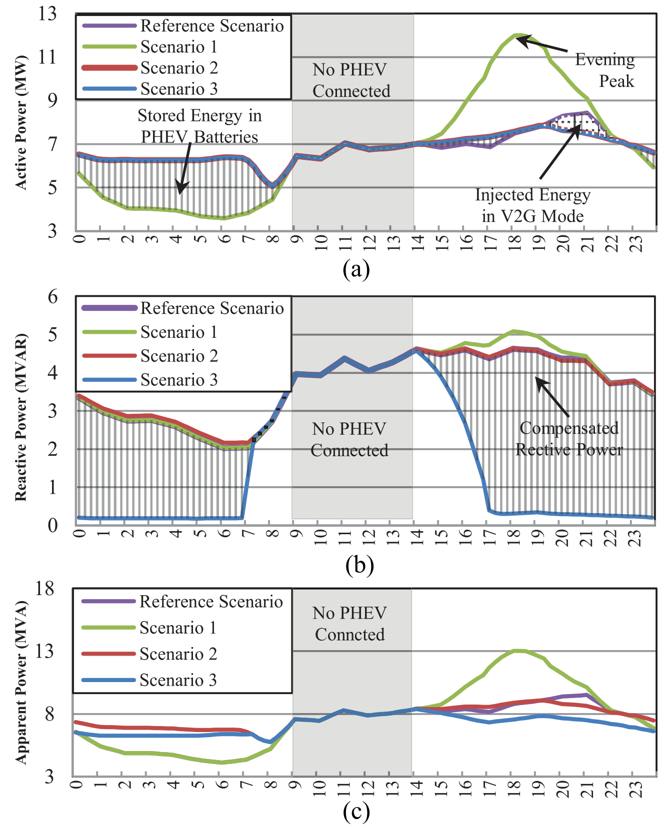

Fig. 7. Primary substation power for the proposed scenarios with 90% PHEV penetration. (a) Active power. (b) Reactive power. (c) Apparent power.

TABLE I
NETWORK DAILY ENERGY LOSS UNDER THE PROPOSED SCENARIOS

Penetration Level (%)	Energy loss (MWh)			CPU Times (sec)		
	Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
10	1.117	1.101	1.045	7010	8563	21239
20	1.144	1.114	1.018	7035	8637	22760
30	1.174	1.129	1.002	7048	8669	24147
40	1.203	1.144	1.000	7079	8701	32492
50	1.238	1.162	1.006	7107	8752	45165
60	1.269	1.179	1.016	7123	8778	49863
70	1.303	1.198	1.030	7153	8901	55384
80	1.338	1.219	1.047	7165	8953	57617
90	1.375	1.241	1.066	7196	8979	62768

In other words, managed charging and discharging of PHEVs is one of the DR approaches which can flatten the load profile out and minimize network energy loss.

To investigate further, the proposed methodology has been examined for all 15-min intervals of the typical day with different penetration level of PHEVs. Table I shows the summary of the results and CPU running time. It should be noted that all figures and tables in this section are based on the mean values of 1000 MCSs.

According to Table I, it is discernible that the energy loss resulting from network operation over a day is within the range of 1–1.375 MWh for various penetration levels of PHEVs. The most discernible point in Table I is that without smart charging of PHEVs, i.e., scenario 1, there is a significant increase in the network energy loss value, as compared to the scenario without PEHVs. This increase is in proportion to PHEV penetration level. Furthermore, by comparing the contents relating to scenario 3, with reference scenario, it can be inferred that the increase in the PHEV penetration level has very little effect on network energy loss.

Without managed charging, the network energy loss increase at 90% penetration level of PHEVs is as much as 1.375 MWh, which is by far much higher energy loss quantities resulting from the other scenarios. More precisely, regarding the smart charging and discharging strategies of PHEVs, it should be noted that scenario 3 seems to have the most advantageous impact on the network energy loss reduction. In fact, when the smart charging strategy is adopted by PHEV owners, network energy loss reduces down to 1.241 and 1.066 MWh using scenarios 3 and 4, respectively.

It is clear that PHEV penetration level plays a major role in network energy loss. As shown in Table I, the network energy loss for scenarios 1 and 2 gradually raises as the penetration level of the connected PHEVs increases. For instance, considering scenario 1, an increase in the penetration level of PHEVs from 30% to 70% makes the network energy loss to rise about 0.13 MWh. Further increase in the penetration level to 90% may cause an additional 0.286 MWh increment in the network energy loss.

This trend is expected to be invariably unchanged for the proposed scenario 3 during the summer weekday of the year. However, in contrast to the other scenarios, the network energy loss for scenarios 3 gradually decreases down to 1 MWh and then progressively raises up to 1.066 MWh as the penetration level of the connected PHEVs increases. This is due to the reason that in low penetration level of PHEVs, reactive power could not be fully compensated. As shown in Fig. 8, for 50%–90% penetration level of PHEVs reactive power profiles of primary substation are very close to each other. In these penetration levels, reactive power is entirely compensated and an increase in the penetration level of PHEVs from 50% to 90% could not decrease energy loss via reactive power compensation.

Fig. 9 exhibits the percentage of energy loss reduction compared to scenario 1, as the penetration level of PHEVs increases during various charging strategies.

As a result, scenario 3 (PHEVs operating both in G2V and in V2G modes together with compensating reactive power) may represent the most favorable charging strategy of PHEVs. As can be perceived from Fig. 9, for the all charging policies, the network energy loss reduction tends to rise as the penetration level of the connected PHEVs increases. This increment is estimated to be in the range of 1.5%–22.5% for the network under study. As a result, network energy loss can be reduced to some extent, when smart charging scenarios are implemented. For the worst penetration level, 90% network energy loss can be reduced down to 22.5%. In compared to

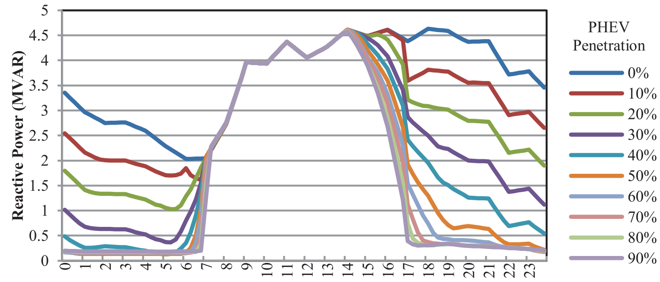

Fig. 8. Reactive power profile of primary substation for scenario 4 with different penetration levels of PHEVs.

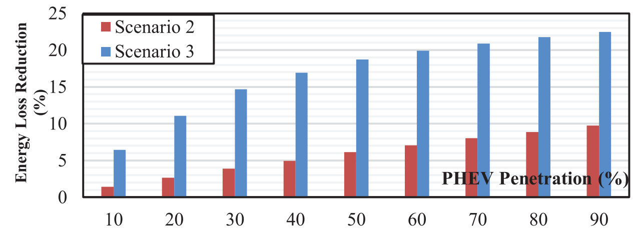

Fig. 9. Impact of PHEVs charging strategies on the network energy loss reduction.

scenario 1, this reduction stems from the fact that active power in peak hours and reactive power over a day can be injected by PHEVs in smart charging scenarios. Similar results can be acquired by applying the proposed methodology to any given network, if the required data are available. These results can provide important signals to microgrid operators who expect to accommodate considerable penetration level of PHEVs in near future and are willing to impose the least adverse impacts on the network operation.

VI. Conclusion

Charging of PHEVs can impose an excessive load on distribution networks and may increase network energy loss, unexpectedly. In this paper, a methodology has been proposed to minimize the network energy loss using smart charging and discharging of PHEVs. The proposed methodology is based on a novel two-stage optimization method, and it does not require a huge amount of calculation burden and running time, which is essential for real-time dispatch. Also, the uncertain nature of customer loads and PHEV charging profile has been included into the analysis through an MCS. The proposed methodology performs a detailed study on the effect of various PHEV charging strategies and penetration levels on the energy loss of a realistic distribution network. The analysis conducted in this paper makes an attempt to quantify the effects of PHEVs on microgrids in the area of reducing network energy loss. From the numerical results, it is concluded that most auspicious impact on the network energy loss will be resulted by assuming PHEVs operating both in G2V and in V2G modes along with compensating reactive power. Furthermore, it is revealed that when 90% of network customers use PHEV, a 22.5% reduction could be expected in the percentage of the network energy loss provided that the smart charging strategies are employed.

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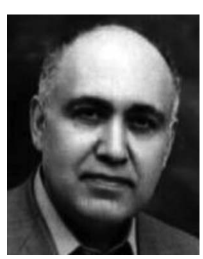

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