An Energy Efficient Network Reconfiguration in Active Distribution Network by Incorporating Losses from Converter-Based DGs

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***Abstract*—The minimization of losses is one of the key objectives behind the operation of the distribution network. To achieve this objective, a number of methods, such as distribution network reconfiguration, active/reactive power injection, etc., are employed. Nowadays, the integration of converter-based distributed generation into the distribution network is gaining popularity due to its price reduction and sustainable nature. The converters employed in such generation can also provide reactive power aid. However, the reactive power aid from the converters leads to losses inside it, which constitutes a major portion of total losses occurring in the network. As a result, this study proposes a day-ahead operation approach for an active distribution network in order to reduce overall energy losses, which include network and converter losses. The primary goal of this framework is to establish the optimal radial topology of the network and reactive power dispatch from photovoltaic sources. The proposed framework is developed as a mixed-integer second-order cone programming problem that offers a global solution and is amenable to being solved by commercial solvers. A modified IEEE 33-bus distribution network is used to test the proposed framework. The findings show that the suggested architecture minimizes the overall energy losses in the distribution network.**

***Index Terms*—Distribution network, converter losses, network reconfiguration, reactive power support, second-order cone program.**

NOMENCLATURE

Indices and Sets:	
i, j	The bus index.
ij, t	The branch, time index.
$\Lambda/\Lambda^{\mathrm{LD}}/\Lambda^{\mathrm{MG}}$	Set of network/load/main grid buses.
Λ^{PV}	PV coupled buses set.
χ	Variable set.
Λ^{i}	Set of buses connected to i^{th} bus.
Λ^{T}	Set of time intervals.
Parameters:	
$P_{i,t}^{\mathrm{LD}}/Q_{i,t}^{\mathrm{LD}}$	Forecast of i^{th} bus active/reactive load demand at t^{th} time interval.
$P_{i,t}^{\mathrm{PV}}$	Forecast of i^{th} bus PV generation at t^{th} time interval.
$S_{i,max}^{\mathrm{PV}}$	Converter rating of i^{th} PV.
$N_{ij,max}^{\mathrm{CSW}}$	Maximum permissible switching actions in a day of ij^{th} CSW.
$P_{i,min}^{\mathrm{MG}}/P_{i,max}^{\mathrm{MG}}$	Minimum/maximum active power limits of main grid.
$Q_{i,min}^{\mathrm{MG}}/Q_{i,max}^{\mathrm{MG}}$	Minimum/maximum reactive power limits of main grid.
$V_{i,max}/V_{i,min}$	Voltage maximum/minimum bounds of i^{th} bus.
$P_{ij,max}/Q_{ij,max}$	Active/reactive power limit of ij^{th} line.
$I_{ij,max}$	Maximum current limits of ij^{th} line.
R_{ij}/X_{ij}	Resistance/reactance of the ij^{th} line.
G_{ij}/B_{ij}	Conductance/susceptance of the ij^{th} line.
Variables:	
$Q_{i,t}^{\mathrm{PV}}/S_{i,t}^{\mathrm{PV}}$	Continuous variables of reactive/apparent powers of i^{th} PV at t^{th} time interval.
$\gamma_{ij,t}^{\mathrm{CSW,UP}}/\gamma_{ij,t}^{\mathrm{CSW,DN}}$	Binary variables referring to up/down regulation status of i^{th} CSW at t^{th} time interval.
$\delta_{ij,t}^{\mathrm{CSW}}$	Binary variable of ij^{th} line at t^{th} time interval, it is equal to 1 if node j is parent of node i and equal to 0 else.
$\zeta_{ij,t}^{\mathrm{CSW}}$	Binary variable of ij^{th} line at t^{th} time interval, it is equal to 1 if line is connected otherwise equal to 0.
$P_{i,t}^{\mathrm{MG}}/Q_{i,t}^{\mathrm{MG}}$	Continuous variables of active/reactive powers of main grid at t^{th} time interval.
$P_{ij,t}/Q_{ij,t}$	Continuous variables referring to active/reactive power ij^{th} line at t^{th} time interval.
$V_{i,t}/\theta_{i,t}$	Continuous variables referring to voltage magnitude/phase angle of i^{th} bus at t^{th} time interval.
$U_{i,t}/W_{ij,t}^{\mathrm{R}}/W_{ij,t}^{\mathrm{I}}$	New defined continuous variables referring to conic programming.

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I. INTRODUCTION

The incorporation of generators based on renewable energy sources (RESs) into the current distribution network (DN) has grown in popularity in recent years as a step toward the development of sustainable energy [1]. Due to this, the DN is being transformed into an active distribution network (ADN). Most of RESs based generators are integrated to the ADNs through suitable power electronics based converters to transform the nature of supply (AC or DC) with flexible operation and control. Along with injecting active power, such converter-based distributed generation (CBDG) is able to support ADNs with reactive power as needed. Since the losses in ADN directly affect its operational cost, the operation of ADN with minimal losses is one of the critical objectives of distribution system operators. The two ways practically implemented on DNs to reduce the losses are distribution network reconfiguration (DNR) and reactive power injection from CBDGs.

The DNs have a number of sectionalizing and tie-line switches, collectively known as controllable switches (CSWs). DNR deals with altering the configuration of the network with altering the level of CSWs to fulfill some predefined objective(s). The DNR can be used to achieve any one or multiple goals out of several goals such as minimization of losses [2]–[5], mitigation of the fluctuations caused by RESs [4], [6], minimization of operational cost of ADN [4], [5], [7], [8], reduction of voltage deviation [4], [5], [8], improvement in voltage stability [4], enhancement in the reliability [5], etc.

Due to technological advancements, CBDGs can be operated in a wide range of power factor starting from zero power factor lag or lead to unity power factor [9]. The appropriate

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reactive power support provided by such converters at the local level minimizes reactive power intake from the main grid (MG) as well as reactive power flow in DN lines. This results in the reduction of line losses in the DNs [10].

A deep learning-assisted optimization-based DNR is proposed in [4] with regard to ADN to minimize a multi-objective function. Similarly, a multi-objective optimization-based strategy considering DNR is proposed in [5]. This problem is framed as a nonlinear programming problem and tackled using a self-adaptive modified crow search-based meta-heuristic solution technique. A centralized day-ahead active-reactive dispatch strategy for ADNs to minimize network losses, power purchase cost, and curtailment cost is proposed in [11]. The volt-var control scheme aiming to diminish the losses and voltage deviation in the high photovoltaic (PV) penetrated DNs is presented in [12]. A model for day operation that takes into account DNR is defined as a mixed integer nonlinear programming problem in [8] and solved in GAMS. Though the reactive power support from a battery energy storage system (BESS) is considered, the losses in the BESSs are not considered in this study. Loss minimization through both approaches, DNR and reactive power support is studied in the works [6], [13]. In these studies, the problem is represented as a convex optimization problem. Summarizing the reported works, the formulations are either non-convex [4], [5], [7], [8] or solved by meta-heuristic techniques [4], [5], [7]. Both of these conditions do not guarantee a global solution. Also, the reactive power support from the CBDGs is not considered in these works [2]–[7].

According to [14], the reactive power from the grid-coupling PV converters in addition to the active power supply causes additional losses inside it. These extra losses can be compensated either by decreasing the amount of active power generation from the PV system or increasing the consumption of active power. The reactive power optimization along with energy arbitrage are explored in [15], [16], taking into account the cost of losses from the PV inverter related to the reactive power supply. These studies provide a mathematical formulation for the losses in PV inverters caused by reactive power injection. Due to the large penetration of CBDGs in ADNs, the converter losses due to reactive power injection are becoming comparable with the line losses of DN. Therefore, to optimize the overall losses of ADN, due consideration must be given to line losses as well as converter losses. No similar study has appeared in the literature, to the best of the author's knowledge.

An energy-efficient day-ahead DNR for ADN by incorporating the losses from CBDGs is proposed in this paper to address the gaps, as mentioned earlier. Here, PV is considered as CBDG. The key task of the proposed scheme is to determine the day-ahead optimal radial configuration of DN considering the admissible maximum number of switching actions in a day and optimal reactive power dispatch from PVs. The proposed framework seeks to minimize the overall energy losses, which comprise the line losses and PV converter losses. The proposed framework is framed as a mixed integer second-order conic programming (MISOCP) problem, that has a theoretical guarantee to yield the global solution [17]. Furthermore, the MISOCP problem is gaining recognition in industries since it can be handled by commercially accessible solvers such as MOSEK, GUROBI, CPLEX, etc. The efficacy of the proposed framework is demonstrated on a modified IEEE 33-bus DN.

The remainder of the paper is structured as follows: Section II contains the proposed framework's mathematical model. Section III includes a case study that demonstrates the applicability of the proposed framework. Finally, in Section IV, the paper's conclusions are expressed.

II. Proposed Framework

The proposed framework needs network data, and a day-ahead forecast of PV generation and load demand as the input. The output of this framework is the optimal radial topology of ADN and reactive power injections of PV at each time interval over a day. The forecast of load demand and PV generation can be executed by either classical or machine learning-based regression techniques [18], which is out of the scope of this paper. The detailed formulations regarding the proposed framework will be discussed in subsequent subsections.

A. Losses in the PV Converter

This subsection discusses the mathematical modelling of losses of the PV converter due to reactive power injection. The active, reactive, and apparent power from a PV converter are related as:

$$\left(P_{i,t}^{\mathrm{PV}}\right)^2 + \left(Q_{i,t}^{\mathrm{PV}}\right)^2 = \left(S_{i,t}^{\mathrm{PV}}\right)^2, \forall t, \forall i \in \Lambda^{\mathrm{PV}} \tag{1}$$

As Eq. (1) is non-convex, it is relaxed to Eq. (2) resulting a convex quadratic expression as:

$$\left(P_{i,t}^{\mathrm{PV}}\right)^2 + \left(Q_{i,t}^{\mathrm{PV}}\right)^2 \leq \left(S_{i,t}^{\mathrm{PV}}\right)^2, \forall t, \forall i \in \Lambda^{\mathrm{PV}} \tag{2}$$

To limit the apparent power from a PV converter within its rated apparent power capacity, the following relation can be given:

$$0 \leq S_{i,t}^{\mathrm{PV}} \leq S_{i,max}^{\mathrm{PV}}, \forall t, \forall i \in \Lambda^{\mathrm{PV}} \tag{3}$$

Now, the mathematical relation to computing the additional losses ($\Delta P_{i,t}^{\mathrm{PV}}$) occurring in a converter on account of reactive power injection can be given as Eq. (4) [14], [15]. Here, $A_{i,self}^{\mathrm{PV}}$, $A_{i,v}^{\mathrm{PV}}$, and $A_{i,r}^{\mathrm{PV}}$ are the constants representing no-load losses, voltage-dependent loss component factor, and current dependent loss factor, respectively. These constants can be calculated from the efficiency curve, usually available in the converter manufacturer's datasheet.

The additional losses in a converter, as given in Eq. (4), is expressed for two different conditions, which cannot occur simultaneously at a given point of time. Therefore, a new binary parameter, $W_{i,t}^{\mathrm{PV}}$ is defined for i^{th} PV to select one condition at a time in each time interval, Δt as:

$$W_{i,t}^{\mathrm{PV}} = \begin{cases} 1, & \text{if } P_{i,t}^{\mathrm{PV}} \neq 0 \\ 0, & \text{if } P_{i,t}^{\mathrm{PV}} = 0, \forall t, \forall i \in \Lambda^{\mathrm{PV}} \end{cases}$$

Now, by using $W_{i,t}^{\mathrm{PV}}$, the energy losses of PV converter during a day, $E^{\mathrm{Loss,PV}}$ can be expressed as Eq. (5). $\overline{W_i^{\mathrm{PV}}}$ is logical inverse of W_i^{PV} and is equal to $(1 - W_i^{\mathrm{PV}})$.

B. Losses due to Line Resistance

This subsection first elucidates the formulations of the DNR and power flow for the proposed framework. The day-ahead

$$\Delta P_{i,t}^{\mathrm{PV}} = \begin{cases} A_{i,v}^{\mathrm{PV}}\left(S_{i,t}^{\mathrm{PV}} - P_{i,t}^{\mathrm{PV}}\right) + A_{i,r}^{\mathrm{PV}}\left(\left(S_{i,t}^{\mathrm{PV}}\right)^2 - \left(P_{i,t}^{\mathrm{PV}}\right)^2\right), & \text{if } P_{i,t}^{\mathrm{PV}} \neq 0 \\ A_{i,self}^{\mathrm{PV}} + A_{i,v}^{\mathrm{PV}} Q_{i,t}^{\mathrm{PV}} + A_{i,r}^{\mathrm{PV}}\left(Q_{i,t}^{\mathrm{PV}}\right)^2, & \text{if } P_{i,t}^{\mathrm{PV}} = 0 \end{cases} \quad \forall t, \forall i \in \Lambda^{\mathrm{PV}} \tag{4}$$

$$E^{\mathrm{Loss,PV}} = \sum_{t\in\Lambda^{\mathrm{T}}} \Delta t \sum_{i\in\Lambda^{\mathrm{PV}}} \left[\overline{W_i^{\mathrm{PV}}}\left(A_{i,self}^{\mathrm{PV}} + A_{i,v}^{\mathrm{PV}} Q_{i,t}^{\mathrm{PV}} + A_{i,r}^{\mathrm{PV}}\left(Q_{i,t}^{\mathrm{PV}}\right)^2\right) + W_i^{\mathrm{PV}}\left(A_{i,v}^{\mathrm{PV}}\left(S_{i,t}^{\mathrm{PV}} - P_{i,t}^{\mathrm{PV}}\right) + A_{i,r}^{\mathrm{PV}}\left(\left(S_{i,t}^{\mathrm{PV}}\right)^2 - \left(P_{i,t}^{\mathrm{PV}}\right)^2\right)\right)\right] \tag{5}$$

energy losses occurring due to power flow through the lines of the network, $E^{\mathrm{Loss,LR}}$ can be expressed as:

$$E^{\mathrm{Loss,LR}} = \sum_{\mathrm{t}\in\Lambda^{\mathrm{T}}} \Delta \mathrm{t} \sum_{\mathrm{ij}\in\Lambda^{\mathrm{E}}} I_{ij,t}^2 R_{ij} \tag{6}$$

Various constraints considered are as follows:

1) Distribution Network Reconfiguration:

$$\left.\begin{aligned} &\delta_{ij,t}^{\mathrm{CSW}} + \delta_{ji,t}^{\mathrm{CSW}} = \zeta_{ij,t}^{\mathrm{CSW}} \\ &\zeta_{ji,t}^{\mathrm{CSW}} = \zeta_{ij,t}^{\mathrm{CSW}} \end{aligned}\right\} \forall t, \forall ij \tag{7}$$

$$\sum_{j\in i} \delta_{ij,t}^{\mathrm{CSW}} = 1,\ \forall t, \forall i \in \Lambda^{\mathrm{LD}} \tag{8}$$

$$\sum_{j\in i} \delta_{ij,t}^{\mathrm{CSW}} = 0,\ \forall t, \forall i \in \Lambda^{\mathrm{MG}} \tag{9}$$

$$\gamma_{ij,t}^{\mathrm{CSW,UP}} + \gamma_{ij,t}^{\mathrm{CSW,DN}} \leq 1,\ \forall t, \forall ij \tag{10}$$

$$\zeta_{ij,t}^{\mathrm{CSW}} - \zeta_{ij,t-1}^{\mathrm{CSW}} = \gamma_{ij,t}^{\mathrm{CSW,UP}} - \gamma_{ij,t}^{\mathrm{CSW,DN}},\ \forall t, \forall ij \tag{11}$$

$$\sum_{t\in T}\left(\gamma_{ij,t}^{\mathrm{CSW,UP}} + \gamma_{ij,t}^{\mathrm{CSW,DN}}\right) \leq N_{ij,max}^{\mathrm{CSW}},\ \forall t, \forall ij \tag{12}$$

Eq. (7) checks whether a line, ij is in a spanning tree at a time interval, t, or not. Eq. (8) restricts every node other than the MG node to have only one parent node. Eq. (9) denotes that the MG node doesn't have a parent node. Eq. (10) restricts the simultaneous upward and downward actions of CSW. Eq. (11) represents regulation constraint and the total number of switching operations of CSWs over a day is limited by Eq. (12).

2) Power Flow: Since the power flow is originally a non-convex problem, the second order cone program (SOCP) based power flow [2], [19] is used in this paper to ensure global optima [17].

The definition of new variables and expressions related to SOCP [2], [19] are given in equations (13)-(15). The linkage between DNR and power flow is given in Eqs. (16)-(17). Eq. (18) ensures that the new variables ($U_{i,t}^{ij}, U_{j,t}^{ij}$), which are defined for each distinct line, ij, are not repeated.

$$U_{i,t} = V_{i,t}^2/\sqrt{2}, \forall t, \forall i \tag{13}$$

$$\left.\begin{aligned} &W_{ij,t}^{\mathrm{R}} = W_{ji,t}^{\mathrm{R}} = V_{i,t}V_{j,t}\cos(\theta_{i,t} - \theta_{j,t}) \\ &W_{ij,t}^{\mathrm{I}} = -W_{ji,t}^{\mathrm{I}} = V_{i,t}V_{j,t}\sin(\theta_{i,t} - \theta_{j,t}) \end{aligned}\right\} \forall t, \forall ij \tag{14}$$

$$2U_{i,t}^{ij}U_{j,t}^{ij} \geq (W_{ij,t}^{\mathrm{R}})^2 + (W_{ij,t}^{\mathrm{I}})^2,\ \forall t, \forall ij \tag{15}$$

$$\left.\begin{aligned} &0 \leq U_{i,t}^{ij} \leq \left(V_{i,max}^2/\sqrt{2}\right)\zeta_{ij,t}^{\mathrm{CSW}} \\ &0 \leq U_{j,t}^{ij} \leq \left(V_{j,max}^2/\sqrt{2}\right)\zeta_{ij,t}^{\mathrm{CSW}} \end{aligned}\right\} \forall t, \forall ij \tag{16}$$

$$\left.\begin{aligned} &0 \leq U_{i,t} - U_{i,t}^{ij} \leq \left[V_{i,max}^2\left(1 - \zeta_{ij,t}^{\mathrm{CSW}}\right)\right]/\sqrt{2} \\ &0 \leq U_{j,t} - U_{j,t}^{ij} \leq \left[V_{j,max}^2\left(1 - \zeta_{ij,t}^{\mathrm{CSW}}\right)\right]/\sqrt{2} \end{aligned}\right\} \forall t, \forall ij \tag{17}$$

$$U_{i,t}^{ji} = U_{i,t}^{ij},\ \forall t, \forall ij \tag{18}$$

The linear active and reactive powers flow of line ij during time-interval, Δt, are given in Eq. (19). The nodal power balance relations for ADN with its all interconnected ingredients are given in Eq. (20). The square of the line current can be represented in the linear form by Eq. (21) [2]. Equations (22)-(25) represent the bounds on power flow variables.

$$\left.\begin{aligned} &P_{ij,t} = \sqrt{2}G_{ij}U_{i,t}^{ij} - G_{ij}W_{ij,t}^{\mathrm{R}} - B_{ij}W_{ij,t}^{\mathrm{I}} \\ &Q_{ij,t} = -\sqrt{2}B_{ij}U_{i,t}^{ij} + B_{ij}W_{ij,t}^{\mathrm{R}} - G_{ij}W_{ij,t}^{\mathrm{I}} \end{aligned}\right\} \forall t, \forall ij \tag{19}$$

$$\left.\begin{aligned} &P_{i,t}^{\mathrm{MG}} + P_{i,t}^{\mathrm{PV}} - P_{i,t}^{\mathrm{LD}} = \sum_{j\in\Lambda^i} P_{ij,t} \\ &Q_{i,t}^{\mathrm{MG}} + Q_{i,t}^{\mathrm{PV}} - Q_{i,t}^{\mathrm{LD}} = \sum_{j\in\Lambda^i} Q_{ij,t} \end{aligned}\right\} \forall t, \forall i \tag{20}$$

$$I_{ij,t}^2 = \sqrt{2}(G_{ij}^2 + B_{ij}^2)(U_{i,t}^{ij} + U_{j,t}^{ij} - 2W_{ij,t}^{\mathrm{R}}), \forall t, \forall ij \tag{21}$$

$$I_{ij,t}^2 \leq I_{ij,max}^2, \forall t, \forall ij \tag{22}$$

$$\begin{aligned} &U_{i,t} = 1/\sqrt{2},\ \forall t, \forall i \in \Lambda^{\mathrm{MG}} \\ &V_{i,min}^2/\sqrt{2} \leq U_{i,t} \leq V_{i,max}^2/\sqrt{2},\ \forall t, \forall i \in \Lambda^{\mathrm{LD}} \end{aligned} \tag{23}$$

$$\left.\begin{aligned} &0 \leq W_{ij,t}^{\mathrm{R}} \leq V_{i,max}V_{j,max} \\ &-V_{i,max}V_{j,max} \leq W_{ij,t}^{\mathrm{I}} \leq V_{i,max}V_{j,max} \end{aligned}\right\} \forall t, \forall ij \tag{24}$$

$$\left.\begin{aligned} &P_{i,min}^{\mathrm{MG}} \leq P_{i,t}^{\mathrm{MG}} \leq P_{i,max}^{\mathrm{MG}} \\ &Q_{i,min}^{\mathrm{MG}} \leq Q_{i,t}^{\mathrm{MG}} \leq Q_{i,max}^{\mathrm{MG}} \end{aligned}\right\} \forall t, \forall i \in \Lambda^{\mathrm{MG}} \tag{25}$$

3) Objective Function: The objective of the proposed framework is to minimize the overall day-ahead energy losses occurring in ADN, which include both network and PV converter losses. As a result, the proposed framework's objective function, OF, can be represented as follows:

$$OF = \min_{\chi}(E^{\mathrm{Loss,LR}} + E^{\mathrm{Loss,PV}}) \tag{26}$$

The day-ahead energy losses due to the resistance of lines of ADN can be computed from Eq. (6) after substituting $I_{ij,t}^2$ from Eq. (21) in it. The day-ahead energy losses due to additional reactive power flow through the PV converter can be computed from Eq. (5).

Summarizing, the statement of the proposed optimization problem can be given with the help of Eq. (26) as the objective function; Eqs. (2), (5), (7)-(12), (15)-(20) as the constraints; and Eqs. (3), (22)-(24) as the bounds on different variables. Since the objective function and the constraints are convex, the proposed framework is also a convex optimization problem, which can provide a global optimum. In an overall sense, the problem is framed as a MISOCP-based optimization problem with the following variable set, χ:

$$\begin{aligned} \chi = \Big[&\delta_{ij,t}^{\mathrm{CSW}}, \zeta_{ij,t}^{\mathrm{CSW}}, \gamma_{ij,t}^{\mathrm{CSW,UP}}, \gamma_{ji,t}^{\mathrm{CSW,DN}}, U_{i,t}, W_{ij,t}^{\mathrm{R}}, \\ &\mathrm{W}_{ij,t}^{\mathrm{I}}, U_{i,t}^{ij}, U_{j,t}^{ij}, P_{ij,t}, Q_{ij,t}, Q_{i,t}^{\mathrm{PV}}, S_{i,t}^{\mathrm{PV}}, P_{i,t}^{\mathrm{MG}}, Q_{i,t}^{\mathrm{MG}}\Big] \end{aligned}$$

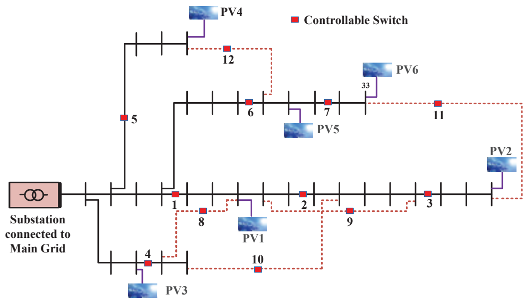

Fig. 1. Modified IEEE 33-bus active distribution network.

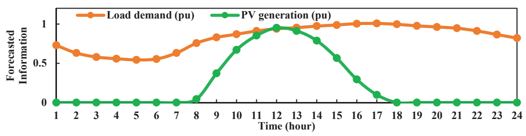

Fig. 2. Forecast of PV generation and nominal load demand.

III. Case Study

This section describes the simulation study conducted to validate the performance of the proposed framework, which is coded in GAMS, solved with CPLEX solver, and executed in an i7, 3.2 GHz, and 16 GB personal computer.

A. Test System

The proposed framework has been tested on an IEEE 33-bus DN with a voltage level of 12.66 kV. The line parameters and nominal load of the test system are obtained from [11]. IEEE 33-bus DN is modified by adding 12 CSWs and 6 PVs, as shown in Fig. 1. Each PV is rated as 600 kWp and has three identical converters, each with a 200 kVA rating. The parameters of the quadratic loss function, $A^{\mathrm{PV}}_{i,self}$, $A^{\mathrm{PV}}_{i,v}$, and $A^{\mathrm{PV}}_{i,r}$ of the converter are 1.347 kW, 1.148×10^{-2} and 1.251×10^{-4}, respectively [14]. The rating of the substation transformer is 6 MVA. The thermal limit of each line is considered as 6 MVA. The minimum and maximum limits of voltage at each bus are 0.9 and 1.1, respectively, on a 12.66 kV base. The hourly forecast of load demand and PV generation over a day is presented in Fig. 2.

B. Results

To demonstrate the efficacy of the proposed framework, five different cases are investigated as given in Table. I. Here, network energy losses (NEL) indicate the losses due to the resistance of the lines; PV energy losses (PVEL) account for the losses occurring in the PV converters due to reactive power injection; and total energy losses (TEL) indicate the sum of NEL and PVEL. C1 represents the base case (*i.e.* without DNR and reactive power support from PVs). In C2 and C3, only the reactive power support from PVs is considered for optimization. In C4 and C5, DNR and reactive power support from PVs are considered for optimization. Further, in C2 and C4, NEL is optimized and the PVEL is calculated using optimal reactive power dispatch from PVs, while in C3 and C5, TEL is optimized.

TABLE I
DIFFERENT CASES

Case	C1	C2	C3	C4	C5
Q support from PV	X	✓	✓	✓	✓
DNR	X	X	X	✓	✓
Objective function		NEL	TEL	NEL	TEL

The proposed framework is applied to each case. Fig. 3 shows the hourly NEL, PVEL, and TEL for all cases. The hourly active/reactive power intake from MG and total reactive power injection from all PVs in all cases are depicted in Fig. 4. The optimal day-ahead dispatch of CSWs in both cases (C4 and C5) are depicted in Fig. 5. A summary of the comparison of system performance for different cases is in Table. II. In C1, PVEL is zero and NEL is obtained as 2.5677 MWh, which is the same as TEL. In C2, PVEL is greater than NEL, and the TEL is 2.9798 MWh. In C3, PVEL reduces significantly as compared to C2. This also reduces TEL in C3 by 0.6676 MWh as compared to C2. In C4, PVEL is greater than NEL, and the TEL is 2.6017 MWh. The PVEL in C5 reduces significantly as compared to C4. This also reduces TEL in C5 by 0.6201 MWh as compared to C4. The TEL in C5 is reduced by 0.5861 MWh as compared to that in C1. Among different cases, C4 results in the minimum value of NEL (Fig. 3 (a)); and C5 results the minimum values of PVEL (Fig. 3 (b)) and TEL (Fig. 3 (c)). This shows the dependency of PVEL on TEL. As observed from Fig. 4 (a), Fig. 4 (b), and Table. II, the active and reactive power intake from MG is minimal in C4. It can also be observed in Fig. 4 (c) and Table. II that C5 requires minimum reactive power support from PV converters among all cases. Due to the DNR problem (a large number of binary variables), the computational time in C4 and C5 increases significantly as compared to C1, C2, and C3 (Table II).

TABLE II
COMPARISON OF DIFFERENT CASES

Item	C1	C2	C3	C4	C5
NEL (MWh)	2.5677	1.4584	1.6619	1.1396	1.3903
PVEL (MWh)	0	1.5213	0.6503	1.4620	0.5912
TEL (MWh)	2.5677	2.9798	2.3122	2.6017	1.9816
Total P intake from MG (MWh)	56.6789	55.5710	55.7745	55.2521	55.5028
Total Q intake from MG (MVArh)	47.5989	7.3578	27.5462	7.2858	29.3789
Total Q injection from PV (MVArh)	0	38.7639	19.4455	39.4361	17.5104
Computational time (sec)	1.23	13.15	22.78	6356.69	6938.12

The proposed framework sets the reactive power dispatch from CBDGs without distinguishing their ownership. In actual practice, all distributed generators (DGs) may not be owned by the utilities. To encourage non-utility DGs to produce reactive power, the utilities offer incentives to such DGs, which are proportional to the energy losses of their converters (from Eq. (5), which is again dependent on the reactive power support from CBDG) [15], [16]. Since the reactive power support from CBDGs is already optimized in the proposed framework, the same solution also yields minimum incentives to CBDGs.

IV. Conclusion

To reduce system losses, an energy-efficient operational framework for ADN is proposed. The primary goal is to set the state of CSWs and reactive power dispatch of PVs in a day-ahead fashion. Along with line losses, the objective function takes into account extra losses in the PV converter on account of reactive power injection. The optimization model is formulated as a MISOCP problem and implemented in GAMS

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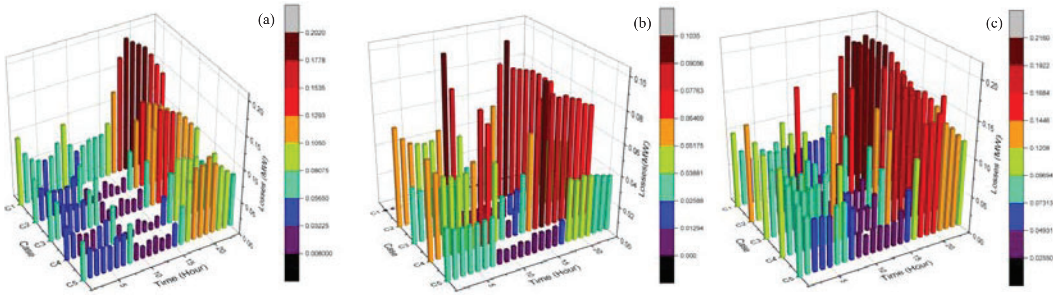

Fig. 3. Power loss in different cases at different time intervals (a) Network power loss (b) PV power loss (c) Total power loss.

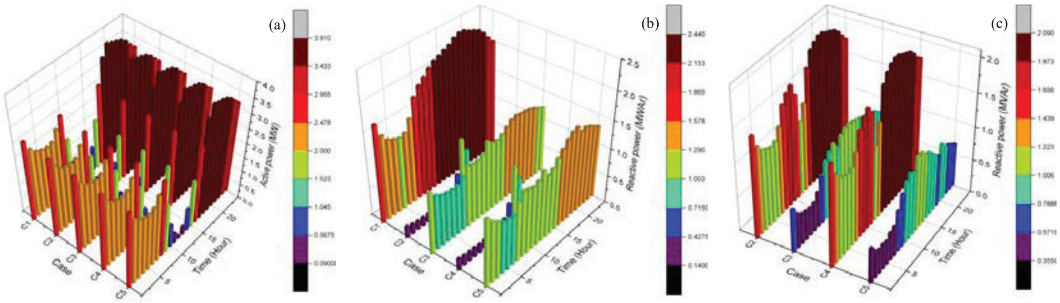

Fig. 4. (a) Active power intake from MG (b) Reactive power intake from MG (c) Total reactive power injection from all PVs.

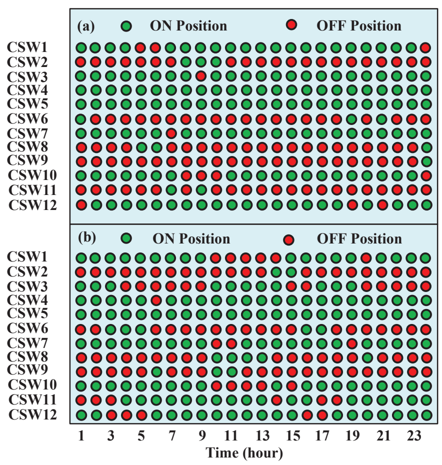

Fig. 5. 24 hours schedule of CSWs (a) Case-4, (b) Case-5.

software which is solved with a CPLEX solver. The outcomes derived after applying the proposed method to a modified IEEE 33-bus DN reveal that 22.81% losses are reduced when compared to the base case. It is observed that the losses from CBDGs are comparable to line losses. Therefore, the minimization of overall network losses results in an energy-efficient performance of the ADN.

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