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Hybrid PSO-TS Based Distribution System Expansion Planning for System Performance Improvement Considering Energy Management

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ABSTRACT Energy management (EM) has become very attractive in smart grid era for both industry and academia. EM in a power distribution system (PDS) can reduce the system losses, operational costs and emissions, and increases system's reliability, voltage stability and efficiency. This article expands the PDS using different distributed energy resources (DERs) and observes their impacts on EM success, operational costs, system losses, and emissions. Moreover, the impacts of integrating reactive sources (RSs), energy storage systems (ESSs), and electric vehicles (EVs) on the system's operational performance is investigated. An index is defined to measure the energy management success rate (EMSR) and several case studies are created for investigating variety of system expansion options individually and collectively. Furthermore, a new reliability index, namely reliability index success rate (RISR), is defined and sensitivity analysis are presented to investigate the DERs impacts on system's voltage controllability and the defined reliability index. A new hybrid PSO-TS optimization algorithm is developed, and the well-known PG&E 69-bus distribution network is selected for the simulations. Several case studies presented in the paper provide a clear understanding of the impacts of integrating different resources on the EM as well as other operational aspects of a PDS. The results reveal that the system expansion using DERs with different capacities along with EM strategies could have significant impacts on PDS performance depending on the DERs types' and capacities. Due to their availability and low operational costs, gas turbine further improves the performance indices comparing to the renewables that have uncertain availability and to diesel generators with their high operational costs.

INDEX TERMS Energy management, power distribution system, distributed generation, renewable energy, ESS, EVs, emission, optimization, PSO-TS.

NOMENCLATURE

c	Scale index
C_{spu_h}	Per unit costs of power at time h
$C_{DGpu\_j\_h}$	Per unit generation cost for j^{th} base DG at time h
$C_{DGpu\_k\_h}$	Per unit costs for k^{th} expanded DGs
$C_{RSpu\_l\_h}$	Reactive power per unit costs for l^{th} RSs
C_{ESS_h}	Per unit cost ESS's real power
C_{EV_h}	Per unit cost EV's real power
$\mathrm{E_{DG}}$	Emissions costs of DGs
f_b (s)	Beta distribution function
h_n	Time segment of the related states
HV^D	Heat value of diesels
N	Total number of branches
N_{st}	Number of probabilistic states
N_{DG}	Total number of base DGs
$\mathrm{N}_{DG,s}$	Total number of expanded DGs
OC_a	Operational costs
P^i_{loss}	Power loss in branch i
P_{s_h}	System generation power at time h
$P_{s\_l\_h}$	Total system loss at time h
$P_{DG\_j\_h}$	Power for j^{th} base DG at time h
$P_{DG\_k\_h}$	Power for kth installed DG
P_{EV_h}	EV's real power in kW
P_{ESS_h}	ESS's real power in kW
$Q_{RS\_l\_h}$	Reactive power for l^{th} RSs
s	Solar irradiance
S	Emission coefficient for natural gas in kg/kwh
$\mathrm{TSC_b}$	Total system costs before EM

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$\mathrm{TSC_a}$	Total system costs after EM
v_m	Mean value of wind speed
v_{ci}	Cut in speed of wind
v_r	Rated speed of wind
v_{co}	Cut out speed of wind
α, β	Beta distribution function parameters
μ	Mean
σ	Standard deviation
ρ_n	Probability of the related generation state
η	ESS discharging efficiency
ρ_{EV}	% of EVs participating in V2G program
η^D	Fuel to electric efficiency for diesel

I. INTRODUCTION

Electrical energy has become fundamental to quality of our lives. The demand for electricity is increasing day by day and the need for expansion of power distribution systems is highly manifested to reduce the system losses, operational costs and emissions, and increase its reliability and efficiency [1], [2]. DERs are usually integrated into the grid at the distribution level, which include renewable- and hydrocarbon-based resources. Due to their different characteristics in terms of operational costs and environmental emissions, an energy management system is needed to effectively manage such DERs in the PDSs. Besides, integrating RSs and ESSs along with DERs with the recent technology advancements, seem to be appropriate actions to improve the PDS operational performance. Proper utilization of these resources can contribute to improve the reliability, supply adequacy, and power quality of a PDS.

Several research papers have been published on expansion of PDS using DERs. For instance, a profit based distributed generator (DG) planning in the PDS is presented in [1] considering economic, technical, and environmental aspects. The authors in [3] proposes a reliability-based distribution network expansion planning problem that considers investment and operating costs of DGs by using MILP formulation for reliability evaluation. A multi-level distribution system expansion (SE) planning problem is proposed in [4] by considering non-utility-owned DG and an independent PDS operator in order to minimize the total system operating costs. In [5], the authors study the power losses in the PDS by increasing the DGs penetration level, along with DG technologies mix, DG dispersion and location, and reactive power control strategy. The authors in [6] simultaneously integrate different DGs in PDS to turn the system into multi-microgrid. In their research, the objective was to maximize the self-adequacy of the designed microgrids by minimizing the active and reactive power flows in the power lines connecting the microgrids and maximize the microgrid islanding success probability. In [7], system losses are minimized by integrating different DGs using a novel hybrid method, combination of metaheuristic and heuristic algorithms, which increases the system robustness and reduces the computational runtime in the PDS. The selection of optimal size and locations for the DGs and their impacts on system loss reduction are discussed in [8]. The authors in [9] upgrade the distribution network by actively planning DGs with a two-stage scheme based on virtual microgrids in order to reduce the system operational costs. Multiple types of RESs are installed in a PDS to minimize the energy losses and maximize the annual net income into the system which are discussed in [10]. The simultaneous allocation of DGs in the PDS for minimizing the system losses and emissions is discussed in [11].

While a large number of interesting research have been published on the integration of DERs, simultaneous integration of various resources with different penetration levels and their impacts on different operational issues are not properly investigated as all in one power distribution system.

In addition to the DERs, the RSs, ESSs, and even EVs can have a key role for enhancing the system performance in the PDS. At the same time, these resources heavily support RESs in the PDS to balance the generation uncertainty of the renewable energy sources (RESs). There are also several research available in the literature in the context of RSs, ESSs, and EVs integration for PDS expansion purposes for different objective functions. For instance, the authors in [12] optimally integrate the ESS in the PDS, mainly to support the RESs to maintain the power balance in the distribution network. A mixed integer nonlinear optimization-based methodology has been proposed for distribution system expansion purposes using DGs, and capacitors placement in the smart grids in order to minimize investment costs and maximizing system reliability [13]. Multiple types of RESs, along with RSs, and ESS are installed in the PDS by considering fourth-stages genetic optimization algorithm in order to minimize the system operational costs which is discussed in [14]. A stochastic multi-period mixed integer conic problem has been proposed in [15] for the distribution system expansion purposes using RESs and ESSs in order to access the system emissions and operational costs over a predefined time horizon. The authors in [2] present a model to analyze the impacts of RSs on system performance in terms of voltage profile improvement, and stability index enhancement. Centralized ESSs are also used as a network expansion option to determine their effects on electricity generation costs in [16]. The authors in [17] integrate RESs and ESSs in the PDS in order to analyze the electricity generation costs reduction. Moreover, the authors in [18] integrate plug in EVs to observe their impact on PDS losses. An impact on EVs with RESs, ESSs, and charging station integrated PDS has been studied in [19] by considering the variability associated with RESs along with the demand requires to incorporate the uncertainty. The objective of this research was to minimize the investment, maintenance, production, losses, and non-supplied energy costs.

Although several valuable research has been published on integration of DERs, RSs, ESSs and EVs in the PDS [1]–[19], a comprehensive assessment of integrating such DERs on PDS's operational performance, specifically energy management, is yet to be addressed. Other than EMSR,

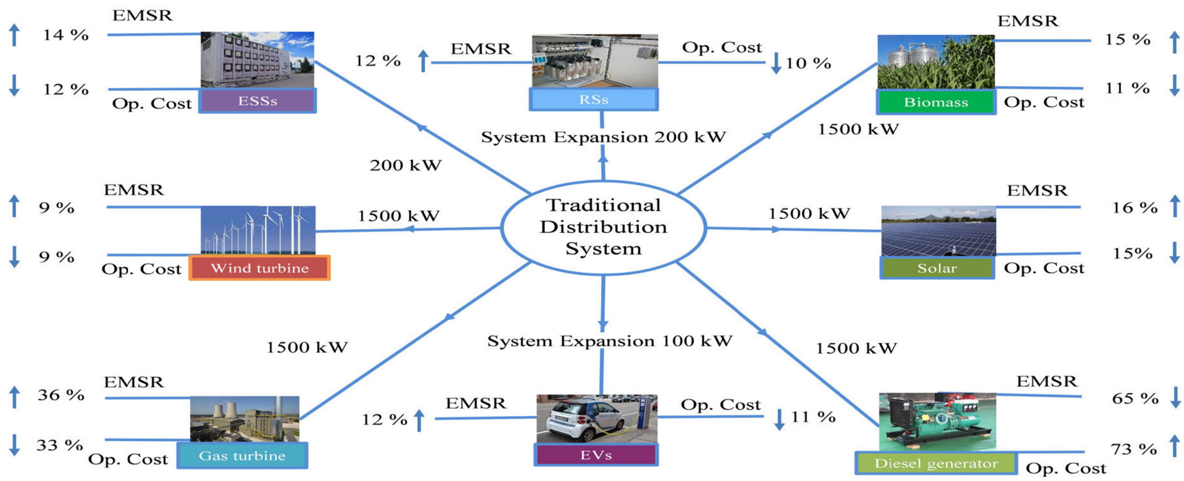

FIGURE 1. System expansion impacts using DERs in the distribution system.

different operational performance aspects could be considered while integrating DERs in PDSs, including operational costs, system losses, emissions, voltage controllability, and system's reliability. Furthermore, integration of such DERs simultaneously could affect their individual performance; therefore, the impact of collective integration of DERs in PDS should also be investigated properly.

The aim of this article is to address such issues and fill this research gap. A comprehensive assessment of integrating DERs, RSs, ESSs and EVs individually and collectively in the PDS is performed and different operational performance aspects such as EMSR, operational costs, system losses, emissions, voltage controllability, and system's reliability are investigated. For this purpose, the PG&E 69-bus PDS is selected as a test system and is expanded by integrating different DERs in their optimal locations for minimizing total system losses and operational costs together. The EMSR, operational costs, energy losses, and environmental emissions are then assessed for the expanded PDS by different penetration levels of such DERs. Moreover, the RSs, ESSs, and EVs are integrated in the system and their impact on operational performance is investigated. The PDS's voltage controllability and reliability are also evaluated in this research. Partial research results are illustrated in Fig. 1. As can be seen, expansion of the PDS and applying EM using different energy resources can have different impacts on the performance of the system. For instance, EM using 1500kW gas turbine can reduce the operational costs of the system by 33% and improve the EMSR by 36%.

A hybrid PSO-TS algorithm is presented in the paper which provides higher quality results in large scale optimization problems. A similar approach is presented in [20] for the substation and feeder expansion purpose. However, to the authors' best knowledge, for the first time, this research uses a hybrid PSO and TS algorithm for the distribution system expansion problem using different ERs and considering different sets of swarms for selecting the best results. The main contributions of the paper are summarized as follows:

- Assessment of energy management improvement in a PDS while integrating multiple dispatchable and non-dispatchable DERs with probabilistic nature, individually and collectively.
- Analyzing the impact of simultaneous and individual integration of DERs, RSs, ESSs, and EVs all in one system and compare the results in terms of energy management success, operational costs, system losses, and emissions.
- Performing several sensitivity analysis to assess the DERs impact on PDS's voltage controllability and reliability indices.
- Developing a new hybrid PSO-TS optimization algorithm for PDS expansion and performance assessments.

The rest of the paper is organized as follows: Section II describes the system expansion options and EM. The problem formulation is described in Section III. The hybrid PSO-TS algorithm for system expansion is discussed in Section IV while the system under study is presented in Section V. DER integration, energy management, and system performance assessment are described in Section VI. Section VII presents further enhancement of the system using ESSs, RSs and EVs. The sensitivity analyses are discussed in Section VIII and finally the conclusion of this article is discussed in Section IX.

II. SYSTEM EXPANSION OPTIONS AND ENERGY MANAGEMENT

The PDS is traditionally connected to large central generating stations through high voltage lossy transmission lines. The central generation stations are also mostly fossil fuel based and have high environmental emissions. Government regulations, financial incentives, and technological innovations are driving the rapid change in the PDS by increasing efficient and environmentally friendly DERs. Moreover, the customers are becoming procurers and are interested in delivering excess energy to the grid and getting paid back. As a result, the traditional PDS has to enable the available DERs to operate in a more reliable, efficient, economic, and environment friendly way. This section explains the resources usually used to expand the PDS along with their overall impacts on energy management.

A. DISTRIBUTED GENERATORS

The most commonly used distributed generators in PDSs are combination of dispatchable, i.e. gas turbines, diesel, and biomass, and non-dispatchable, i.e. wind turbines and solar PV modules. Gas turbines and diesel generators are active power sources in a PDS that have certain power generation if the fuels are available. When these generators are optimally integrated in the system, they can minimize the system losses and operational costs. However, in some cases, the operational costs might increase depending on the fuel types. Wind turbine and solar power have probabilistic intermittent nature for the generation and during their integration, the system needs information about their power generation profile to ensure the load generation balance with the help of other available resources. The predicted wind speed data can be used for modeling and expanding the system with the non-dispatchable DGs [21]. The solar irradiance for the PV modules is usually modeled hourly by the Beta probability density function (PDF) using historical data [22].

$$f_b\left(\mathrm{s}\right) = \frac{\tau\left(\alpha + B\right)}{\tau\left(\alpha\right)\tau\left(\beta\right)} \times s^{(\alpha-1)} \times (1-\mathrm{s})^{\beta-1} \qquad 0 \le \mathrm{s} \le 1; \alpha, \beta \ge 0 \tag{1}$$

where α and β can be calculated by using μ and σ of s.

$$\alpha = \frac{\mu \times B}{1-\mu} \times s^{(\alpha-1)} and \beta = 1 - \mu \times \left(\frac{\mu \times (1+\mu)}{\sigma^2} - 1\right) \tag{2}$$

The wind speed of wind turbine is modeled hourly by the Weibull PDF by using historical data [22].

$$f\left(\mathrm{v}\right) = \left(\frac{2v}{c^2}\right) \times exp\left[-\left(\frac{v}{c}\right)^2\right] \tag{3}$$

where the mean value v_m can be measured from equation (4).

$$v_m = \int_0^\infty vf\left(\mathrm{v}\right)dv = \int_0^\infty v\left(\frac{2v}{c^2}\right) \times exp\left[-\left(\frac{v}{c}\right)^2\right]dv = \frac{\sqrt{\pi}}{2}c \tag{4}$$

The output power of wind turbine is calculated by (5)

$$Pv_w\left(v_{aw}\right) = \begin{cases} 0, & 0 \le v_{aw} \le v_{ci} \\ P_{rated} \times \dfrac{v_{aw} - v_{ci}}{v_r - v_{ci}}, & v_{ci} \le v_{aw} \le v_r \\ P_{rated}, & v_r \le v_{aw} \le v_{co} \\ 0, & v_{co} \le v_{aw} \end{cases} \tag{5}$$

Here Pv_w is the output power of wind during state w and v_{aw} is the average speed of wind during state w.

Moreover, the biomass generators provide controllable sustainable energy. There might be uncertainty in generation due to the unavailability of biomass fuels during critical situations, like constant rain and flood. In such cases, the biomass generators can be modeled probabilistically using historical data similar to PVs and wind turbines.

B. REACTIVE SOURCES, ENERGY STORAGE SYSTEMS, AND EVS

The RSs are used as fixed or variable capacitors in the PDS for the reactive power compensation, power factor correction or voltage profile improvements. In this article, RSs are modeled as fixed reactive power generators which could be fixed capacitors, or an auxiliary service provided by DERs. ESS has led to increasing popularity of clean energy (wind, PV) that can store extra power during off-peak times for later use and helps to increase the system efficiency and reliability. ESSs act as loads or generators in the PDS depending on their status of charging period or discharging period, respectively. The performance of the ESS is usually based on the operational goal for a 24-hour period. The energy management system makes the decision whether to receive power from storage or any other sources during peak time or any extreme situations. From power flow point of view, the EVs have similar characteristics as the ESSs; the only difference with EVs is their uncertain nature in terms of their location and capacity. EVs in the PDS operate as a load, or as a generator, depending on the EVs owners participating in vehicle to grid (V2G) program or not. During the charging period, EVs operate as loads, modeled probabilistically with normal distribution [23]. The charging periods are selected based on the real time pricing data, normally during the off-peak period of the day, while discharging the energy to the PDS as a generator using a V2G program during peak load period.

C. ENERGY MANAGEMENT DURING SYSTEM EXPANSION

In the PDS expansion process, usually different resources are integrated into the system. Integration of such resources could affect the operational performance of the system, specifically energy management. An energy management system balances the load and generation in a power distribution system. Since at certain times there is more potential for power generation in a system than the power consumption, there are more than one option for reaching such balance. Moreover, due to the probabilistic nature of some of the resources, e.g. solar PV or wind turbine, and the loads, e.g. EVs, managing the energy flow would be more crucial. In this scenario, selecting the appropriate generators to supply the loads at a certain times can have significant impacts on the PDSs performance in terms of operational costs, system losses, emissions, etc. Due to such significant impacts, evaluating the energy management success while expanding power distribution networks could benefit the PDS expansion planners and operators. In this research, the system operational costs, losses, and emissions are considered as objective functions for performing energy management using different energy resources in a PDS as explained in the next section.

III. PROBLEM FORMULATION

This research includes three different stages. As shown in Fig. 2, among the three different stages, the first two stages include optimization problems which are solved by the proposed PSO-TS algorithm. The third stage includes assessment of the results acquired in the previous stages. More specifically, the first stage is the planning stage, and the goal is to expand the PDS by integrating new DERs, RSs, ESSs, and EVs and minimize the power losses and operational costs. The second stage, the operational stage, will perform energy management in the expanded system with the goal of optimizing the defined EMSR index. Finally, at the third stage the system performance indices are evaluated which include voltage controllability, and reliability. The formulation of three stages as well as load-generation models are described with details in this section.

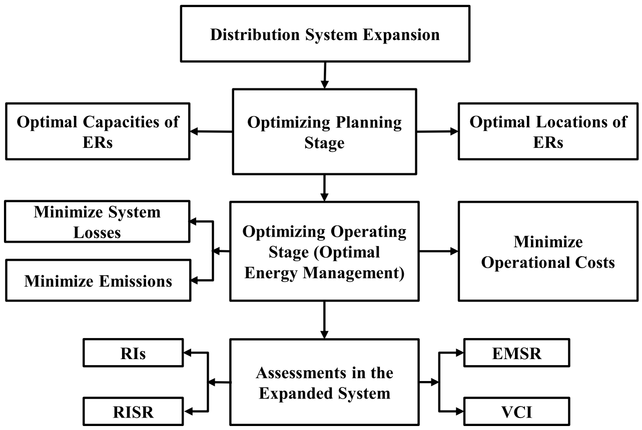

FIGURE 2. System expansion problem stages.

A. SYSTEM EXPANSION OBJECTIVE FUNCTION

The objective function for integrating DERs, RSs, ESSs, and EVs is to minimize the PDS losses and the system operational costs together by finding their optimal locations and capacities. The objective function (OF) in this research can be formulated as follows:

$$Minimize\ OF = \sum_{\mathrm{h}=1}^{24}\sum_{i=1}^{N} \mathrm{P_{loss}}^{i} + OC_a \tag{6}$$

Since the PDS is expanded with some probabilistic nature DGs, i.e. wind and solar, the system loss is calculated by

$$P_{loss} = \sum_{n=1}^{N_{st}} P_{loss} \times \rho_n \times h_n \tag{7}$$

where OC_a for individual and collective DERs can be calculate using equation (11)-(15) and N_{st} can be calculated using equation (29). For dispatchable DGs, ρ_n and h_n will be equal to 1.

B. ENERGY MANAGEMENT OBJECTIVE FUNCTION

The main goal of performing energy management is reducing the operational costs, system losses, and emissions. So, in this research, the EM objective function can be formulated as follows to minimize the total system's cost after energy management:

$$Minimize\ EM\ OF = \sum_{h=1}^{24} TSC_a \tag{8}$$

In order to better analyze the impacts of energy management in a system, this section introduces an index to show how EM affects the system's operational costs, losses, and emissions. The proposed EMSR (shown in (9)) is calculated by using the total system costs (operational costs, system losses, and emissions) before and after EM [21].

$$EMSR = \frac{TSC_b - TSC_a}{TSC_b} \times 100 \tag{9}$$

If the PDS already has some installed generators, the TSC_b can be calculated from (10) for a 24-hour period considering the operating costs of such DGs.

$$\begin{aligned} TSC_b = &\sum_{h=1}^{24} (P_{s\_h} + P_{s\_l\_h}) \times C_{spu\_h} \\ &- \sum_{h=1}^{24}\sum_{j=1}^{N_{DG}} P_{DG\_j\_h} \times C_{DGpu\_j\_h} + \sum_{h=1}^{24}\sum_{j=1}^{N_{DG}} E_{DG} \end{aligned} \tag{10}$$

Since this research performs EM for DER's individual and collective operation, the total system costs of such DGs, RSs, ESSs and EVs are calculated individually and collectively. The individual operational costs of the DGs is calculated by (11).

$$\begin{aligned} OC_{a,DGs} = &\sum_{h=1}^{24} (P_{s\_h} + P_{s\_l\_h}) \times C_{spu\_h} \\ &- \sum_{h=1}^{24} \left(\sum_{j=1}^{N_{DG}} P_{DG\_j\_h} \times C_{DGpu\_j\_h} \right. \\ &\left. + \sum_{k=1}^{N_{DG,s}} P_{DG\_k\_h} \times C_{DGpu\_k\_h} \right) \end{aligned} \tag{11}$$

The gas turbine, diesel, biomass, wind turbine, and PVs are integrated in the PDS in this research. Therefore, the generation costs of existing ($P_{\mathrm{DG,j}}$) and expanded ($P_{\mathrm{DG,k}}$) as well as energy losses costs are the total costs of the utility. It is seen from equation (11) that if the power of DGs increase, the original system's or utility's generation decreases, to make the load generation balance. Moreover, the costs of the total system will depend on several factors. If the generation costs of DGs for a time period is more than that of the system, total costs will increase and if the power generation costs of DGs is less than that of the system, total system costs will decrease.

After individual integration of the DGs in the PDS, RSs, ESSs, and EVs are also integrated for an effective and economic use of the existing DGs. The operational costs due to

RSs integration is calculated by:

$$OC_{a,RSs} = OC_{a,DGs} + \sum_{h=1}^{24}\sum_{l=1}^{N_{RS}} Q_{RS\_l\_h} \times C_{RSpu\_l\_h} \quad (12)$$

The ESSs and EVs operate in two stages. The ESS take utility power for charging during the off-peak period to minimize the charging costs and deliver power to the utility during peak period and get more financial benefit as a generator. In the same way, the owners of the EVs could get power from utility for charging the vehicle during cheap energy times and sell the energy to the utility during higher peak prices. The EV owner is responsible for paying the charging costs during the charging period. This research did not consider EM from the EV owner's point of view; it considered only for the PDS operator's benefits. The operational cost due to ESSs is calculated by:

$$OC_{a,ESSs} = OC_{a,DGs}\begin{cases} +\sum_{h=1}^{24}\sum_{m=1}^{N_{ESS}} P_{ESS_h} \times C_{ESS_h}, & \text{if charging} \\ -\sum_{h=1}^{24}\sum_{m=1}^{N_{ESS}} \eta P_{ESS_h} \times C_{ESS_h}, & \text{if discharging} \end{cases} \quad (13)$$

Similarly, the operational cost due to EVs is calculated by:

$$OC_{a,EVs} = OC_{a,DGs}\begin{cases} +\sum_{h=1}^{24}\sum_{n=1}^{N_{EV}} P_{EV_h} \times C_{EV_h}, & \text{if charging} \\ -\sum_{h=1}^{24}\sum_{n=1}^{N_{EV}} \rho_{EV} P_{EV\_h} \times C_{EV\_h}, & \text{if discharging} \end{cases} \quad (14)$$

In this stage, the collective integration of DGs, RSs, ESSs, and EVs are performed and the operational costs are investigated as shown in (15).

$$\begin{aligned} OC_a = &\sum_{h=1}^{24}(P_{s\_h} + P_{s\_l\_h}) \times C_{spu\_h} - \sum_{h=1}^{24}\Bigg(\sum_{j=1}^{N_{DG}} P_{DG\_j\_h} \times C_{DGpu\_j\_h} \\ &+ \sum_{k=1}^{N_{DG,s}} P_{DG\_k\_h} \times C_{DGpu\_k\_h} \mp \sum_{m=1}^{N_{ESS}} \eta P_{ESS_h} \\ &\times C_{ESS_h} \mp \sum_{n=1}^{N_{EV}} \rho_{EV} P_{EV\_h} \times C_{EV\_h}\Bigg) \end{aligned} \quad (15)$$

Thus, the total operational costs due to systems losses, operational costs, and system emissions is shown in (16).

$$\begin{aligned} TSC_a = &\sum_{h=1}^{24}(P_{s\_h} + P_{s\_l\_h}) \times C_{spu\_h} - \sum_{h=1}^{24}\Bigg(\sum_{j=1}^{N_{DG}} P_{DG\_j\_h} \times C_{DGpu\_j\_h} \\ &+ \sum_{k=1}^{N_{DG,s}} P_{DG\_k\_h} \times C_{DGpu\_k\_h} \mp \sum_{m=1}^{N_{ESS}} \eta P_{ESS_h} \\ &\times C_{ESS_h} \mp \sum_{n=1}^{N_{EV}} \rho_{EV} P_{EV\_h} \times C_{EV\_h}\Bigg) + \sum_{h=1}^{24}\sum_{j=1}^{N_{DG}} E_{DG} \end{aligned} \quad (16)$$

This research integrates natural gas, diesel, PVs, wind turbine, and biomass in the PDS and observes their impacts on environmental emissions. Since solar irradiance, wind and biomass are clean energy resources and have almost no environmental impacts, only the emissions from natural gas and diesel are considered in this research and calculated using (17) and (18) [24]:

$$C_E = P \times \sum_{j=1}^{m} S \quad (17)$$

$$D_E = \frac{P_D}{\eta^D} \times HV^D \quad (18)$$

C. DISTRIBUTION SYSTEM PERFORMANCE ASSESSMENTS

In this section, distribution system performance indices are investigated in terms of systems' controllability and its reliability.

1) Voltage Controllability Index (VCI): Voltage controllability of distribution systems has always been a challenge for distribution engineers. Traditionally voltage control is performed through the substation voltage regulator, which is usually slow. Since DGs can have faster response, they can be used for voltage control and support. The VCI shows how controllable the system's voltage is after integrating DERs, etc. Voltage variation (ΔV_i) of the system buses caused by variation in the real and reactive power of the DGs is calculated in (19) [22].

$$\Delta V_i = \left[\frac{\partial V_i}{\partial P_m}\right] \times \Delta P_{DG_m} + \left[\frac{\partial V_i}{\partial Q_m}\right] \times \Delta Q_{DG_m} = 1, 2, ..n \text{ bus} \quad (19)$$

where V_i is the voltage at bus i, P_m and Q_m are the real and reactive power injected to bus m and ΔP_{DG} and ΔQ_{DG} are the available real and reactive power capacities of DGs respectively.

The voltage measurement threshold ΔV_{th} is used at each load generation state to determine its controllability.

$$\begin{cases} \text{if } \Delta V_{i,s} \geq \Delta V_{th}, & \rho_{s,i} = 1 \\ \text{Otherwise}, & \rho_{s,i} = 0 \end{cases} \quad (20)$$

The voltage controllability index is then calculated by

$$VCI = \sum_{s=1}^{N_{st}} \rho_s \times \left(\sum_{i=1}^{N_{bus}} \rho_{s,i}/N_{bus} \right) \times 100 \tag{21}$$

where N_{bus} is the number of buses, and ρ_s is the probability of occurrence in the load generation state s.

2) Reliability Index: In this research, three well-known indices are used for reliability evaluation.

$$SAIDI = \frac{\sum N_i \times U_{ai}}{\sum N_{Li}} \tag{22}$$

$$CAIDI = \frac{\sum N_i \times U_{ai}}{\sum N_i} \tag{23}$$

$$SAIFI = \frac{\sum N_i \times \gamma_{ai}}{\sum N_i} \tag{24}$$

where N_i is the total number of customers interrupted, N_{Li} is the total number of customers, U_{ai} is the restoration time in minutes, and γ_{ai} is the failure rate. After calculating each index separately using (22) to (24), reliability index (RI) is calculated by averaging such indices and the new proposed RISR is then calculated as follows:

$$RISR = \sum_{N=i}^{TI} \frac{RI_b - RI_a}{RI_b} \times 100/TI \tag{25}$$

where TI is the number of reliability indices for the system, and RI_b and RI_a represents the reliability index before and after EM.

D. CONSTRAINTS

The constrains considered for solving the optimization problem in this research are summarized as follows:

- Power flow equations should be modified to consider the real and reactive power generated by the DERs.
- The penetration level of different DERs is another constraint.

$$\sum_{i=1}^{n} P_{DG\_i} = \%DG_i \text{ of feeder capacity} \tag{26}$$

- Reactive power limit for RSs should be maintained.

$$Q_{min} \leq Q_{t,i} \leq Q_{max} \quad \forall_{t,i} \neq 1 \tag{27}$$

- Voltage limit at all the system buses and current limit at all the power line should be maintained.

$$V_{min} \leq V_{t,i} \leq V_{max} \forall_{t,i} \neq 1 \quad I_i \leq I_{max,i} \quad \forall_i \tag{28}$$

E. PROBABILISTIC NATURE OF LOAD AND GENERATION

The load in this research is considered as firm hourly and the hourly load data is calculated as a percentage of daily peak load presented in IEEE RTS [25]. Wind turbines, PVs and EVs are considered as non-dispatchable DGs for system expansion (SE) options and their output power is uncertain in nature. The probability density functions related to the output power of wind turbines, PVs, and EVs are divided into the selected number of states in such a way that the results reflect the nearest state without consuming extra computing time. In this research, the load generation stages are considered according to the wind speed, solar irradiance, and EVs behavior, based on their historical distribution. For example, in each hour of the day, 4 wind-speed states (N_w), 4 solar-irradiance states (N_s), and 4 EVs charge/discharge states (N_e) are selected for the probability density functions with different probabilities. The inter-temporal or any other correlations are not considered; therefore, for each hour, the number of load generation states can be calculated by simply multiplying all the states of wind speed, solar irradiance, and behavior of EVs for a 24-hour period (H = 24) as shown [22]:

$$N_{st} = N_w \times N_s \times N_e \times H \tag{29}$$

IV. HYBRID PSO-TS ALGORITHM FOR SYSTEM EXPANSION

The goal for integration of DERs in PDS is to minimize the system losses, and operational costs by finding the appropriate locations and capacities of DERs, etc. This research uses a hybrid PSO-TS optimization algorithm combined with the Newton Raphson (NR) power flow method for distribution system expansion purpose to find optimal locations and capacities of the resources i.e. $P_{DG,}Q_{RSs,}P_{ESSs,}$ and P_{EVs}. The next stage, $E_i(i = 1, 2, \ldots .N_E)$ which is performing energy management is also an optimization problem. The objective function for performing EM in DERs integrated PDS is to minimize the system operational costs, losses, and emissions together by finding the optimal schedule of the DGs for a 24-hour period. Therefore, two different optimization problems are defined and solved using hybrid PSO-TS.

The traditional metaheuristic algorithms (PSO, TS) have the capability to find the optimum solutions and are also capable of finding the global optimal solution in a complex problem. TS algorithm can find the best local optimal solution while looking for the global optimum, whereas PSO also can find the global optimal solution in the searching space by using several swarms. Even though these metaheuristic algorithms are capable to find the best optimal solution in a complex problem, they may not guarantee to find the global optimal solutions in a high dimension distribution network [20]. Thus, by combining the two methods, PSO and TS, this research proposed a new hybrid PSO-TS algorithm that has stronger capability rather than PSO or TS individually, to find the optimal solutions in the large-scale optimization problem. The details of the proposed hybrid PSO-TS algorithm are explained in the next subsections.

A. PARTICLE SWARM OPTIMIZATION

In PSO, there are a predetermined number of particles in the searching space. These particles are the decision variables that are set to optimize the objective function. In the first iteration, each particle randomly chooses the position and the initial velocity is set to zero. Each particle follows the position and velocity-updating equation to decide its position for the next iteration. This is done based on the history of particles' own best and current locations with those of the best positions attained by other particles in the swarm, including some random perturbations. Thus, in subsequent iterations, the swarm achieves the best solution to the fitness function in the problem space, with a pre-defined number of particles working together. Particles in PSO are updated using equation (30) and (31).

$$v_i^{k+1} = wv_i^k + c_1 r_1^k \left(pbest_i^k - x_i^k\right) + c_2 r_2^k \left(gbest_i^k - x_i^k\right) \tag{30}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{31}$$

where v_i^k and x_i^k are the velocity and position of ith particle at kth iteration, $pbest_i^k$ and $gbest_i^k$ are the personal best and the global best positions of particle i at kth iteration. w represents inertial weight which guaranties the convergence of particles, c_1, c_2 represent acceleration constants, r_1^k,r_2^k represent random numbers in the range of [0, 1]. Iterations will continue until the objective functions are not changed and provide optimally best results.

B. TABU SEARCH

Tabu Search is a neighborhood evaluation based heuristic algorithm that effectively guide the search to a good solution in a combinatorial-optimization problem [21]. The extensive use of different memory structures of TS provides capability of searching the solution space economically and effectively. At the same time, the memory structures are used to direct the search to attractive regions and to avoid revisiting solutions that have already been considered. TS also allows a non-improving solution to be accepted in order to escape from a local optimum and also is applicable for both discrete and continuous solution spaces.

C. PROPOSED HYBRID PSO-TS ALGORITHM

Even though the TS and PSO algorithm have the capability to find the best solution in the distribution network, the stronger solution will be achievable by utilizing their outstanding properties together. In this research, a new hybrid PSO-TS optimization algorithm is proposed by combining some characteristics of PSO and TS. For this purpose, the initial solutions of each particle is selected by using PSO and is sent to TS. TS will then search for the best neighbor of each initial solution based on the experience within different sets of swarm and then finally selected the best solution among each sets of swarms. Afterwards, PSO will receive the best local optimal results from TS and find out the particles' own best and global best among all the particles. The steps in order to implement the hybrid PSO-TS solution algorithm are illustrated in Fig. 3.

V. SYSTEM UNDER STUDY

In this research, the well-known PG&E 69-bus PDS is chosen for the case studies and sensitivity analysis. Two options can be considered for the base system: 1) the original system

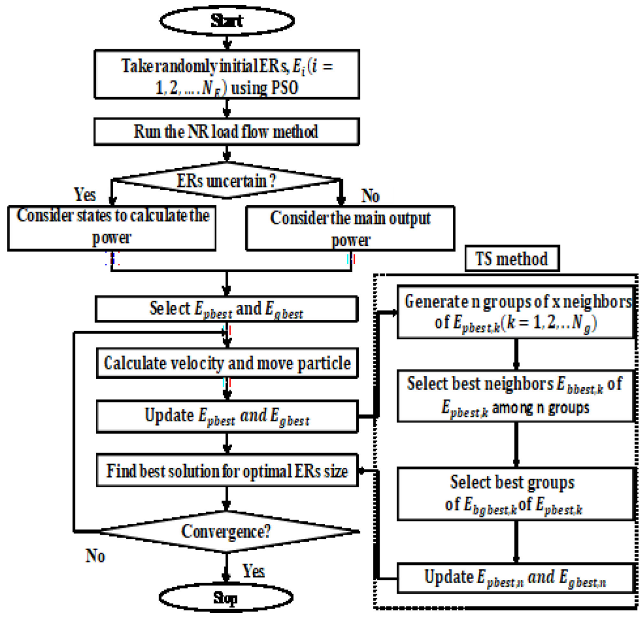

FIGURE 3. Solution Algorithm.

TABLE 1. Base system data for a day.

Distribution System	Operational costs ($)	Emissions ($)	Losses ($)	Total cost ($)
Without DGs	8491.2	0	419.17	8910.4
With DGs	7951.6	3.32	368.9	8323.8

having no DGs in the network, 2) the original system having four types of DGs including natural gas, biomass, wind turbine, and PVs. Since the PDS may already have some installed generators, in this research, the second option is considered as the base system and is used for assessing system expansion options using different DERs. For this purpose, 225 kW of natural gas, 150 kW of wind turbine, 100 kW of PV and 50 kW of biomass are considered for the base system, shown in Fig. 4. The energy price of the original system is calculated per kWh based on [21] and the operational costs of each DG is calculated per kWh based on Energy Information Administration data [26]. The total losses and emissions of the system is recorded for a 24-hour period based on [24]. The operational costs, emissions, and system losses are calculated for the base system with and without DGs and are shown in Table 1. The detailed discussion about each resource and its

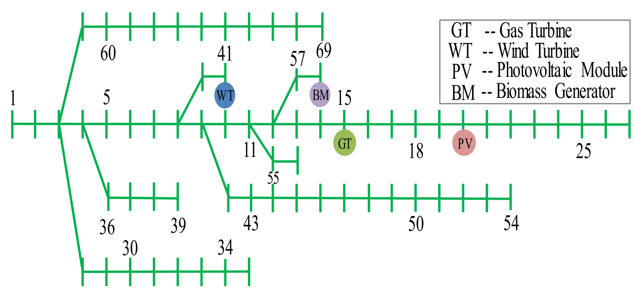

FIGURE 4. PG & E 69 bus system network before expansion with base DGs.

characteristics are described in section II. Uncertain behavior is considered for renewable-based DGs and EVs to get more accurate results and data is taken from [27], [28] for 24 hours.

VI. DER INTEGRATION, ENERGY MANAGEMENT AND SYSTEM PERFORMANCE ASSESSMENT

In this section gas turbine, diesel, biomass, wind turbine, and PV modules are integrated in PDS, EM is performed and their impacts on system performance is investigated. The operational costs of gas turbine, wind and PVs is considered as 0.03 \$/kWh and 0.08 \$/kWh for biomass [26]. The diesel generator operational costs are taken from [24]. Since the goal of this research is to assess the operational performance of PDS, only the operational costs of DERs are considered, and the capital investment costs are ignored. After optimally installing the DGs based on the objective function by an optimization process, the impacts on the EM process is investigated. The EM using each DG individually is investigated in Subsections A to E and the results are compared and analyzed in Subsection F. The simultaneous integration of different types of DGs is also analyzed in Subsection G. Table 2 presents the optimal locations and capacities of each DG by using TS-PSO algorithm with the goal of loss and operational costs minimization.

TABLE 2. Selected buses and capacities for different DGs.

DGs	SE (kW)	DGs locations (Buses)	Capacities (kW)
GT	300	53, 52, 50, 49, 17	70, 70, 70, 70, 20
	600	53, 52, 50, 13, 49	140, 140, 140, 40, 140
	900	27, 53, 52, 50, 49	60, 210, 210, 210, 210
	1200	53, 52, 50, 19, 49	280, 280, 280, 80, 280
	1500	53, 52, 50, 16, 49	350, 350, 350, 100, 350
Diesel	300	53, 52, 22, 50, 49	70, 70, 20, 70, 70
	600	53, 52, 50, 49, 17	140, 140, 140, 140, 40
	900	53, 52, 50, 19, 49	210, 210, 210, 60, 210
	1200	27, 53, 52, 50, 49	80, 280, 280, 280, 280
	1500	53, 52, 50, 16, 49	350, 350, 350, 100, 350
BM	300	53, 52, 50, 49, 17	70, 70, 70, 70, 20
	600	53, 52, 50, 49, 17	140, 140, 140, 140, 40
	900	27, 53, 52, 50, 49	60, 210, 210, 210, 210
	1200	53, 52, 50, 19, 49	280, 280, 280, 80, 280
	1500	53, 52, 50, 16, 49	350, 350, 350, 100, 350
WT	300	53, 52, 50, 19, 49	70, 70, 70, 20, 70
	600	53, 52, 50, 13, 49	140, 140, 140, 40, 140
	900	27, 53, 52, 50, 49	60, 210, 210, 210, 210
	1200	53, 52, 50, 19, 49	280, 280, 280, 80, 280
	1500	53, 52, 50, 16, 49	350, 350, 350, 100, 350
PVs	300	53, 52, 22, 50, 49	70, 70, 20, 70, 70
	600	53, 52, 50, 49, 17	140, 140, 140, 140, 40
	900	53, 52, 50, 19, 49	210, 210, 210, 60, 210
	1200	27, 53, 52, 50, 49	80, 280, 280, 280, 280
	1500	53, 52, 50, 16, 49	350, 350, 350, 100, 350

A. ENERGY MANAGEMENT USING GAS TURBINES

Gas turbines are considered to be dispatchable DGs in this research. EM can optimally control the output power of gas turbines for minimizing the total system operational costs. After successful installment of the DGs in the system using gas turbines with different capacities, the total operational costs, emissions, losses, and EMSR are recorded in Table 3 for a 24-hour period. It is seen that when the gas turbines are optimally controlled with capacities from 300 kW to 1500 kW, the amount of emissions increases from \$8.1 to \$26.7. On the other hand, total operational costs are reduced from \$7634.1 to \$5370.5 and system losses are reduced from \$250.4 to \$23.8.

TABLE 3. System data for installing different DGs.

DGs	SE (kW)	Emission (\$)	Loss (\$)	Total cost (\$)	EMSR (%)
GT	300	8.1	250.4	7634.1	8.4
	600	12.8	159.3	6998.5	16
	900	17.4	91.4	6411	23.1
	1200	22.1	47.1	5863.7	29.6
	1500	26.7	23.8	5370.5	35.6
Diesel	300	4.8	250.3	9309.6	-11.7
	600	6.2	158.8	10354.5	-24.3
	900	7.5	91.7	11444.6	-37.3
	1200	8.9	46.94	12582.1	-51
	1500	10.3	23.8	13762.5	-65.2
BM	300	3.3	250.1	7968.1	4.4
	600	3.3	158.2	7680.2	7.8
	900	3.3	91	7441	10.7
	1200	3.3	46.5	7246.4	13.03
	1500	3.3	23.1	7094.9	14.9
WT	300	3.3	354	8163	2.03
	600	3.3	340.1	8017.9	3.8
	900	3.3	328.7	7875.8	5.5
	1200	3.3	318.5	7735	7.2
	1500	3.3	308	7596	8.8
PVs	300	3.3	339	8045	3.5
	600	3.3	315.1	7787	6.6
	900	3.3	293.3	7533.6	9.6
	1200	3.3	273	7284.7	12.6
	1500	3.3	256.2	7041	15.5

B. ENERGY MANAGEMENT USING DIESEL GENERATORS

Due to the high operational costs of the diesel generators they are primarily used as dispatchable DGs for emergency situations [29]. The output power of DGs is controlled based on minimizing the system losses and operational costs together. After successful installment of the diesel DGs in the system with different capacities, the total operational costs, emissions, EMSR and loss reduction are recorded in Table 3 for a 24-hour period. It is noticeable that, when diesel generators are optimally controlled with capacities from 300 kW to 1500 kW, the total operational costs increase from \$9,309.6 to \$13,762.5, which is significantly higher than \$8,323.8 (total operational costs before system expansion and EM). Therefore, the EMSR value will be negative according to (9).

C. ENERGY MANAGEMENT USING BIOMASS GENERATORS

Biomass DGs are also considered as dispatchable DGs with no uncertainty in this research. The biomass is a pure energy source, with no pollution. After installation of DGs in the system using biomass generators of 300 kW to 1500 kW, the energy management success rate increases from 4.4 to 14.9. The system losses, and the total system operational costs reduces and the results are presented in Table 3.

D. ENERGY MANAGEMENT USING WIND TURBINES

Wind turbines are considered as non-dispatchable DGs. It is assumed that the system always takes maximum power from wind generators, which are cheap and pollution-free energy sources. The EM and performance assessment results using wind turbine are shown in Table 3. It is seen that when the system is expanded with wind turbine with a range from 300 kW to 1500 kW, the system losses are decreased from \$354 to \$308 and the total system operational costs are also reduced from \$8163 to \$7596 for a period of 24-hour. Since, wind turbines are considered as non-dispatchable DGs, the EMSR is comparatively low in this stage.

E. ENERGY MANAGEMENT USING SOLAR PVS

This stage considers the EM using solar PVs in the PDS. Solar energy resources are also regarded as non-dispatchable DGs. The generation costs, losses, and EMSR of the system are shown in Table 3. It is seen that when the system is expanded with PVs with the same range from 300 kW to 1500 kW, the total system operational costs are reduced from \$8045 to \$7041. It is an interesting point that, with the same range of system expansion using PVs compare to wind turbines, the operational performance is not the same. The reason is the difference in uncertainty modelling of the DGs and having different output power in different times of the day. Since solar PVs are considered as non-dispatchable DGs, they cause lower EMSR in the system comparing to the dispatchable DGs.

F. RESULTS DISCUSSION AND COMPARISON

This section summarizes and compares the results presented in previous subsections. The results show that EM using gas turbine is the most cost effective comparing to other DGs. It will not be economically and environmentally efficient to use the diesel generators as DGs since they have large operational costs compare to other DGs shown in Fig. 5. Biomass generators and solar PVs have a moderate impact in terms of system operational costs. In terms of system losses, natural gas, diesel, and biomass have significant contributions to reduce losses as shown in Fig. 6. Wind turbine, PVs and biomass are clean sources of energy, thus, they have almost no impact on system emissions in contrast with natural gas, which has the highest emission level. The EMSR using different DGs form 300 kW to 1500 kW is shown in Fig. 7.

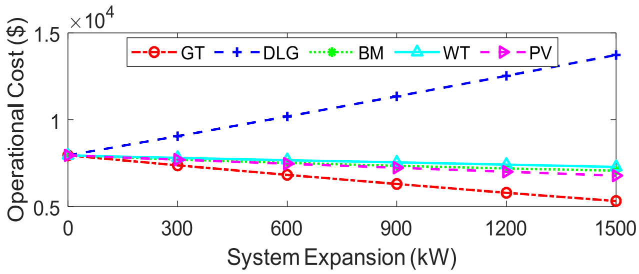

FIGURE 5. Operational costs for different DGs.

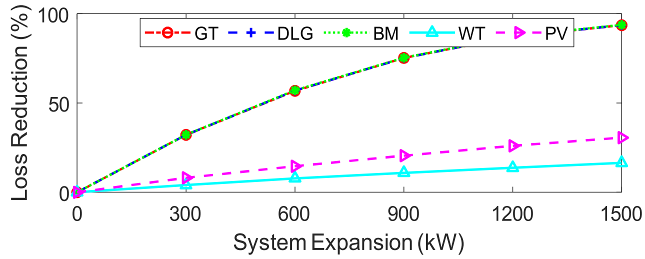

FIGURE 6. Loss reduction for different DGs.

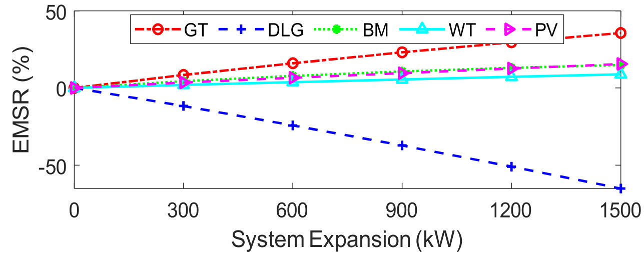

FIGURE 7. System EMSR for different DGs.

G. ENERGY MANAGEMENT USING ALL DERS

After observing the results for applying EM in a PDS using different DGs individually, this stage investigates the performance while integrating all the DGs simultaneously. For this purpose, 525 kW of natural gas, 150 kW of diesel, 75 kW of biomass, 525 kW of wind, and 225 kW of solar PVs are integrated into the PDS simultaneously. When all the selected DGs are optimally controlled in the network, the EMSR, operational costs, loss and emissions reductions, are improved considerably as shown in Table 4. It is an interesting point that when all the DGs are installed collectively, they benefit each other, and the system performance improves significantly. The per unit kWh energy generation costs are considered for each DG, the same as it was considered for each stage discussed in the previous sections.

TABLE 4. System data for installing all DGs.

Capacities (kW)	Emissions (\$)	Losses (\$)	Total cost (\$)	EMSR (%)	% Loss reduction
1500	12.23	196.9	7378	11.5	46.67

VII. FURTHER ENHANCEMENTS

This section extends the PDS having different DGs (extension of section VI-G) by integrating RSs, ESSs, and EVs individually and collectively. After adding such resources EM is applied to investigate the updated system's performance.

A. ENERGY MANAGEMENT USING RSS, ESSS, AND EVS INDIVIDUALLY

The RSs are considered as fixed capacitors which are installed in multiple locations in an optimal way such that the system has minimum losses, and operational costs. The ESSs and the EV charging stations are also optimally located in the system. The EM is performed for each case and the results are shown

TABLE 5. System data for installing all DGs.

DERs	Capacities (kW/kVAr)	Emissions ($)	Total cost ($)	EMSR (%)	% Loss reduction
RSs	200	12.23	7343.9	11.86	46.58
	500	12.23	7344.93	11.85	46.63
	800	12.23	7346.9	11.83	46.55
ESSs	200	12.23	7191.9	13.7	49.31
	500	12.23	6978.4	16.3	51.55
	800	12.23	6781.9	18.6	52.33
EVs	100	12.23	7301.5	12.4	46.59
	150	12.23	7280.13	12.6	46.65
	200	12.23	7260.9	12.9	46.74
All DER	2075/500	12.23	6917.23	17	51.6

in Table 5. It is considered that the efficiency of the ESS is 90%. It should be noted that when the system is expanded by RSs from 200 kVAr to 800 kVAr, and EM is applied to control the RSs, there is almost no change in systems operational costs, system losses, and overall the EMSR is unchanged. This happens due to the fact that the DGs already have reactive power generation capabilities. The system emissions also remain the same since the RSs have no impact on system emissions. When the ESSs are optimally controlled from 200 kW to 800 kW, the EMSR is increased from 13.7% to 18.6% and system losses are reduced to 52.33% as shown in Table 5.

Moreover, the EVs capacity is considered to be100 kW to 200 kW based on the EVs battery capacity and number of EVs operating in the system and are shown in Table 5. The EV aggregate charging stations and the times of charging and discharging period are considered based on energy price from the utility. As seen in Table 5, the operational costs is reducing and the EMSR is increasing for controlling the EVs using optimization process. The changes of operational costs, system losses reduction and EMSR due to RSs, ESSs, and EVs integration in the PDS are compared and the results are shown in Fig. 8, Fig. 9 and Fig. 10, respectively.

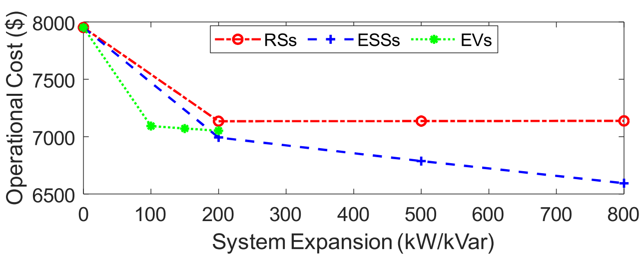

FIGURE 8. Operational costs for RSs, ESSs, and EVs.

B. ENERGY MANAGEMENT USING RSS, ESSS, AND EVS COLLECTIVELY

After observing the results for applying EM in a PDS using RSs, ESSs, and EVs each at a time, this stage investigates the PDS performance using RSs, ESSs, and EVs collectively. For this purpose, 1500 kW of DERs (section VI-G), 500 kVAr of RSs, 500 kW of ESSs, and 150 kW of EVs are

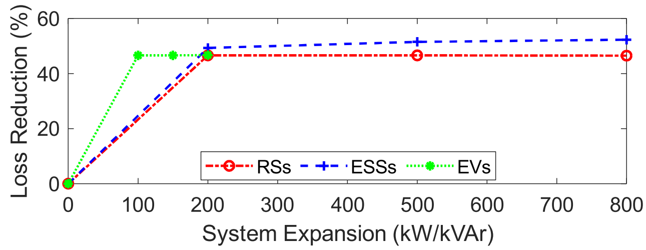

FIGURE 9. Loss reduction for RSs, ESSs, and EVs.

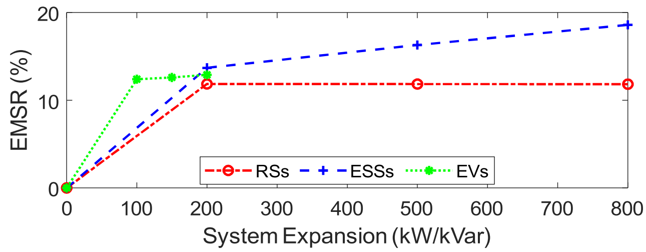

FIGURE 10. System EMSR for RSs, ESSs, and EVs.

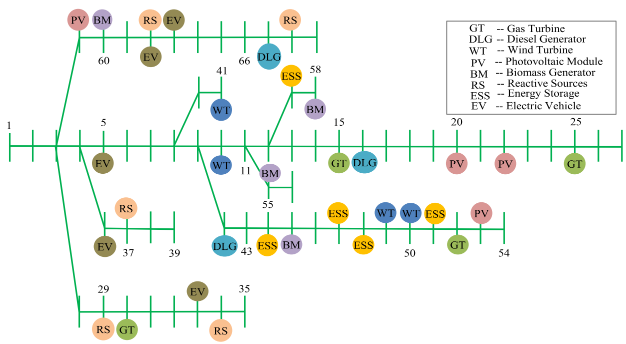

FIGURE 11. PG & E 69 bus system network with DGs, RSs, ESSs, and EVs.

considered for system expansion and EM, which is shown in Fig. 11. The interesting point is that after controlling all the dispatchable DGs, RSs, ESS, and EVs together, the EMSR increases to 17% which is much higher than 11.5% for controlling the DGs without RSs, ESS, and EVs discussed in section VI (Subsection G). In addition, system losses significantly reduce to 51.6% comparing to 46.67% for previous case shown in Table 4. Since, RSs, ESSs, and EVs are not responsible for emissions, its value is remaining the same $12.23 as before.

VIII. SENSITIVITY ANALYSIS

Due to the importance of voltage controllability and Reliability in a PDS, this section provides sensitivity analysis to assess the DERs impact on PDS's VCI, RI, and RISR. The results are investigated in the following subsections.

A. VOLTAGE CONTROLLABILITY IMPACTS OF THE DERS

The voltage controllability index defined in [22] is used in this section for the assessment of DGs integration in the PDS. For this purpose, the voltage change threshold is set to 0.2 and

TABLE 6. Voltage controllability for installing DGs.

DERs	ΔV_{th} (%)	DG location	DG capacity	VCI (%)
GT	0.1	53,52,50,16,49	350,350,350,100,350	62.33
	0.3	53,52,50,16,49	350,350,350,100,350	48.92
	0.5	53,52,50,16,49	350,350,350,100,350	11.3
Diesel	0.1	53,52,50,16,49	350,350,350,100,350	62.33
	0.3	53,52,50,16,49	350,350,350,100,350	48.92
	0.5	53,52,50,16,49	350,350,350,100,350	11.3
BM	0.1	53,52,50,16,49	350,350,350,100,350	62.33
	0.3	53,52,50,16,49	350,350,350,100,350	48.92
	0.5	53,52,50,16,49	350,350,350,100,350	11.3
WT	0.1	53,52,50,16,49	350,350,350,100,350	30.5
	0.3	53,52,50,16,49	350,350,350,100,350	3.3
	0.5	53,52,50,16,49	350,350,350,100,350	0
PVs	0.1	53,52,50,16,49	350,350,350,100,350	23.56
	0.3	53,52,50,16,49	350,350,350,100,350	15.1
	0.5	53,52,50,16,49	350,350,350,100,350	2.8
All DG	0.1	53,52,50,16,49	525,150,525,225,75	60.3
	0.3	53,52,50,16,49	525,150,525,225,75	26.2
	0.5	53,52,50,16,49	525,150,525,225,75	6.3

the results are shown in table 6. A maximum of 20% of DERs real power is assumed to be used for voltage control purpose [22]. It is seen that increasing threshold voltage has significant impacts on the VCI. For example, when the system is expanded using gas turbines, and the voltage measurement threshold ΔV_{th} are changed from 0.1 to 0.5%, the VCI is also changed from 62.33 to 11.3%. For wind turbine and solar PV, the VCI is comparatively lower than any other DGs because of their uncertain and probabilistic characteristics.

B. RELIABILITY IMPACTS OF THE DERS

The reliability indices of the PDS are evaluated after integration of DERs in the PDS in this section. Several assumptions have been made in this research for reliability index calculations similar to the approach presented in [30].

For this purpose, the total number of customers are assumed to be 20000 based on the total power of the loads. The U_{ai} has been considered as 8 minutes and the γ_{ai} for the system is assumed to be 0.02. In case of faults in the PDS, the total number of affected customers will be 5164, 6728, 6119, 11220, and 12664 for 1500 kW capacities of natural gas, diesel, biomass, wind turbine, and PVs respectively. It should be noted that the number of affected customers depends on the capacity and location of different DGs. Also, due to the uncertainties of solar and wind powers, the total number of affected customers are considerably higher for wind turbine and PVs. The reliability data of system components are considered to be the same for both cases with and without DGs installment into the PDS to make a more reasonable comparison. The RIs are calculated in terms of SAIDI, CAIDI, and SAIFI for different DGs individually and collectively by integrating 1500 kW of DERs. As can be seen from Table 7, when the DGs are installed in the PDS, the RIs improve for all indices that ultimately help to improve RISR. Table 7 illustrates that natural gas DGs have more impacts on reliability than any other resource because of the continuous energy generations while wind turbine and PVs have less impacts on reliability due to their uncertain and probabilistic characteristics.

TABLE 7. Reliability indices before and after installing DGs.

DGs	SAIDI	CAIDI	SAIFI	RISR (%)
Base (Without DGs)	5.9	7.9	0.75	-------
Gas	1.8	7	0.26	48.7
Diesel	2.6	7.8	0.33	37.7
Biomass	2.4	7.9	0.3	39.8
Wind	4.4	7.8	0.56	17.3
PV	5	7.8	0.64	10.4
All DGs	3	7.8	0.41	32.7

IX. CONCLUSION

This article investigates PDS expansion using different penetration levels of DERs and analysis their impacts on energy management success. The overall system performance in terms of operational costs, system losses, and environmental emissions is also evaluated during system expansion. As further enhancements, the impacts of integrating different levels of RSs, ESSs, and EVs on operational issues are also investigated. A hybrid PSO and TS based optimization method has been applied in this research renamed as hybrid PSO-TS that is a more powerful heuristic-based algorithm specifically in this high dimension optimization problem. The PG&E 69 bus system has been used as the test system for the simulations and case studies. The results show that integration of different DERs along with EM strategies could have positive or negative impacts on PDS performance depending on the DERs types. Diesel generator, gas turbine, and biomass have more impact on reducing system losses while PVs, wind turbine, and biomass have more impact in reducing environmental impacts. Moreover, this research shows that RSs, ESS, and EVs along with DERs, play a significant role in achieving operational goals of the PDS. Lastly, sensitivity analysis has been done for analyzing voltage controllability and reliability of PDS by calculating VCI, RI, and RISR. The case studies presented in this article provides information for power engineers to compare different system's performance indices during integration of different DERs and helps them make more reasonable decisions while expanding traditional PDSs using different types of RSs, ESSs and EVs. As future work, the system can be expanded by considering different planning and operational performance indices, e.g. system's resiliency. The indices could be combined with different weights based on their importance for the distribution system operator. Moreover, incentive-based policies could be designed and considered during expansion planning for profit-oriented entities, utilities and consumers to promote the renewable-based DERs integration for a more environment friendly energy system.

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