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Optimization Planning Method of Renewable distributed Generation in Radial Distribution Systems

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ABSTRACT

Introduction: This study presents an effective method with high stability called the coyote optimization algorithm (COA) for the optimal integration of renewable distributed generation units (DGUs), including biomass units (BMs), wind turbine units (WTs) and photovoltaic units (PVs). The main aim of the study is to minimize the annual power loss cost considering three hybrid systems with the combination of PV and WT, BM and PV, and BM and WT in the time-varying load demand and operating condition of DGUs simultaneously under constraints of bus voltage, branch current and penetration of DGUs. **Methods**: Apply coyote optimization algorithm (COA) for determining the optimal integration of hybrid distribution systems to minimize the annual operating costs. **Results**: The obtained results in the IEEE 69-bus radial distribution system have demonstrated that determining the proper integration of DGUs can reduce power loss, save annual operating costs, and improve the voltage profile significantly. In addition, the introduced method (COA) and recently published methods such as the slime mould algorithm (SMA) and improved particle swarm optimization algorithm (IPSO) are also implemented and compared together in solving the optimization problem. Compared to a standard IEEE 69-node system, the hybrid systems with the implementation of COA can reduce the annual power loss cost by 83.84%, 91.27% and 92.74%, respectively. On the other hand, COA can reach smaller annual power loss cost than IPSO by 0.96%, 2.17% and 2.1% and SMA by 0.72%, 1.64%, and 1.6%, respectively. **Conclusions**: The results indicate that hybrid systems are operating more effectively than base systems without DGUs, and COA is a strong method providing good solutions for reduction of annual power loss cost.

Key words: Coyote optimization algorithm, wind turbine, photovoltaic, biomass, power loss, voltage profile

INTRODUCTION

In recent years, problems related to environmental pollution and instability in fuel prices have contributed significantly to increasing the penetration of DGUs in distribution systems[1]. The main purpose of integrating DGUs is to inject energy into the system. However, with a suitable integrated strategy, DGUs can provide other great benefits. In some typical examples of the benefits of DGUs[2–4], the power loss on the branches of the distribution system was strongly reduced thanks to the penetration of DGUs. In addition, the voltage quality and reliability of the system are also enhanced[5,6]. On the other hand, loss compensation, reactive power support and frequency control are also additional benefits of connecting DGUs[7]. Conversely, improper integration of DGUs into the distribution system can lead to an increase in power loss, overvoltage, and reverse power flow[8,9].

In the past, determining the DGU installation strategy for power loss minimization has attracted the attention of many researchers. For the most part, they focus on developing different optimization algorithms to reduce losses at the peak load and the fixed power output of DGUs[10,11]. Therefore, the found solution may not be optimal when the load demand and output condition of the DGUs change. Specifically, mixed integer programming[12,13], optimal power flow[14], and heuristic algorithms[15–17] are prime examples for such studies. Only a relatively limited number of papers have considered the variation in load demand and output conditions of DGUs, but these studies have not fully mentioned different types of DGUs and have ignored consideration of the power factor for DGUs[18,19]. In this paper, a study was implemented to overcome the existing shortcomings of previous studies. The optimization problem of the location and capacity as well as the operating power factor of individual DGUs are considered to minimize the annual power loss cost in the distribution system where constraints of the bus voltage, the branch current and the renewable energy penetration level are satisfied. Moreover, three different hybrid systems are also analyzed, including hybrid systems

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of PV and WT, BM and PV, and BM and WT under consideration of time-varying load demand and their operating conditions simultaneously. In addition, a forward-backward sweep (FW-BWS)-based numerical technique is applied to solve the load flow problem and calculate power loss before and after connecting DGUs[20]. On the other hand, to obtain the maximum benefit from integrating DGUs into a distributed system, an efficient algorithm with high stability, named the coyote optimization algorithm (COA)[21], is suggested for solving the optimization problem. The obtained results of the COA are also compared with recently introduced methods in 2020 and 2021, such as the slime mould algorithm (SMA)[22] and improved particle swarm optimization (IPSO) algorithm[23], respectively, to show the superior effectiveness of the suggested method. In summary, the contributions of this study can be briefly presented as follows:

- The study considers the optimal integration of three hybrid systems, including BM and WT, WT and PV, and BM and WT, into the distribution system considering the time-varying load demand and generation under constraints of bus voltage, branch current and penetration level of connected units.
- The study successfully determines the optimal position and capacity of the BM, WT and PV in the distribution system to maximize the achieved economic benefit of annual power loss cost reduction for the three hybrid systems mentioned above while still satisfying the technical criteria.
- The study introduces an effective method with high stability, called the coyote optimization algorithm (COA), for solving the optimization problem of the installation of the BM, WT and PV. The study compares the COA with recently published robust methods such as SMA and IPSO to demonstrate the COA's superiority in handling optimization problems.

The rest of the paper is divided as follows: Section 2 describes the objective function and constraints. Section 3 introduces the suggested method. The flowchart of the suggested method for solving the optimization problem is presented in Section 4. Section 5 focuses on the analysis of the obtained results from the simulation. Finally, Section 6 is a summary of the whole paper.

PROBLEM FORMULATION

Objective function

Power loss in the distribution system plays an important role in evaluating power quality as well as the efficiency of system operation. The smaller the power loss on the branches, the greater the cost savings. The formulation for calculating total power loss on the j^{th} branches can be presented as[24]:

$$P_{LS} = \sum_{j=1}^{N_{br}} I_j^2 \times R_j \tag{1}$$

where R_j and I_j are the resistance and current magnitude of the jth branch, respectively.
Assuming a year has 365 days, the annual energy loss cost (Cost_{Ls}) in the distribution system with a time duration (Δh) of 1 hour should be expressed by[7,24]:

$$Cost_{Ls} = 365 \times Price_{Ls} \times \sum_{h=1}^{N_{hr}} P_{Ls}^h \times \triangle h \tag{2}$$

Constraints

The power balance constraints

To ensure system frequency stability, total power generation needs to be equal to total power consumption. Thus, the power balance equation should be described in the mathematical model as[25]:

$$P_{Grid}^h + \sum_{i=1}^{N_{DGU}} P_{Gen,i}^h = \sum_{j=1}^{N_{br}} P_{Ls,j}^h + \sum_{k=1}^{N_{ld}} P_{Ld,k}^h \tag{3}$$

$$Q_{Grid}^h + \sum_{i=1}^{N_{DGU}} Q_{Gen,i}^h = \sum_{j=1}^{N_{br}} Q_{Ls,j}^h + \sum_{k=1}^{N_{ld}} Q_{Ld,k}^h \tag{4}$$

In the above equation, $Q_{Gen,i}^h$ can be determined by[26]:

$$Q_{Gen,i}^h = P_{Gen,i}^h \times \tan\left(\cos^{-1}\left(PF_{Gen,i}\right)\right) \tag{5}$$

In this research, $PF_{Gen,i}$ is the operating power factor of the DGUs.

The branch current limit

The current on the branches should not exceed the maximum allowable limit[27]:

$$I_j^{\square} \le I_j^{Max};\ j = 1,2,3...,N_{br} \tag{6}$$

The bus voltage limits

The bus voltage should be kept in the upper and lower bounds[28]:

$$V^{Min} \le V_b^{\square} \le V^{max},\ b = 1,2,3,...,N_{bu} \tag{7}$$

The penetration of DGUs

The rated capacity of individual DGUs needs to be predefined in the lower and upper bounds. In addition, total power generation does not exceed total power consumption to avoid undesirable effects such as overvoltage, system unreliability and reverse power flow in the distribution systems[29]:

$$P_{DGU}^{Min} \leq P_{DGU,i}^{Rated} \leq P_{DGU}^{Max};\ i = 1,2,3,...,N_{DGU} \tag{8}$$

$$\sum_{i=1}^{N_{DGU}} P_{Gen,i}^{h} \leq \alpha \times \sum_{k=1}^{N_{ld}} P_{LD,k}^{h};\ h = 1,2,3,...,N_{hr} \tag{9}$$

COYOTE OPTIMIZATION ALGORITHM (COA)

In recent years, real-world optimization problems have been formulated as computational codes for almost all fields, such as mechanical, civil, aerospace, chemicals and health science. Thus, the quality of the found solution for solving the optimization problems depends on the performance of the algorithm. The development of novel optimization algorithms is always welcomed. In 2018, Pierezan and Coelho published a powerful algorithm called the coyote optimization algorithm (COA) for solving a variety of real problems[21]. This algorithm is inspired by the canis latrans species and has a high ability to find the global optimal solution with high stability. Based on the nature of canis latrans species, this community can be divided into groups ($N_{gr}^{\square}$), and each group consists of many members ($N_{ca}^{\square}$). Therefore, the result of ($N_{ca}^{\square} \times N_{gr}^{\square}$) is considered the population of this species[30].

To run the algorithm, the social condition and quality of social condition are assigned as two important factors that represent the proposed solution and its fitness, respectively, in solving the optimization problems. Similar to other metaheuristic algorithms, the initial solution of the COA is randomly generated within the predetermined limits, and the mathematical model can be presented as[30]:

$$\begin{aligned} So_{gr,ca}^{\square} &= So_{\square}^{Min} + r\left(So_{\square}^{Min} + So_{\square}^{Max}\right); \\ gr &= 1,2,3,...,N_{gr}^{\square}\ \&\ ca = 1,2,3,...,N_{CA}^{\square} \end{aligned} \tag{10}$$

where $So_{\square}^{Max}$ and $So_{\square}^{Min}$ are the upper and lower bounds of the control variables in the solution. r is defined as a random number in the interval of [0, 1]. After obtaining initial solutions, every solution will be evaluated by the fitness function, and the current best solution will be kept.

The next step is to update the solutions to their new positions by applying the first generation equation, which is formulated by[21]:

$$\begin{aligned} &So_{gr,ca}^{New} = So_{gr,ca}^{\square} + r.\left(So_{best,gr}^{\square} - So_{r1,gr}^{\square}\right) \\ &+ r.\left(So_{cent,gr}^{\square} - So_{r2,gr}^{\square}\right);\ gr = 1,2,3,...,N_{gr}^{\square} \\ &\&ca = 1,2,3,...,N_{ca}^{\square} \end{aligned} \tag{11}$$

Obviously, in equation (11), there are two jumps, including ($So_{best,gr}^{\square} - So_{r1,gr}^{\square}$) and ($So_{cent,gr}^{\square} - So_{r2,gr}^{\square}$). While ($So_{best,gr}^{\square} - So_{r1,gr}^{\square}$) tends to search the possible solutions around the best solution in each group, ($So_{cent,gr}^{\square} - So_{r2,gr}^{\square}$) focuses on finding the good solution around the center point of the group. This greatly contributes to avoiding omitting good solutions, thereby significantly improving the performance of the algorithm. Similarly, each newly created solution is evaluated by the objective function, and the current best solution is updated through comparison. In addition, the second generation equation is also used in COA for generating a new solution in each group, and the equation is built on the randomization mechanism as[30]:

$$So_{gr}^{New} = \begin{cases} So_{gr,r1}^{\square},\ if\ r < 1/N_{cv} \\ So_{gr,r2}^{\square},\ if\ 1/N_{cv} \leq r < 5 + 1/N_{cv} \\ So_{gr,r}^{\square},\ otherwise \end{cases} \tag{12}$$

To extend opportunities for finding new solutions in the larger space and avoid missing good solutions, equation (12) is developed with three randomly produced solutions ($So_{gr,r1}^{\square}$, $So_{gr,r2}^{\square}$ and $So_{gr,r}^{\square}$) that are selected according to specific conditions. While $So_{gr,r1}^{\square}$ and $So_{gr,r2}^{\square}$ can be established for each group by incidentally selecting random variables from available solutions in each group, then $So_{gr,r}^{\square}$ is randomly generated within the allowable limits of predetermined control variables. At this stage, the created solution is qualitatively compared with the worst solution in the group, and the better solution is retained. This eliminated the worst quality solution in each group, leading to enhanced general quality for the proposed solutions. In addition, to simulate the movement of the coyotes from this group to other groups, the exchange action is performed. If the condition of equation (13) is satisfied, two solutions are randomly selected from two different random groups in the community to swap their positions[30].

$$\gamma < \frac{10^{-2}}{2} \times N_{ca}^{2} \tag{13}$$

Here, γ is a randomly generated number between 0 and 1. Clearly, the coyote migration rate is proportional to the population number in each group. The larger the number of coyotes in the group, the greater the probability of coyote exchange action. Finally, the best solution in the community is also determined by comparing their fitness values.

FLOWCHART FOR APPLYING THE COA TO SOLVE THE CONSIDERED PROBLEM

This paper develops the integration of three hybrid systems of PV and WT, BM and WT, and BM and PV to minimize the annual energy cost by applying the coyote optimization algorithm. This algorithm executes iteratively until the maximum iteration value ($Iter_{\square}^{Max}$) is reached to solve the optimization problem. The flowchart for finding the global optimal solution is shown in Figure 1.

SIMULATION RESULTS

In this paper, three hybrid systems are considered for minimizing the annual power loss cost in the IEEE 69-bus radial distribution system considering the time-varying load demand and operating condition of DGUs. The structure of the system is presented in Figure 2 with a nominal voltage of 12.66 kV and a total power load of 3.802 MW and 2.694 MVar. The bus data and line data of the implemented system are taken from [25].

For the simulation of applied methods, initial parameters were investigated, and the obtained results were $Iter_{\square}^{Max}$ and $N_{\square}^{Run} = 30$. In this research, IPSO is implemented as one of the compared methods with the parameters of the inertia weight (a = 0.9 and b = 0.5) and the acceleration factor (c_{1i} = 2.5, c_{1f} = 0.5, c_{2i} = 0.5 and c_{2f} = 2.5) clearly described in [23]. For running SMA, in the formula for updating the location, the condition value (z) is set as 0.05, and r is a random number in the range of [0,1] [23]. The population (N_{pop}) of IPSO and SMA is selected through a survey, and its value is assigned as 30. On the other hand, the setting parameters for COA, including $N_{ca}^{\square}$ and $N_{gr}^{\square}$, are the same value, equal to 5. Additionally, this study has assumed that the BM is simulated as a synchronous machine with the output power of the BM being constant and generating at its rated power during 24 hours of a day. PV and WT apply converters for integration with the output powers that change over time and are plotted in Figure 3. The load data and output power data used for both PV and WT are presented in Table 2 in APPENDIX [7]. As mentioned, the study is implemented for three different cases as follows:

(1) Case 1: Hybrid system with PV and WT

(2) Case 2: Hybrid system with BM and PV

(3) Case 3: Hybrid system with BM and WT

To determine the optimal size of DGUs, the capacity of the BM is varied from 0 MW to 2.0 MW, and the minimum and maximum numbers for PV and WT are (2,000 modules and 30,000 modules) and (01 turbine and 20 turbines), respectively. The rated capacity of the PV module is also assumed to be 75 W [31], and the rated capacity of each turbine is 200 kW [32]. Moreover, this paper chose the operating power factor of the PV, WT and BM to be 0.9 (lagging) [7,33].

The optimal solutions from IPSO, SMA and COA for three different hybrid systems are reported in Table A.2, APPENDIX, and the obtained results regarding power loss are presented in Table 1. Obviously, when DGUs are connected, the annual power loss is significantly reduced compared to the system without DGUs. Specifically, the annual loss has fallen from 1756.5174 MW of the base system to 286.5806 MW, 285.8858 MW and 283.8602 MW (in case 1) to 156.6442 MW, 155.8214 MW and 153.266 MW (in case 2) and to 130.8121 MW, 127.9270 MW and 127.5543 MW (in case 3) for IPSO, SMA and COA, respectively. The loss reduction has greatly contributed to reducing the cost of operating the distribution system, and this is considered one of biggest benefits for integrating DGUs into the system in addition to supplying power to load demand as the primary purpose. Assuming the electricity price for the power loss is \$60/MWh [25], the annual cost was strongly decreased thanks to the integration of DGUs, and the amount of annual cost reduction for the three cases is reported in detail in Figure 4. Figure 8 in APPENDIX serves as a good example of loss reduction after connecting DGUs to the system by applying the optimal solution from COA. This resulted in annual loss cost reductions of 83.84%, 91.27% and 92.74% for case 1, case 2 and case 3, respectively. Obviously, the PV and WT hybrid system is the least efficient, and the BM and WT hybrid system is the most efficient. This is due in part to the capacity factor that can represent the individual characteristic for the output stability of each unit. That value is defined as the ratio of the actual amount of electricity generated to the energy that can be generated at full capacity for the same period of time [34]. In addition to the capacity factor, the solution of the location and sizing of DGUs also contributes significantly to improving the efficiency of the hybrid systems. Compared, the optimal solution from COA is more positive than the remaining methods. Specifically, in case 3, the cost reduction of annual power loss from COA occupies 92.74%, corresponding to only \$7,653/year, while IPSO and

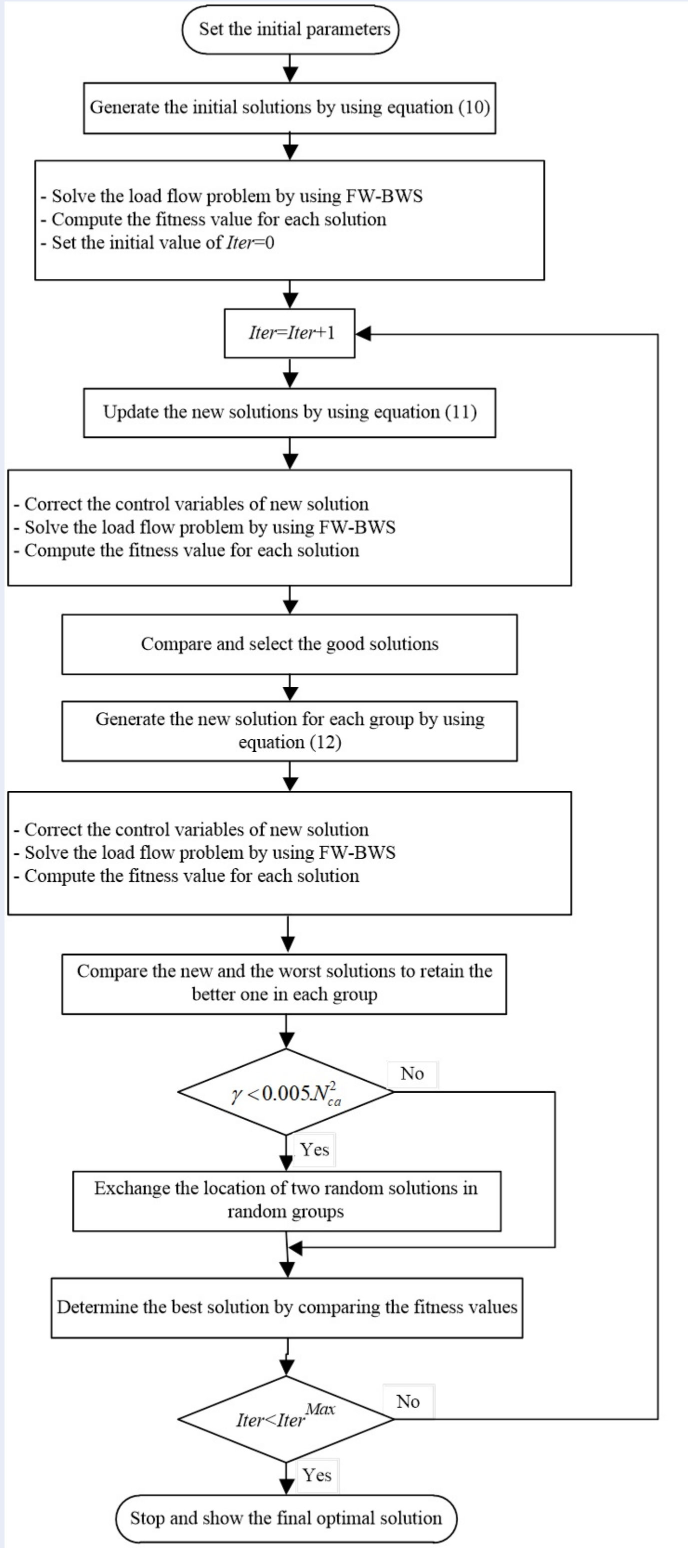

Figure 1: Flowchart for finding the optimal solution in the considered problem

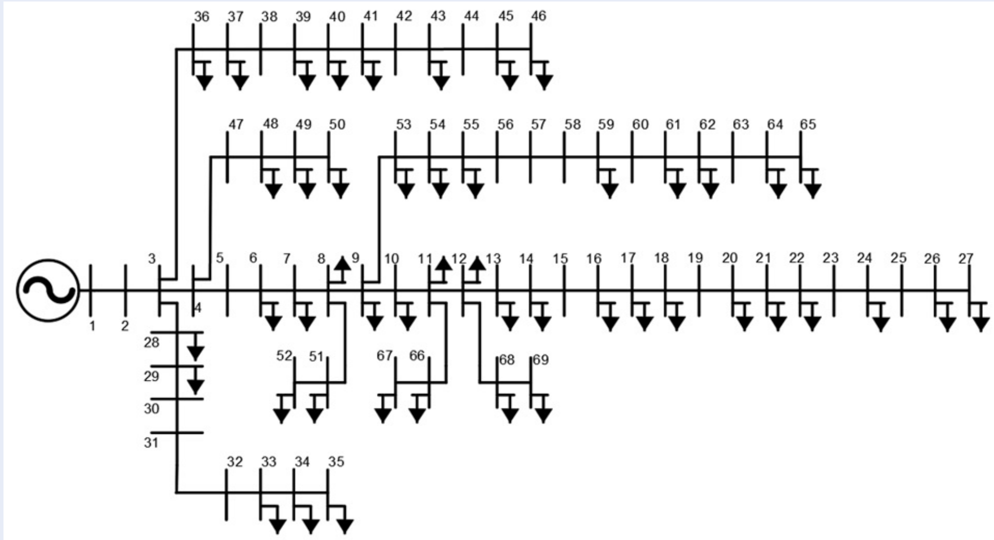

Figure 2: The IEEE 69-bus radial distribution system.

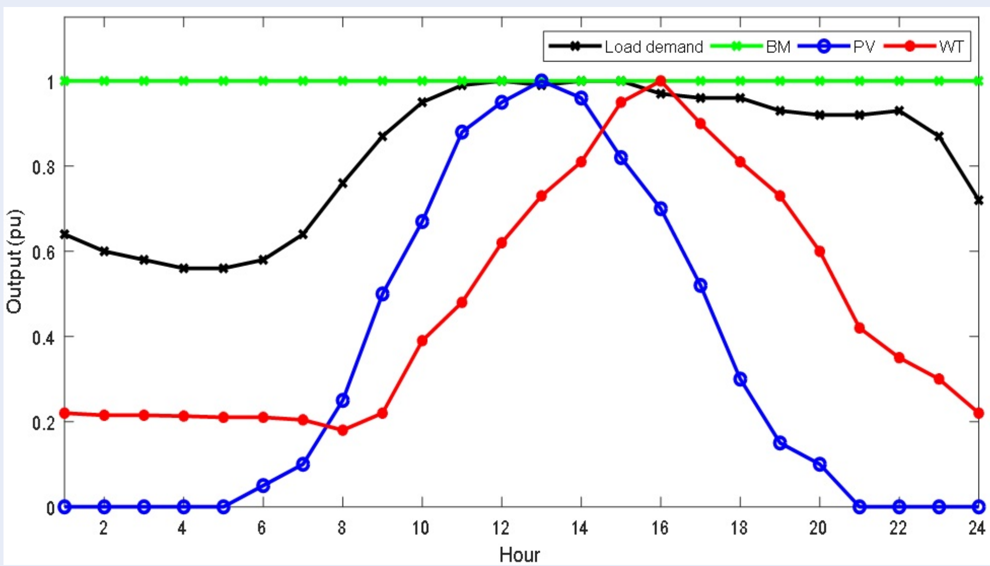

Figure 3: The daily load demand, BM, PV, and WT output curves.

SMA are 92.55% and 92.72%, corresponding to up to \$7,849/year and \$7,680/year, respectively. For an exact performance comparison, the annual cost savings of COA are calculated. COA can reach smaller annual costs than IPSO by \$165, \$204 and \$165 and SMA by \$123, \$153, and \$123 for Case 1, Case 2 and Case 3, respectively. The saving cost values are equal to the 0.96%, 2.17%, and 2.1% annual costs of IPSO and the 0.72%, 1.64%, and 1.6% annual costs of SMA for Case 1, Case 2 and Case 3, respectively. This indicates that COA is a higher performance method than IPSO and SMA for the problem.

Figure 5 presents the actual output power of DGUs considering the time-varying load demand and operating condition of DGUs simultaneously for the three cases. The total amount of load demand power in a day requires 75.66 MW, while the DGUs only provide 37.05 MW, 44.84 MW and 46.31 MW for case 1, case 2 and case 3, respectively, as shown Figure 6. Therefore, the remaining power of 38.61 MW, 30.82

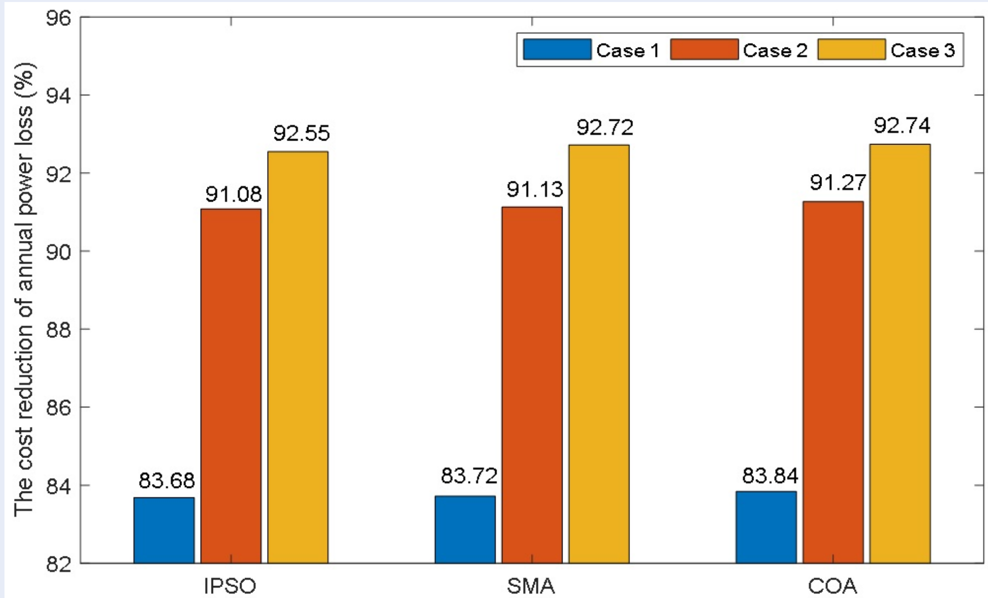

Figure 4: **The cost reduction of annual power loss (%) in three cases for implemented methods**.

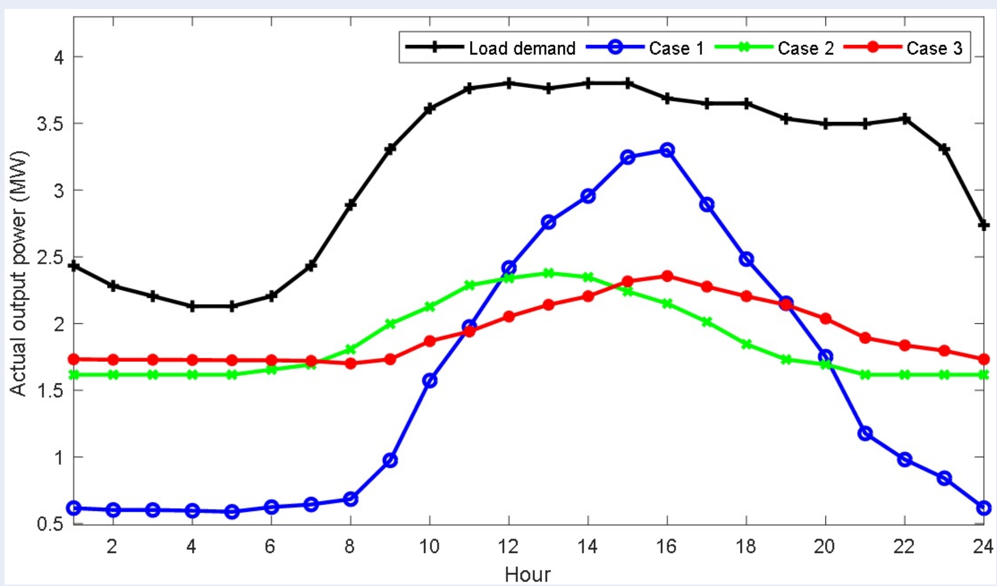

Figure 5: **The actual output power of implemented cases and load demand**.

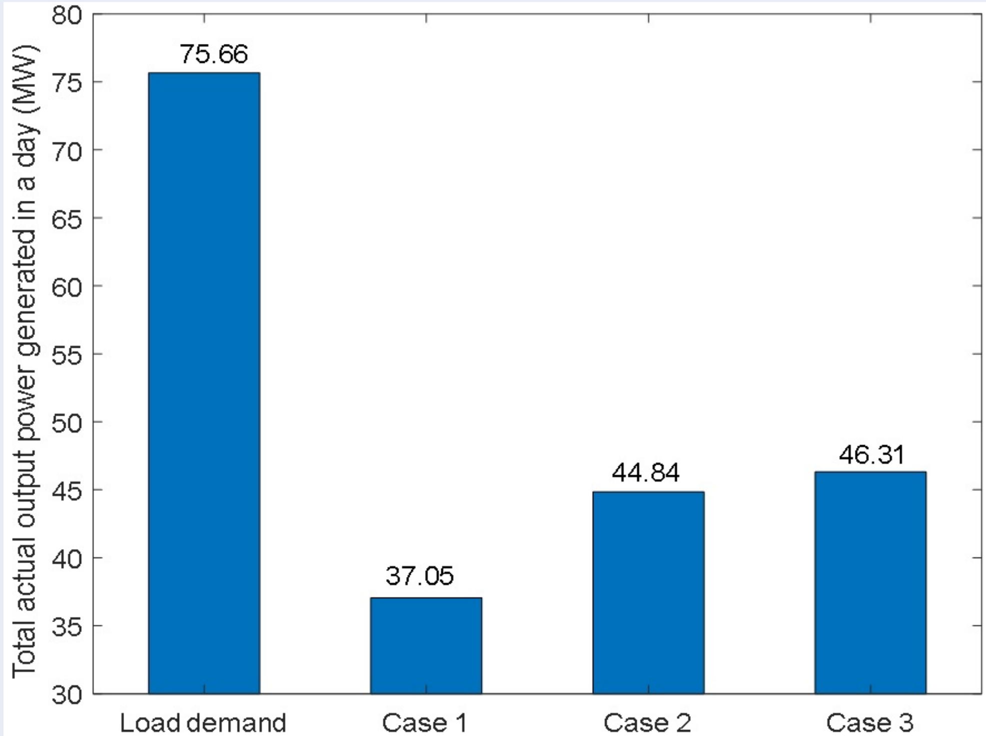

Figure 6: **Total actual output power of DGUs for cases in a day.**

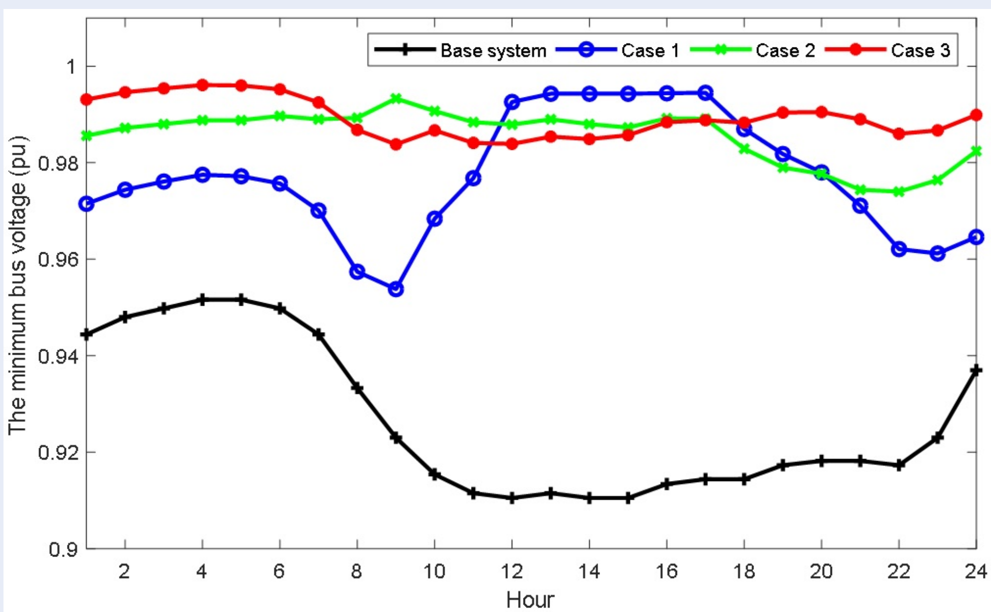

Figure 7: **The minimum bus voltage of cases**.

Table 1: The obtained results from implemented methods for three cases

Applied method	Case 1		Case 2		Case 3	
	The annual power loss (MW)	The annual cost for power loss ($)	The annual power loss (MW)	The annual cost for power loss ($)	The annual power loss (MW)	The annual cost for power loss ($)
IPSO	286.5806	17,195	156.6442	9,400	130.8121	7,849
SMA	285.8858	17,153	155.8214	9,349	127.9270	7,680
COA	283.8602	17,030	153.2660	9,196	127.5543	7,653

MW and 29.35 MW for three cases that are not yet supplied by DGUs will be supplied by the main grid through the substation. In addition, at each time , the generated power did not exceed the load demand. This completely satisfies the constraint of the penetration level from DGUs to avoid undesirable effects such as overvoltage, system unreliability and reverse power flow. Moreover, another important constraint of the bus voltage is also considered and analyzed in this section. Figure 7 plots the minimum bus voltage values at each time *h* of the cases before and after connecting DGUs by the suggested method. For the base system, the minimum voltage value is 0.909 (pu) and falls on peak load times at the 12^{th}, 14^{th} and 15^{th} hours. In addition, the voltage profile without DGUs at each time *h* is also shown in Figure 9, APPENDIX. Clearly, many voltage values are out of the allowable voltage range of [0.95 1.05] (pu). However, by properly connecting the DGUs, the voltage profile of the distribution system is enhanced drastically and satisfies the bounds of the bus voltage. For example, in the COA, by connecting suitable DGUs, the voltage profile is improved well, with minimum voltages of 0.954 (pu), 0.974 (pu) and 0.984 (pu) for case 1, case 2 and case 3, respectively. The voltage profiles with DGUs are also presented in Figures 10, 11 and 12 in APPENDIX for the three cases. Compared, the voltage profile of case 3 is better than the others, which contributed to the claim of case 3's effectiveness over the two compared cases. From the above arguments, it can be affirmed that determining the optimal DGU installation strategy can reduce power loss on distribution lines, cut operating costs and significantly enhance voltage.

CONCLUSIONS

In this study, the cost of annual power loss is minimized and compared between three effective methods, including IPSO, SMA, and COA, in the IEEE 69-bus radial distribution system. The paper considered the hybrid systems of PV and WT, BM and PV, and BM and WT in the time-varying load demand and operating conditions of DGUs simultaneously. The obtained solutions have proven the superior effectiveness of the COA in solving the optimization problem of the location and sizing of DGUs.

- The annual loss has cut from 1756.5174 MW of the original system to 286.5806 MW, 285.8858 MW and 283.8602 MW in case 1 to 156.6442 MW, 155.8214 MW and 153.266 MW in case 2 and to 130.8121 MW, 127.9270 MW and 127.5543 MW in case 3 for IPSO, SMA and COA, respectively. Clearly, by integrating suitable distributed generation units, the power loss can be greatly reduced, and economic well-being can be improved.
- In addition, by comparing the implemented methods in the best case (case 3), COA is better than the others since the cost reduction can reach 92.74%, while this value is 92.55% and 92.72% for IPSO and SMA, respectively. In summary, determining a suitable installation for DGUs can reduce loss, reduce system operating costs, and enhance the voltage profile.

In this study, harmonic distortions in the distribution system that are caused by nonlinear loads and inverters of the PV, WT and BM are ignored. Therefore, in the future, harmonics will be considered to ensure compliance with IEEE Std. 519. In addition, to minimize the discrepancy between the predicted and actual generation powers of DGUs, more hours should be considered. Specifically, 96 hours, which represent the typical 4 days of 4 seasons (spring, summer, autumn and winter) in a year, will be implemented in future works.

AUTHOR'S CONTRIBUTIONS

Thai Dinh Pham: Programming and writing entire paper. Le Chi Kien: Contributing ideas, supervising and editing paper. Tran Huu Tinh: Contributing ideas and collecting results.

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COMPETING INTERESTS

The authors declare that they have no competing interests.

LIST OF SYMBOLS

$\triangle V_{b,gr,ca}^{\square}, \triangle V_{j,gr,ca}^{\square}$ The penalty amounts of the b^{th} bus voltage and the j^{th} branch current at the ca^{th} solution of the gr^{th} group

$FF_{gr,ca}^{\square}$, $OF_{gr,ca}^{\square}$ The fitness and objective function values at the ca^{th} solution of the gr^{th} group

$FF_{gr,ca}^{New}$ The new fitness of the ca^{th} solution of the gr^{th} group

I_j, I_j^{Max} Current magnitude and maximum allowable current magnitude at the i^{th} branch

L_i^{Min}, L_i^{Max} The maximum and minimum limits of the location for DGUs

$N_{hr}^{\square}$, $N_{cv}^{\square}$ The number of considered hours and control variables, respectively

$N_{br}^{\square}$, $N_{bu}^{\square}$, $N_{ld}^{\square}$, $N_{DGU}^{\square}$ The number of branches, buses, loads and DGUs

$P_{DGU,i}^{Rated}$ The rated power of the i^{th} DGU

P_{DGU}^{Min}, P_{DGU}^{Max} The minimum and maximum rated power of the DGU

$PF_{Gen,i}$ The operating power factor of the i^{th} DGU

$PF_{Gen,i}^{h}$, $Q_{Gen,i}^{h}$ The actual active and reactive power of the i^{th} DGU at the h^{th} hour

$P_{Grid}^{\square}$, $Q_{Grid}^{\square}$ The active and reactive power supplied by the main grid through the substation

$P_{L,d,k}^{h}$, $Q_{L,d,k}^{h}$ The active and reactive power load of the k^{th} load at the h^{th} hour

$P_{Ls,j}^{h}$, $Q_{Ls,j}^{h}$ The active and reactive power loss of the j^{th} branch at the h^{th} hour

$P_{Ls}^{\square}$ The active power loss of the system

P_{Ls}^{h} The active power loss at the h^{th} hour

$Price_{Ls}^{\square}$ The electricity price ($/MW.h)

Si_i^{Max}, Si_i^{Min} The maximum and minimum limits of the capacity for DGUs

$So_{\square}^{Max}$, $So_{\square}^{Min}$ The upper and lower bounds of solutions

$So_{best,gr}^{\square}$, $So_{cent,gr}^{\square}$ The best solution and the central solution of the gr^{th} group

$So_{gr,ca}^{\square}$, $So_{gr,ca}^{New}$ The ca^{th} solution and the ca^{th} new solution of the gr^{th} group

So_{gr}^{New} The new solution is generated at the gr^{th} group

$So_{r1,gr}^{\square}$, $So_{r2,gr}^{\square}$ The randomly taken solutions of the gr^{th} group

$Va_{cv,gr,ca}^{New}$ The created new control variable at the ca^{th} solution of the gr^{th} group

$Va_{cv}^{Max}, Va_{cv}^{Min}$ The upper and lower bounds of the control variables

V_b, $V_{\square}^{Min}$, $V_{\square}^{Max}$ The voltage magnitude at the b^{th} bus, minimum and maximum allowable voltage magnitudes of the system, respectively

ρ_v, ρ_l The penalty factors of the bus voltage and branch current, respectively

α The penetration level of DGUs

APPENDIX

Tables 2 and 3 and Figures 8, 9, 10, 11 and 12

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Table 2: The data used for simulating the load and output power of the BM, PV and WT

Hour No.	Load (pu)	Output power of BM (pu)	Output power of PV (pu)	Output power of WT (pu)
1	0.64	1.0	0	0.220
2	0.60	1.0	0	0.215
3	0.58	1.0	0	0.215
4	0.56	1.0	0	0.213
5	0.56	1.0	0	0.210
6	0.58	1.0	0.050	0.210
7	0.64	1.0	0.100	0.204
8	0.76	1.0	0.250	0.180
9	0.87	1.0	0.500	0.220
10	0.95	1.0	0.670	0.390
11	0.99	1.0	0.880	0.480
12	1.00	1.0	0.950	0.620
13	0.99	1.0	1.000	0.730
14	1.00	1.0	0.960	0.810
15	1.00	1.0	0.820	0.950
16	0.97	1.0	0.700	1.000
17	0.96	1.0	0.520	0.900
18	0.96	1.0	0.300	0.810
19	0.93	1.0	0.150	0.730
20	0.92	1.0	0.100	0.600
21	0.92	1.0	0	0.420
22	0.93	1.0	0	0.350
23	0.87	1.0	0	0.300
24	0.72	1.0	0	0.220

Table 3: The optimal solutions from implemented methods for three cases

Applied method	Case 1		Case 2		Case 3	
	PV	WT	PV	BM	WT	BM
IPSO	Bus 18 – 10,092 modules	Bus 61 – 14 turbines	Bus 13 – 13,080 modules	Bus 61 – 1.6058 MW	Bus 15 – 05 turbines	Bus 61 – 1.5653 MW
SMA	Bus 22 – 8,418 modules	Bus 61 – 14 turbines	Bus 21 – 9,667 modules	Bus 61 – 1.6213 MW	Bus 17 – 04 turbines	Bus 61 – 1.5976 MW
COA	Bus 17 – 9,558 modules	Bus 61 – 14 turbines	Bus 17 – 10,160 modules	Bus 61 – 1.6161 MW	Bus 17 – 04 turbines	Bus 61 – 1.5562 MW

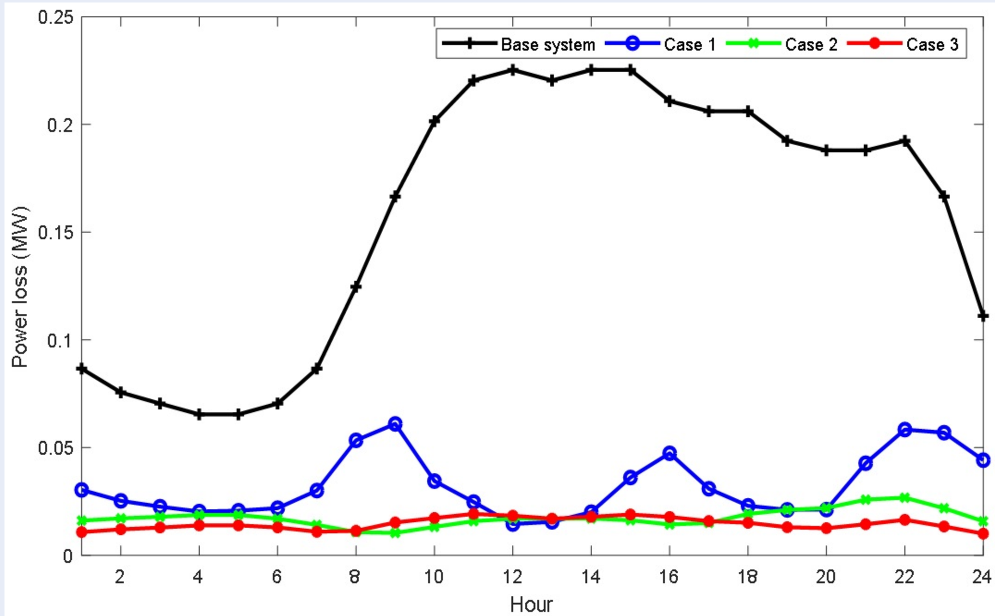

Figure 8: The power loss before and after connecting DGUs by using COA's solution at cases

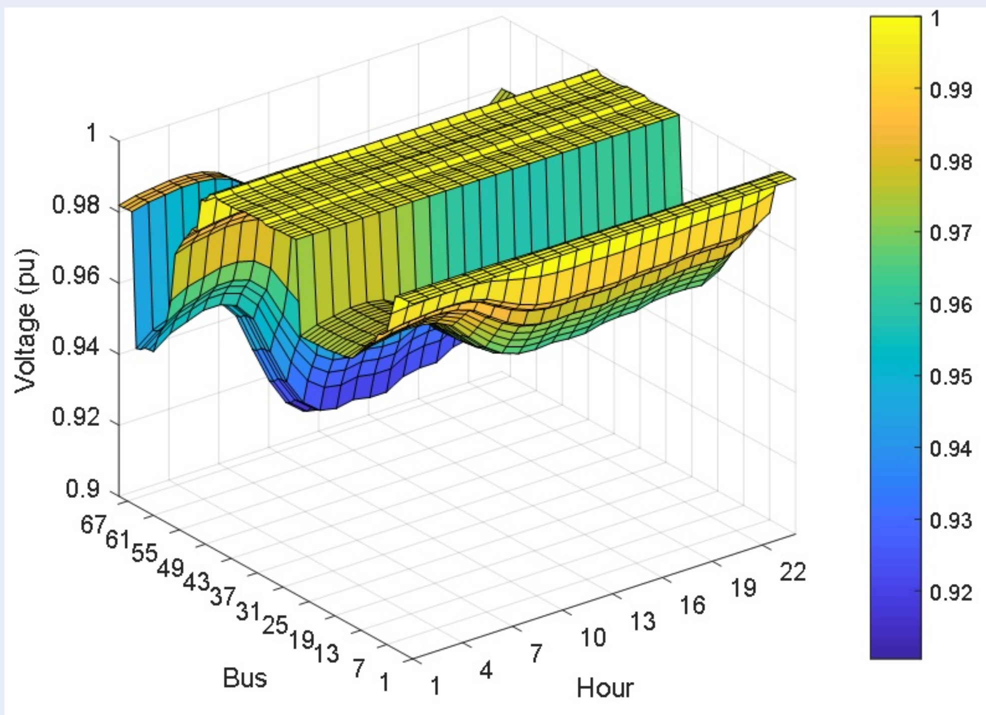

Figure 9: The voltage profile without DGUs

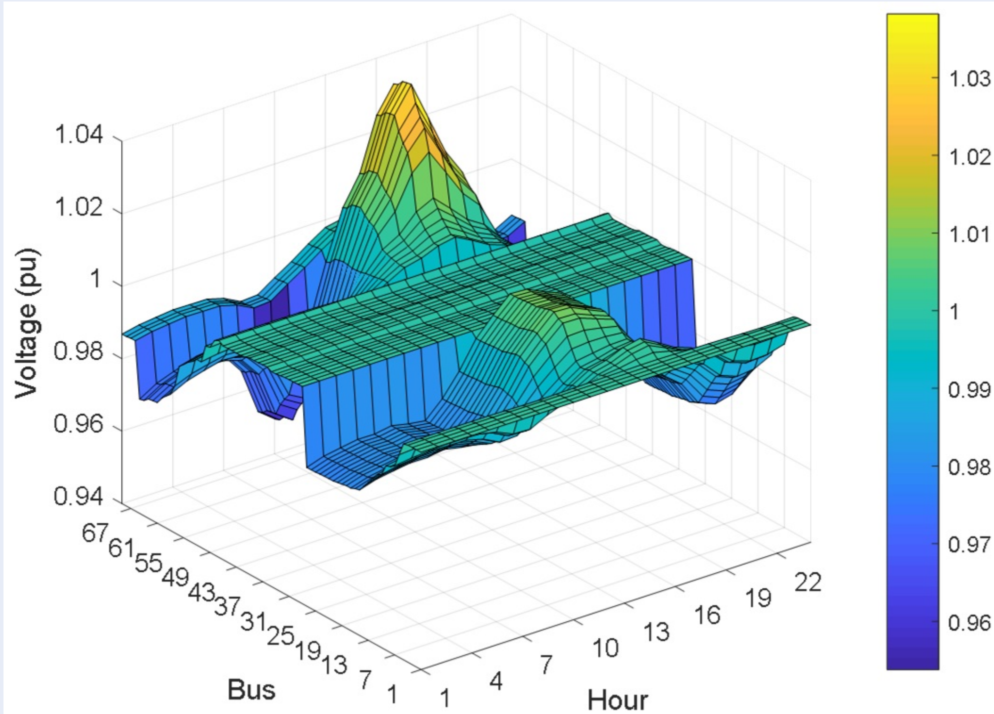

Figure 10: The voltage profile with DGUs from COA's solution at case 1

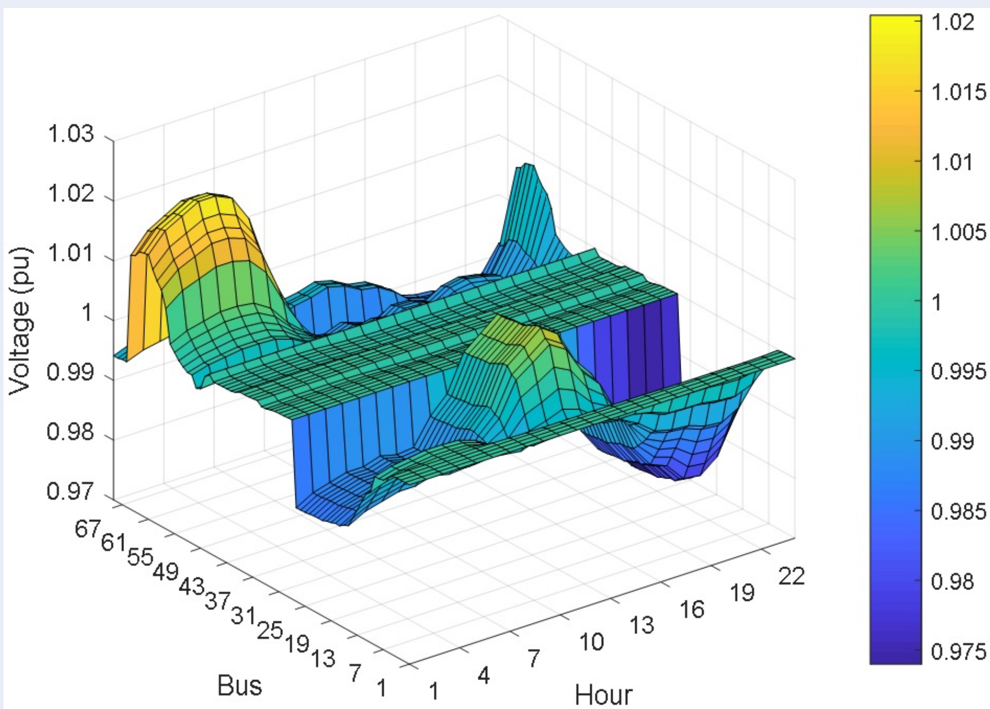

Figure 11: The voltage profile with DGUs from COA's solution at case 2

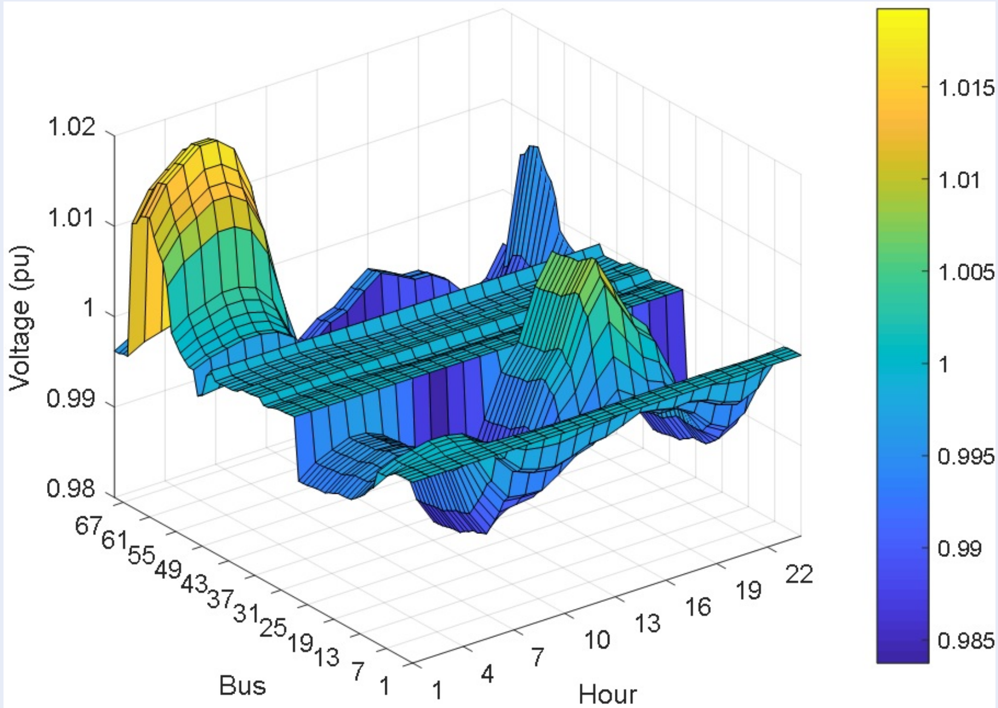

Figure 12: The voltage profile with DGUs from COA's solution at case 2

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