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Optimizing PV Integration Using COA: Power Loss Reduction and Voltage Stability Under Time-Varying Loads

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***Abstract*— The increasing use of renewable energy (RE) especially photovoltaic (PV) systems has made it essential to optimize their integration into power distribution networks, especially under time-varying load conditions. This study addresses the challenge of aligning PV generation with fluctuating load demands to reduce power losses and enhance voltage stability by analyzing the impact of multiple PV systems on industrial, residential and commercial loads within the IEEE 69-bus distribution network. The Coyote Optimization Algorithm (COA) is employed to determine the optimal location and size of PV systems. The results indicate a significant 45.9553% reduction in power loss for commercial loads with three PV systems, along with the most substantial improvement in voltage profiles compared to other load types. These findings highlight the importance of strategic PV placement and demonstrate the effectiveness of COA in enhancing network performance.**

***Index Terms*— Photovoltaic, Coyote Optimization Algorithm, Time-Varying Load, Power Losses, Voltage Profile.**

I. INTRODUCTION

The growing global demand for energy, driven by increasing population and the desire for a higher standard of living, has highlighted the urgent need to transition from finite fossil fuels to sustainable energy sources like wind, solar, and biomass [1]. Among these, photovoltaic (PV) systems have emerged as a leading solution due to their sustainability and decreasing costs, leading to widespread adoption in power networks, particularly in large-scale projects. By the end of 2019, PV installations had exceeded 600 GWp, contributing to 3% of global electricity production [2].

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PV systems can be categorized into off-grid and on-grid configurations. Off-grid systems are typically utilized in remote or isolated locations where extending the main grid is not feasible, thereby providing electricity to approximately 14% of the global population without access [3]. On-grid systems, which accounted for over 95% of PV capacity in 2018, are connected to the main grid and are further classified into residential, commercial/industrial, and utility-scale systems. Residential and commercial/industrial PV systems primarily meet local energy demands and are connected at the distribution level, while utility-scale systems, which made up about 66% of PV capacity by 2019, inject energy directly into the transmission grid [2].

While PV systems offer significant benefits, such as reducing greenhouse gas emissions and providing decentralized energy production, their effectiveness depends heavily on optimal placement and sizing within the electrical grid. Improper placement can lead to increased power losses, voltage instability and decreased operational efficiency highlighting the critical need for strategic planning. To address these challenges, various methods have been employed to determine the optimal placement and sizing of PV systems. For example, [4] assessed how Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) performed within an adaptive control method for grid-tied PV systems using active power filters. The study concluded that PSO provided the best solution, faster convergence and shorter running time indicating its potential for efficient optimization of PV systems in distribution networks. Similarly, [5] introduced a multi-objective algorithm designed to determine the optimal size and placement of PV systems in radial distribution networks, with a focus on improving voltage profiles and minimizing power losses. Additionally, [6] employed the PSO to find the ideal placement and sizing of PV systems in the IEEE 14-bus and 39-bus networks, which resulted in enhanced voltage stability and increased grid reliability.

Further research in [7] utilized the Marine Predators Algorithm (MPA) to design a mathematical model aimed at reducing active power losses. The study ensured that voltages and line currents stayed below permissible limits, resulting in the ideal location and sizing of several PV systems in a distribution network. Moreover, [8] focused on optimizing the placement and sizing of Hybrid Renewable Energy Systems (HRES) in Electrical Distribution Systems (EDS) using the Ant Lion Optimizer (ALO) algorithm on the IEEE 33-bus. The goal was to minimize power losses, voltage deviations and costs while improving system reliability. As PV penetration in power networks continues to grow, challenges such as steady-state overvoltage, voltage fluctuations and increasing system losses have become more prevalent, largely due to the inherent variability of solar power generation influenced by environmental factors [9] [10]. Traditionally, most studies have focused on constant load models, often neglecting the variable nature of PV generation and load demand. This oversight has limited the applicability of these findings to real-world scenarios where demand naturally fluctuates. Recognizing the importance of accounting for load variations and the dynamic nature of PV output, recent research has increasingly shifted towards optimizing PV integration to maximize system benefits.

In response to these challenges, metaheuristic methods have emerged as powerful optimization techniques excelling at solving complex problems despite requiring longer computation times than traditional methods. Continuous improvements have enhanced their ability to address both single and multi-objective models by leveraging their strengths and minimizing their weaknesses [11], [12]. As a result, several techniques have been developed in recent years to determine the optimal location and sizing of PV systems taking into account different load models and their variability. For example, [13] optimized the allocation of microgrid components for different type of loads (constant, residential, industrial, commercial and mixed) by employing PSO and a fuzzy max–min approach to evaluate cost, emissions, power loss and voltage deviation. The result finds that constant power loads lead to higher costs and losses, while constant impedance loads offer better loading capability.

Moreover, taking into account the uncertainties in load demand and solar irradiation, [14] enhanced the integration of Photovoltaic Distributed Generation (PV-DG) and Distributed Static Compensator (DSTATCOM) in distribution systems. The author employed a Modified Ant Lion Optimizer (MALO) to achieve cost reduction and improve voltage profiles, demonstrating significant advantages over other optimization methods in the IEEE 69-bus and 118-bus systems. In another study, [15] proposed a Teaching-Learning hybrid with Artificial Bee Colony (TLABC) technique to optimize the PV location and Battery Energy Storage (BES) to reduce 24-hour power losses. The study takes into consideration uncertainties in both energy generation and demand. TLABC outperforms the genetic and differential evolution algorithms in most scenarios. On the other hand, [16] introduced the RLEO algorithm, an improved equilibrium optimizer using reinforced learning to determine the placement and sizing of PV and BES units in distribution networks. Applied to commercial, industrial and residential loads, RLEO significantly reduces power losses and improves voltage profiles compared to existing methods.

While there has been growing interest in studying PV integration under time-varying load conditions, there is still a notable lack of research focused on optimizing PV placement and sizing specifically for different load types in these scenarios. This research aims to fill this gap by employing the Coyote Optimization Algorithm (COA) to determine the optimal placement and sizing of PV systems within the IEEE 69-bus distribution network. By focusing on industrial, residential and commercial load profiles, this study seeks to reduce power losses and improve voltage stability through strategic PV integration. By achieving these objectives, the research contributes to the more efficient integration of renewable energy sources into distribution networks, promoting a sustainable and effective energy system.

II. METHODOLOGY

This study concentrates on optimizing the integration of PV systems within the IEEE 69-bus network, utilizing various load models that simulate industrial, residential, and commercial demands. The COA is applied to identify the optimal PV locations and sizes, aiming to reduce power losses and enhance voltage stability. Simulations are performed under defined constraints to validate the approach.

A. Test System

1) IEEE 69-Bus System

The IEEE 69-bus system comprises 69 buses interconnected by 68 branches, with a total real power load of 3802.19 kW and a total reactive power load of 2694.60 kVAR. The system is designed for a base power of 12.66 kV, 100 MVA. Fig. 1 displays the IEEE-69 bus's single line diagram [17], [11], [18].

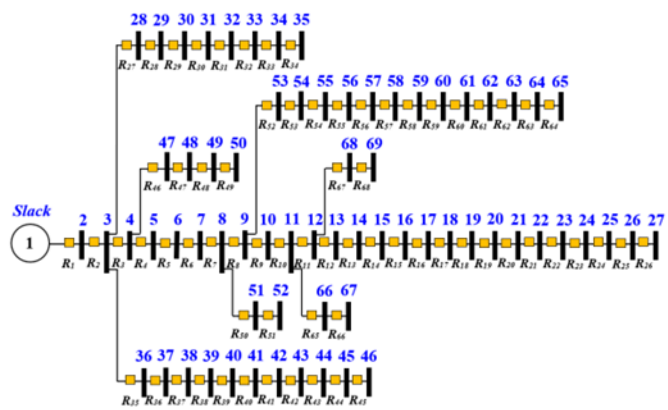

Fig 1: IEEE 69-bus system

B. Load Demand Modelling

Traditional load flow analysis assumes constant power demands, independent of voltage levels at corresponding buses. However, in this study, voltage-dependent load models are employed, reflecting the influence of voltage levels on power demands for industrial, residential, and commercial loads. These voltage-dependent load models are static and represent the power-voltage relationship through an exponential formula which integrates time-varying loads at period *(t)* as detailed below [19]:

$$P_{Dnew,i}(t) = \gamma P_{Di}(t) * V_i^{\sigma}(t) \tag{1}$$

$$Q_{Dnew,i}(t) = \gamma Q_{Di}(t) * V_i^{\rho}(t) \tag{2}$$

$P_{Dnew,i}$ and $Q_{Dnew,i}$ represent the reactive and active loads under normal operating conditions, respectively. The coefficients σ and ρ correspond to the load models, with their specific values provided in Table 1 [20].

TABLE I. LOAD TYPES WITH THE EXPONENT VALUES

No	Load Type	σ	ρ	γ
1	Constant	0	0	1
2	Industrial	0.18	6.00	1
3	Residential	0.92	4.06	1

The load factor γ serves as a multiplier to either increase or decrease the power demand across all nodes in the network, while V_i denotes the voltage at the i-th load bus. Fig. 2 presents the load demand patterns in per unit (p.u.) for three types of loads: industrial, residential and commercial over a 24-hour period as considered in this study.

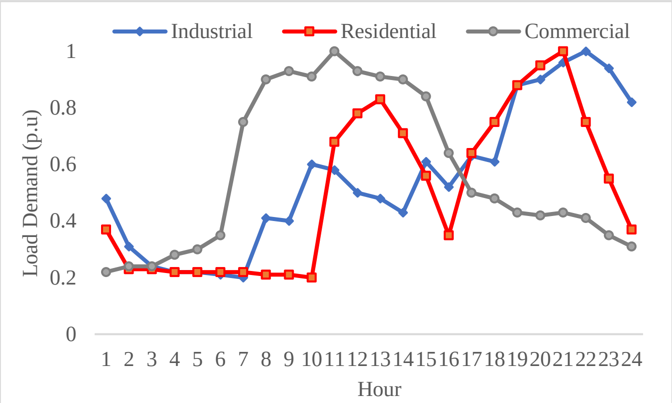

Fig. 2 Hourly load demand profiles for industrial, residential, and commercial load

C. Hourly PV Output Data

The PV output generation data was gathered using a data logger that recorded readings every half hour over an eight-month period in Penang. Fig. 3 presents the average PV generation pattern across a 24-hour span, showing an increase in power output starting at 8:00 AM, peaking between 12:00 PM and 3:00 PM and then gradually decreasing after 6:00 PM with minimal output by 8:00 PM.

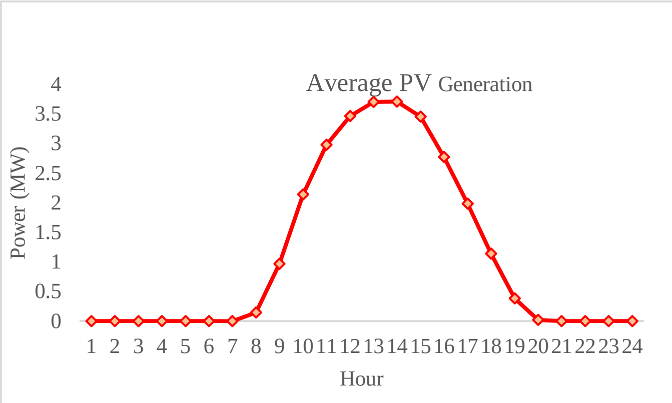

Fig.3 Average eight-month PV output

This trend reflects the typical daily cycle of solar power generation with the highest output occurring around midday when solar irradiance is strongest.

D. Objective Function

The objective function aims to minimize the system's power losses after the PV integration. Therefore, the total power loss P_{loss}^{PV} is expressed as follows [19]:

$$P_{loss(i,j)}^{PV} = R_{ij}\left[\frac{(P_{Di}-P_{PVi})^2+(Q_{Di}-Q_{PVi})^2}{|V_i|^2}\right] \tag{3}$$

$$Q_{loss(i,j)}^{PV} = X_{ij}\left[\frac{(P_{Di}-P_{PVi})^2+(Q_{Di}-Q_{PVi})^2}{|V_i|^2}\right] \tag{4}$$

$$P_{loss}^{PV} = \sum_{i=1}^{N_{bus}}\left(P_{loss(i,j)}^{PV} + Q_{loss(i,j)}^{PV}\right) \tag{5}$$

$P_{loss(i,j)}^{PV}$ denotes the active power loss, and $Q_{loss(i,j)}^{PV}$ represents the reactive power loss between buses i and j after PV integration. The term R_{ij} and X_{ij} represent the resistance and reactance of the branch connecting these buses respectively, while N_{bus} represents the total number of buses in the system.

E. Simulation Constraints

1) PV Location

Bus 1 is designated as the slack bus in distribution networks. As a result, PV systems can be integrated at any bus within the distribution network, up to the highest bus number in the system, N_{bus}.

$$2 \leq PV_{location} \leq N_{bus} \tag{6}$$

2) Voltage magnitude limit

The voltage magnitude limit is 1.0 p.u.

$$V_{min} \leq V \leq 1.0 \tag{7}$$

3) PV Size

The PV size must be within the range of zero to the maximum load demand P_{Di}.

$$0 \leq PV_{size} \leq \sum_{i=1}^{N_{bus}} P_{Di} \tag{8}$$

F. Coyote Optimization Algorithm (COA)

The COA is a metaheuristic technique that mimics the social and evolutionary behaviors of coyotes, a species native to North America. Introduced by Pierezan and Coelho in 2018, COA leverages swarm intelligence, where coyotes adjust their social dynamics and share knowledge within their packs to achieve optimal solutions [21]. This algorithm has been widely researched and effectively applied to numerous challenges in the electrical field, demonstrating strong performance and positive outcomes. In COA, the population is separated into multiple packs, N_p with each pack consisting of a fixed number of coyotes, N_c. The total population size is the product of these two values. COA focuses on the social conditions of coyotes within the packs, with each coyote representing a potential solution and its social condition reflecting the objective function value.

The algorithm starts by randomly initializing the social conditions of the coyotes within the search space. As the algorithm progresses, coyotes in each pack interact, share information, and adapt their social conditions. The alpha coyote or the best solution in each pack leads the group's evolution. COA also incorporates natural processes like birth and death replacing less adapted coyotes with new ones to maintain diversity. This iterative process of updating social conditions based on the alpha coyote and pack dynamics continues until the algorithm finds the optimal solution making COA effective for solving complex optimization problems. Fig. 4 illustrates the process of optimizing PV location using COA.

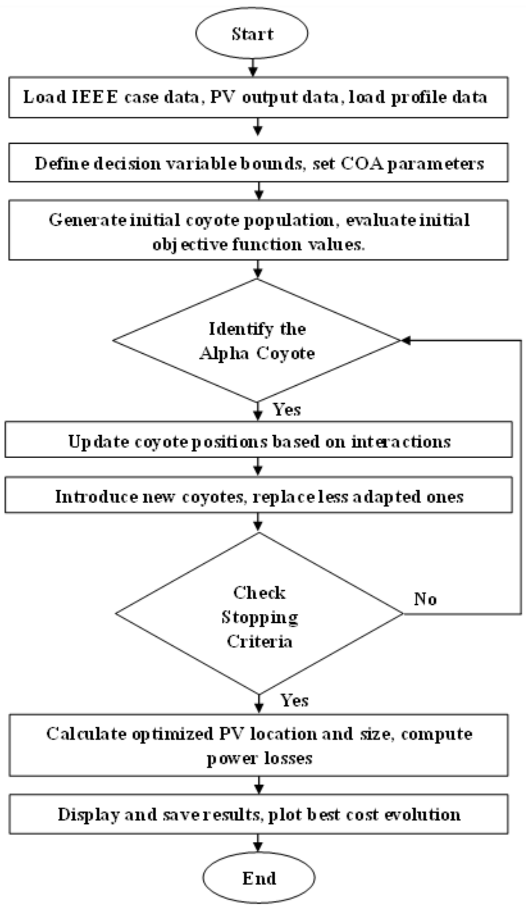

Fig. 4 Flowchart of the optimization process using COA

III. Results And Discussion

This section presents the simulation results and a detailed analysis of the impact of integrating multiple PV systems into the IEEE 69-bus distribution network focusing on industrial, residential and commercial load types. The analysis covers the effects of different numbers of PV installations on power loss reduction, load demand alignment with PV generation and voltage profile improvements across the network. The results provide insights into the effectiveness of strategic PV placement in optimizing network performance, highlighting the significant benefits of PV integration and the diminishing returns observed when adding more than two PV systems. These findings underscore the importance of understanding the load-specific impacts of PV integration to maximize efficiency and stability in power distribution networks.

A. Simulation Results

Table II summarizes the performance metrics for the IEEE 69-bus network with a single PV location. The PV systems are all placed at Bus 61, with sizes ranging from 1.2565 MW to 1.9427 MW depending on the load type. The commercial load shows the greatest reduction in power loss (41.8444%) with smaller reductions for residential (26.8433%) and industrial loads (17.9955%). Reductions in reactive power loss also follow this trend, with commercial loads seeing the most benefit (40.0023%). This data highlights the effectiveness of strategically sized and located PV systems especially for commercial loads.

Table III shows the impact of using two PV locations on power loss and reactive power loss in the IEEE 69-bus network for industrial, residential and commercial loads. For industrial loads, PV systems at Buses 17 and 61 (0.3474 MW and 1.1918 MW) reduce power loss by 19.54%, while residential loads with PVs at the same buses (0.4014 MW and 1.3657 MW) achieve a 29.11% reduction. Commercial loads benefit the most, with PVs at Buses 17 and 61 (0.5410 MW and 1.8598 MW) cutting power loss by 45.29%. Reactive power loss reductions follow a similar trend, highlighting the effectiveness of distributed PV placement.

TABLE II. System Performance Metrics for IEEE 69-Bus Network with Single PV Location Across Different Load Types

Parameters	Industrial	Residential	Commercial
PV location @ Size (MW)	1.2565 @ 61	1.4460 @ 61	1.9427 @ 61
Ploss with PV (kW)	1543.4220	1247.8079	1206.3314
Ploss base case (kW)	1882.1189	1705.6637	2074.3183
Ploss reduction (%)	17.9955	26.8433	41.8444
Qloss with PV (kVAR)	709.1633	577.0489	566.2497
Qloss base case (kVAR)	856.693	776.4073	943.7858
Qloss reduction (%)	17.2208	25.6770	40.0023

TABLE III. SYSTEM PERFORMANCE METRICS FOR IEEE 69-BUS NETWORK WITH TWO LOCATIONS ACROSS DIFFERENT LOAD TYPES

Parameters	Industrial	Residential	Commercial
PV location @ Size (MW)	0.3474 @ 17 1.1918 @ 61	0.4014 @ 17 1.3657 @ 61	0.5410 @ 17 1.8598 @ 61
Ploss with PV (kW)	1514.3680	1209.2257	1134.7576
Ploss base case (kW)	1882.1189	1705.6637	2074.3183
Ploss reduction (%)	19.5392	29.1053	45.2949
Qloss with PV (kVAR)	697.6884	561.8263	537.8127
Qloss base case (kVAR)	856.6930	776.4073	943.7858
Qloss reduction (%)	18.5603	27.6377	43.0154

TABLE IV. SYSTEM PERFORMANCE METRICS FOR IEEE 69-BUS NETWORK WITH THREE LOCATIONS ACROSS DIFFERENT LOAD TYPES

Parameters	Industrial	Residential	Commercial
PV location @ Size (MW)	0.3454 @ 11 0.2559 @ 18 1.1350 @ 61	0.3859 @ 11 0.2979 @ 18 1.3245 @ 61	0.55336 @ 11 0.39509 @ 18 1.7860 @ 61
Ploss with PV (kW)	1509.0105	1201.9619	1121.0583
Ploss base case (kW)	1882.1189	1705.6637	2074.3183
Ploss reduction (%)	19.8239	29.5311	45.9553
Qloss with PV (kVAR)	695.3511	558.6556	531.8368
Qloss base case (kVAR)	856.693	776.4073	943.7858
Qloss reduction (%)	18.8331	28.0461	43.6486

Table IV highlights the effectiveness of distributing PV systems across Buses 11, 18, and 61 in reducing power loss (Ploss) and reactive power loss (Qloss) in the IEEE 69-bus network. For industrial loads, this configuration achieves a 19.8239% reduction in Ploss and an 18.8331% reduction in Qloss. Residential loads see a 29.5311% decrease in Ploss and a 28.0461% reduction in Qloss. Commercial loads benefit the most, with a 45.9553% Ploss reduction and a 43.6486% Qloss reduction. This distribution strategy significantly enhances network performance, especially for commercial loads.

Overall, the analysis demonstrates that integrating multiple PV systems into the IEEE 69-bus network significantly reduces power losses across industrial, residential, and commercial loads. Among these, commercial loads consistently achieve the highest percentage reductions in both active and reactive power losses, benefiting the most from PV integration. The results suggest that while adding additional PV systems typically increases efficiency, the most significant improvements happen when expanding from one to two PV locations, with smaller benefits observed when a third PV system is introduced. This highlights the crucial importance of strategic PV placement in optimizing network performance and efficiency.

B. PV Generation vs. Load Demand Across Different Load Types

In Fig. 5, the industrial load demand shows multiple peaks particularly in the late afternoon and evening hours. However, the PV generation represented by the curves for 1 PV, 2 PVs, and 3 PVs peaks around midday. This misalignment between peak load demand and peak PV generation suggests that while PV systems provide significant power during daylight hours, they do not adequately meet the industrial demand during the late-day peak periods. This indicates a potential need for additional energy sources or storage solutions to support the industrial load during these critical hours. While. Fig. 6 illustrates the residential load demand which remains low during the early morning and gradually increases reaching its peak in the evening. The PV generation profiles corresponding to 1 PV, 2 PVs and 3 PVs, peak around midday providing substantial power during the day but not aligning with the residential peak demand that occurs after sunset. This mismatch highlights the limitations of PV systems in addressing residential energy needs during evening peak hours suggesting the possible necessity of energy storage or supplementary solutions.

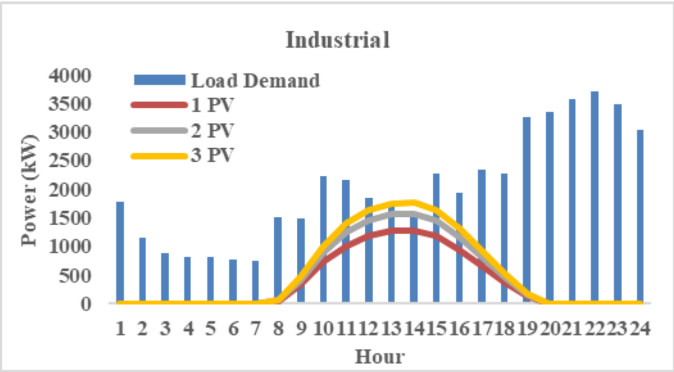

Fig. 5 Industrial Load Demand vs. Multiple PV Generations

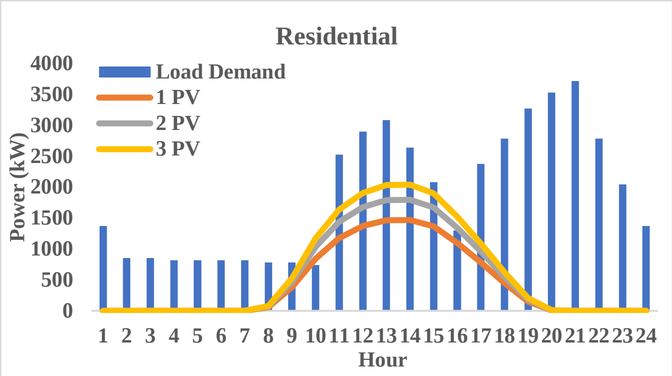

Fig. 6 Residential Load Demand vs. Multiple PV Generations

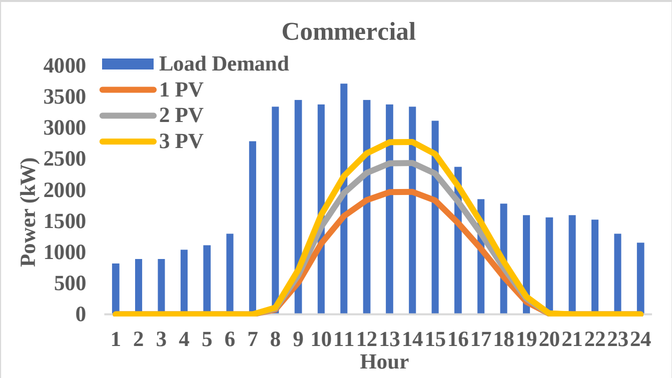

Fig. 7 Commercial Load Demand vs. Multiple PV Generations

In Fig. 7, the commercial load demand is depicted rising steadily in the morning and peaking around midday. This pattern closely aligns with peak PV generation times. The curves for 1 PV, 2 PVs and 3 PVs in Fig. 7 show that the PV systems are particularly effective in matching the commercial load during its highest demand periods. This alignment underscores the suitability of PV systems for commercial operations, where they can significantly reduce energy costs and reliance on other power sources during peak hours.

C. Power Losses

In Fig. 8, the power loss profile for the industrial load is displayed over a 24-hour period. The base case denoted by the blue line shows higher power losses throughout the day, especially peaking during the evening hours. However, with the integration of 1 PV, 2 PVs, and 3 PVs (represented by the orange, gray, and yellow lines respectively), the power losses are significantly reduced during daylight hours. Notably, the differences between the power loss curves for 1 PV, 2 PVs and 3 PVs are minimal, suggesting that additional PV systems beyond the first provide only marginal further reductions in power losses for the industrial load.

Fig. 9 presents the power loss profile for the residential load. The base case shows a substantial peak in power losses during the midday to early afternoon period which aligns with peak solar generation times. The introduction of 1 PV dramatically reduces these losses, as seen by the orange line. Further reductions are observed with the addition of 2 PVs and 3 PVs (gray and yellow lines), especially in the early afternoon and late evening. The power loss is nearly eliminated during midday when three PV systems are in place, indicating a significant impact of PV generation on reducing losses for residential loads during periods of high solar irradiance.

In Fig. 10, the power loss profile for the commercial load is depicted. The base case (blue line) shows the highest power losses during the morning and midday peaking around 9:00 AM. However, with the integration of 1 PV, 2 PVs and 3 PVs (orange, gray, and yellow lines respectively), the power losses are notably reduced during the morning and midday hours. The reduction in power losses becomes more pronounced with each additional PV system particularly during the hours of peak solar generation. This indicates that the commercial load benefits significantly from multiple PV systems, with each additional PV installation further reducing the overall power losses especially during periods of high demand.

Across all three figures, the integration of PV systems results in a noticeable reduction in power losses for industrial, residential and commercial loads. While the industrial load shows only marginal improvements with additional PV systems beyond the first, the residential and commercial loads benefit more significantly from multiple PV installations, especially during peak generation hours. This trend highlights the importance of strategically placing and sizing PV systems to optimize power loss reduction based on the specific load characteristics.

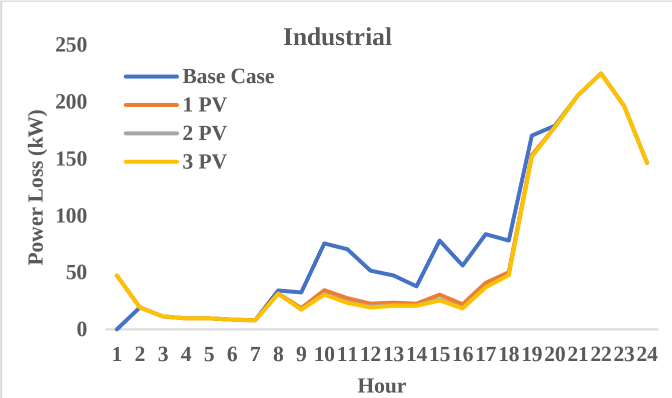

Fig. 8 Power Loss Profile for Industrial Load with Multiple PVs

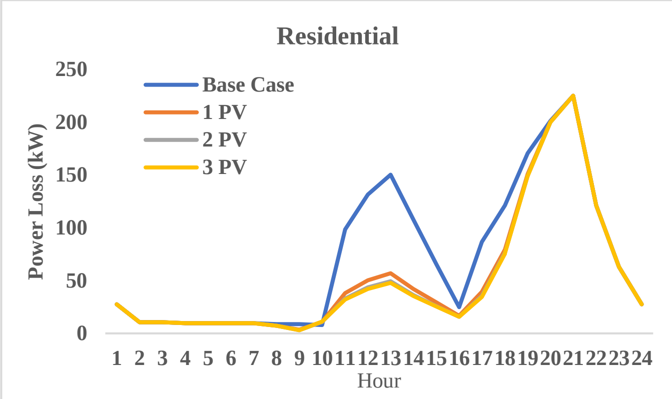

Fig. 9 Power Loss Profile for Residential Load with Multiple PVs

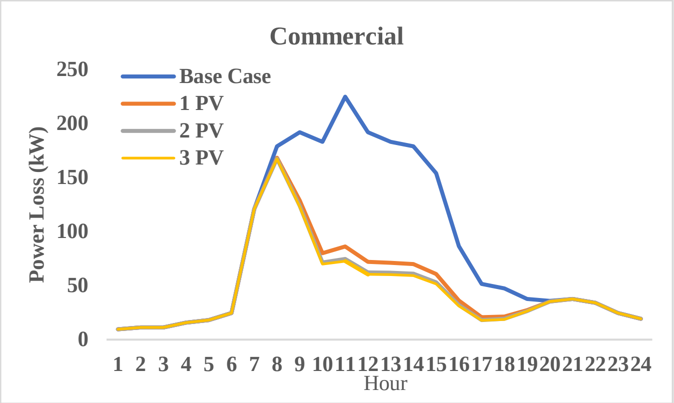

Fig. 10 Power Loss Profile for Residential Load with Multiple PVs

D. Voltage Profile

In Fig. 11, the voltage profile for the industrial load is displayed across the bus numbers from 1 to 69. The base case represented by the blue line shows a decline in voltage as the bus number increases, reaching its lowest point around bus 60 before recovering slightly. The integration of 1 PV (orange line), 2 PVs (gray line) and 3 PVs (yellow line) results in noticeable voltage improvements, particularly after bus 25. The curves for 2 PVs and 3 PVs are almost identical, indicating that adding a third PV provides minimal additional benefit for the industrial load's voltage stability.

Fig. 12 illustrates the voltage profile for the residential load across the same bus numbers. The base case (blue line) experiences a significant voltage drop, especially between buses 25 and 50. The introduction of 1 PV (orange line) slightly mitigates this drop, while the addition of 2 PVs (gray line) and 3 PVs (yellow line) provides further voltage stabilization. Notably, the voltage profile for 2 PVs and 3 PVs are quite similar, suggesting that for residential loads, two PV systems may be sufficient to achieve an optimal voltage profile.

In Fig. 13, the voltage profile for the commercial load is depicted. The base case (blue line) shows a steep decline in voltage, particularly around buses 50 to 60. The integration of 1 PV (orange line), 2 PVs (gray line) and 3 PVs (yellow line) results in significant voltage improvements across the network. Unlike the industrial and residential loads, the commercial load continues to benefit from each additional PV system, as seen by the increasing voltage stability with 2 PVs and 3 PVs, although the difference between 2 and 3 PVs is less pronounced.

Across all three figures, the integration of PV systems leads to improved voltage profiles for industrial, residential and commercial loads. The industrial load shows significant improvements after the first PV, with diminishing returns for additional PVs. The residential load also benefits from PV integration, particularly with two systems, while the commercial load consistently improves with each additional PV system, indicating that commercial loads may require more extensive PV integration to fully stabilize voltage across the network.

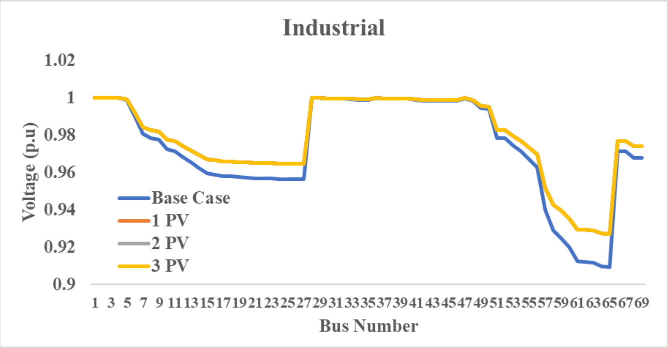

Fig. 11 Voltage Profile for Industrial Load with Multiple PVs

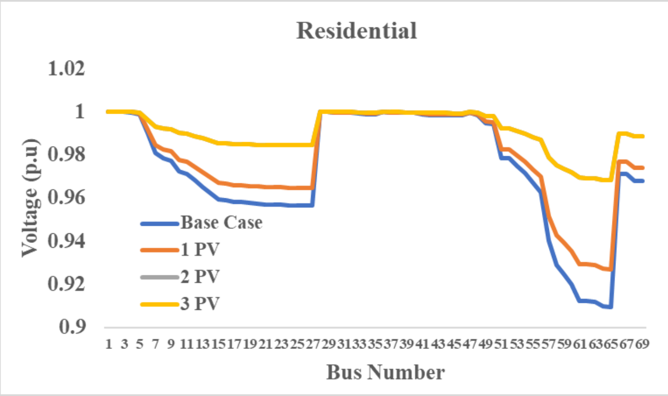

Fig. 12 Voltage Profile for Residential Load with Multiple PVs

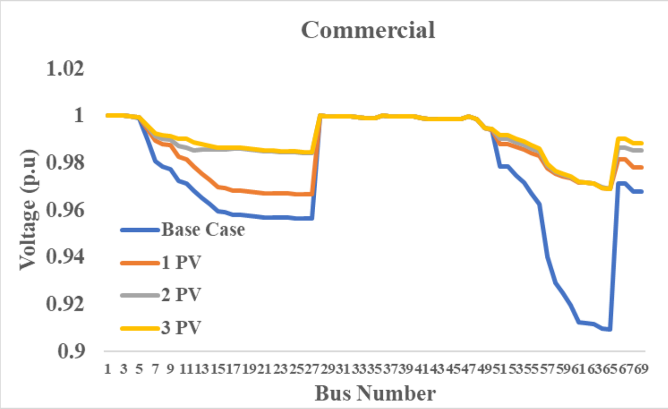

Fig. 13 Voltage Profile for Commercial Load with Multiple PVs

IV. CONCLUSION

The integration of multiple photovoltaic (PV) systems into the IEEE 69-bus distribution network has demonstrated significant improvements in reducing power losses and stabilizing voltage profiles across industrial, residential and commercial loads. The Coyote Optimization Algorithm (COA) proved to be an effective tool in determining the optimal placement and sizing of PV systems, leading to enhanced network performance. The study highlights that the most substantial efficiency gains are achieved when transitioning from one to two PV systems, with diminishing returns observed upon the addition of a third PV system. Significantly, commercial loads benefited the most from PV integration, achieving the highest percentage reductions in both active and reactive power losses. These results emphasize the critical role of strategic PV placement and the efficacy of COA in optimizing renewable energy integration within power distribution networks, thereby contributing to a more efficient and stable electrical grid.

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