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Firefly Algorithm for Optimal Allocation of Photovoltaic Systems to Enhance the Resiliency of Radial Distribution Networks: An Iraqi Case Study

***Abstract:* -**This paper presents an intelligent optimization approach to enhance voltage stability and resilience in radial distribution systems in Iraq through the strategic integration of photovoltaic (PV) units. A modified IEEE 35-bus radial feeder, reflecting the actual characteristics of Iraqi power grids, was used to simulate various operational scenarios, including base load, single and multiple PV placements, varying load levels, and fault conditions. To determine the optimal placement and sizing of PV units, a nature-inspired metaheuristic — the Firefly Algorithm (FA) — was employed. The FA effectively addresses nonlinear, multi-objective optimization challenges in practical power distribution planning, especially under fault-prone conditions. System performance was assessed using voltage deviation, total power loss, and energy not supplied (ENS) as evaluation metrics. The results demonstrate that improper PV placement can worsen voltage instability; however, this issue is effectively mitigated through FA-based optimization. The FA achieved a minimum bus voltage of 0.9508 p.u., outperforming the Genetic Algorithm and conventional methods. Multi-run simulations further validated the robustness and consistency of the FA under varying load and fault scenarios. The proposed intelligent PV planning framework offers a scalable, adaptable solution for enhancing resilience and enabling renewable energy integration in Iraq and other developing nations with radial distribution networks and high solar potential .

Keywords: **:** Photovoltaic Systems, Radial Distribution Networks, Voltage Profile Enhancement, Power System Resilience, Firefly Algorithm, Metaheuristic Optimization Techniques .

I. INTRODUCTION *(HEADING 1)*

Persistent challenges in Iraq's distribution networks — including voltage instability, high technical and non-technical losses, and frequent outages — hinder reliable power delivery. The country's abundant solar irradiance, averaging 5.5–6.5 kWh/m²/day across major cities, offers a significant opportunity for photovoltaic (PV) integration. However, uncoordinated PV installations may exacerbate grid weaknesses, particularly in radial feeders. This study proposes an intelligent approach to optimize PV allocation, considering the unique characteristics and operational limitations of Iraq's distribution networks. The Firefly Algorithm (FA), a nature-inspired metaheuristic known for its strong global search capability in nonlinear, multi-objective domains, is applied to optimize PV siting and sizing. The study evaluates resilience parameters, including voltage deviation and energy not supplied (ENS), using a modified IEEE 35-bus radial feeder adapted to Iraqi grid conditions [1], [2].

This does not take away from the fact that the Iraqi grid has to operate with such persistent challenges, including high technical and non-technical losses, voltage instability, chronic load shedding, and low infrastructure investment [3]–[5]. Problems are aggravated by the nature of centrally generated power and very long radial distribution feeders in rural and semi-urban areas [6]. Incorporating photovoltaic (PV) systems at the distribution grid is, therefore, strategically positive in mitigating these challenges. The former reduces power demand on transmission infrastructure. The latter also reduces losses apart from decentralized resilience. However, in the case of Iraq, with most of the power distribution systems being less complicated and not featuring smart grids, unanticipated or unwise deployment can result in power flowing back to the system, an increase in voltage, and low power quality. This is a risk that such extreme environmental conditions, for example, high temperatures, and normal operations (for example, line faults, transformer outages) bring into operation in Iraq [10], [11].

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Resilience according to power systems is the ability to anticipate absorb adapt and recover rapidly from any disruption that is caused by an event. The priority that has been set in recent energy research is the enhancement of the resilience of the distribution network via the integration of optimal PV. Simply, it has not been a common routine that traditional grid planning methods take into consideration such dynamic behaviour multi-objective optimization and uncertain photovoltaic (PV) generation. Thus, metaheuristic algorithms particularly personalized for the optimal sizing and siting of PV are becoming popular. Of these, the Firefly Algorithm (FA) is simple and strong and does not fall to local best solutions in multi-peak problem domains. Power flow optimization, planning for the management of dispersed generation, and study into microgrid stability have used the algorithm, motivated by the luminous mode of communication of fireflies [15]–[17]. Very few studies within the Iraqi context have applied either the FA or any similar algorithm to improve the resilience or the reliability of the whole system [18], [19].

Though several studies have been carried out in Iraq on PV integration, most of them emphasize economic dispatch or loss reduction, without explicitly looking at resilience factors like energy not supplied or voltage performance during and post fault, recovery time, or the strength of the system in extreme events. Furthermore, little consideration has been given to the dynamic and fault-prone nature of the distribution infrastructure in Iraq when integrating PV into the radial systems. This study presents a novel approach utilizing the Firefly Algorithm to determine the optimal location and capacity of PV units in a representative Iraqi radial distribution network. The objective is to enhance grid resilience, minimize power losses, and improve voltage profiles under both normal and contingency conditions. The test system is based on a modified IEEE 35-bus feeder tailored to reflect the voltage levels, load behaviour, and solar characteristics typical of Iraqi distribution systems. The model integrates solar irradiance data from Baghdad, synthetic load profiles derived from local usage patterns, and fault-simulation scenarios. The outcome of this work is expected to provide a scalable and adaptable planning framework that supports Iraq's transition toward a more robust and renewable-based power distribution system. The main innovations of the paper can be summarized as follows:

1) A method for hybrid scheduling of solar allocation is given, using the Firefly Algorithm and adapted to the topology of the Iraqi radial grid environment.
2) Uses multi-objective optimization including voltage stability, power loss, and energy not supplied (ENS) under fault conditions.
3) Modify the IEEE 35-bus system to exactly mimic the Iraqi grid, integrating the limitations and load profiles of real-world conditions.
4) This document introduces the maiden resilient-based ENS-oriented numerical analysis custom-made for photovoltaic integration in Iraqi feeders.
5) The Firefly Algorithm shows better stability and performance as compared to the existing methods via a multirun comparative study.
6) Shows that the suggested design might help decentralized PV integration in developing nations and is scalable.
7) Fault simulation scenarios are used to assess grid performance under contingency, which has been overlooked by previous Iraqi studies.
8) Real irradiance data is integrated with load patterns simulated to make the site-specific realistic.

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II. LITERATURE REVIEW

A. *PV Integration in Distribution Networks*

The upsurge in global need for clean energy has prompted the incorporation of photovoltaic (PV) systems within distribution networks. The PV systems come with a package of benefits which include better voltage profiles, reduced line losses, and less dependency on centralized generation. However, if not well coordinated, the integration of PV may result in operational challenges including but not limited to voltage rise, reverse power flow, harmonic distortion as well as protection malfunctions. Iraq has studies that prove there is a high potential for the installation of photovoltaic systems due to the presence of consistent solar irradiance throughout the year. However, the technical challenges and inefficiencies in the planning process have resulted in a low penetration of renewable energy within the distribution sector. There have been several works that have highlighted the need for intelligent planning of photovoltaic systems to ensure system stability under varying conditions of solar input. The modified IEEE 35-bus system serves as a practical model for evaluating such integration scenarios in a typical Iraqi feeder.

B. Grid Resilience and Optimization Needs

Recent studies, such as Zhou et al. 2024, have explored resilience-oriented PV integration under fault scenarios in radial networks, highlighting the growing importance of such optimization frameworks in developing power systems. Power system resilience is defined as the ability of a system to withstand and recover from unexpected disruptions such as faults, extreme weather, or equipment failures [28]. In radial networks like the IEEE 35-bus test system—representative of Iraqi topologies—faults can result in large-scale outages due to the absence of alternative power paths [29]. The integration of distributed PV sources can enhance resilience when optimally placed and managed [30]. Conventional optimization methods—such as exhaustive search or linear programming—fail to handle the nonlinear and multi-objective nature of PV placement problems effectively [31]. As a result, metaheuristic algorithms have become preferred tools in modern planning frameworks [32].

C. Firefly Algorithm in Power System Applications

The Firefly Algorithm (FA), introduced by Yang in 2008 [33], is a nature-inspired metaheuristic based on the bioluminescent behavior of fireflies. It has gained attention for its simplicity, strong global search capability, and robust convergence. FA has been widely applied in power systems to solve problems such as optimal power flow [34], optimal capacitor placement [35], and distributed generation (DG) allocation [36]. FA is particularly advantageous in handling nonlinear constraints and complex objective functions, making it suitable for large-scale distribution systems like the 35-bus network [38]. Comparative studies have found that FA often outperforms traditional algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) in solution accuracy, speed, and robustness [37-42].

Recent studies have extended FA's application to improve resilience in power systems, especially in scenarios involving fault tolerance, renewable energy variability, and cyber-physical disruptions. For example, Ali and Ghasemi (2024) [40] applied FA for the resilient dispatch of battery energy storage systems under fault scenarios, demonstrating its superiority in minimizing recovery time and maintaining voltage stability. To provide a broader perspective, several other recent studies have explored different optimization approaches to enhance resilience:

- Gao & Liu (2023) [45] used Genetic Algorithms to model and evaluate grid resilience under space weather events, focusing on adaptive recovery mechanisms.
- Mquqwana & Krishnamurthy (2024) [46] applied PSO in hybrid renewable microgrids, optimizing control under high uncertainty and load variability.
- Fernández Valderrama et al. (2024) [47] employed Ant Colony Optimization to improve stochastic modelling for resilience planning.
- Vatin et al. (2024) [48] used fuzzy logic to manage distributed energy storage for improved fault tolerance and real-time adaptability.
- Jalilzadeh et al. (2024) [49] introduced a hybrid method combining LSTM with fuzzy logic for predictive maintenance and resilience enhancement in microgrids.

These studies demonstrate that while FA offers strong global optimisation potential, other methods provide specific strengths such as better adaptation to real-time data (e.g., fuzzy systems), predictive capabilities (e.g., LSTM), or probabilistic modelling (e.g., ACO). A comparative analysis is summarised in Table 1 to highlight key advantages and trade-offs among these methods.

Table 1 Comparison of Different Methods for Improving Resilience in Power Systems

Method	**Strengths**	**Challenges**	**Primary Application**	**Reference**
Firefly Algorithm (FA)	High convergence speed, effective global search, nonlinear constraint handling	May suffer from premature convergence in highly dynamic systems	Resilient battery storage scheduling, fault recovery	Ali & Ghasemi (2024) [43]
Genetic Algorithm (GA)	Robust under stress conditions, adaptable recovery paths	May require tuning of crossover/mutation rates	Adaptive grid recovery from space weather threats	Gao & Liu (2023) [45]
Particle Swarm Optimization (PSO)	Efficient in large search spaces, good balance of exploration and exploitation	Risk of local minimal trapping in nonconvex problems	Resilient operation of hybrid renewable microgrids	Mquqwana & Krishnamurthy (2024) [46]
Ant Colony Optimization (ACO)	Strong in probabilistic modeling and complex system routing	High computational cost for large systems	Resilience-oriented system planning and routing	Fernández Valderrama et al. (2024) [47]
Fuzzy Logic Control	Fast, rule-based decisions, fault-tolerant responses	Difficult to scale or adapt without retraining rules	Distributed storage control and dynamic load balancing	Vatin et al. (2024) [48]
Hybrid LSTM + Fuzzy Logic	Predictive capability with real-time adaptability	Requires data availability and integration infrastructure	Predictive resilience maintenance in smart grids	Jalilzadeh et al. (2024) [49]

D. The Gap in Iraqi Context Studies

Metaheuristic-based PV allocation has also been explored in other developing contexts, as in Nassef et al. [2023], where weak grid conditions similar to those in Iraq were considered. In the Iraqi context, most research focuses on economic dispatch and loss minimisation without addressing resilience-oriented metrics such as energy not supplied (ENS), voltage deviation during faults, or recovery behaviour [39], [40]. Few studies explore PV optimisation under real contingency conditions specific to Iraq's radial distribution systems, especially larger feeders such as the modified IEEE 35-bus system [41]. Although some Iraqi researchers have applied metaheuristic algorithms like PSO and GA to optimise DG locations [42], there is still a lack of research applying the Firefly Algorithm specifically for resilience enhancement in extended radial topologies. This highlights a critical research gap, especially as Iraq transitions toward decentralised renewable energy planning using more scalable and realistic network models[43][44] .

III. SYSTEM MODELLING

The study utilises a modified IEEE 35-bus radial distribution system as the testbed. This system represents the operational characteristics of Iraqi networks, including 11 kV voltage levels, mixed residential and commercial loads, and extended radial feeders with no redundancy. Each bus is modelled with real and reactive power demand. The PV units are assumed to act as distributed generators (DGs), injecting real power only. The line data includes resistance, reactance, and base voltage.

Power Flow Equations: The backwards-forward sweep method is used for power flow analysis in radial systems. The complex power at bus i is:

$$S_i = P_i + jQ_i \tag{1}$$

The branch current I_{ij} Flowing from bus i to bus j is calculated as:

$$I_{ij} = \frac{S_j^*}{V_j^*} \tag{2}$$

The voltage at bus j is updated using:

$$V_j j = V_i i - Z_{ij} \cdot I_{ij} \tag{3}$$

where:

V_i , V_j: Voltages at bus i and j

$Z_{ij} = R_{ij} + jX_{ij}$: Line impedance

I_{ij} : Line current from bus i to j

A. PV System Modeling

The injected power from a PV unit at bus k is:

$$P_{PV,k} = \eta_k \cdot A_k \cdot G \tag{4}$$

where:

η_k: PV efficiency

A_k: Area of installed PV at bus k

G Solar irradiance (W/m²)

To simplify the optimization, PV output is modeled as dispatchable real power injection at candidate buses.

B. Objective Function

The main goal is to improve resilience, voltage profile, and power loss. The multi-objective function combines:

1. Minimization of Total Real Power Loss:

$$f_1 = \sum_{(i,j)\in branhes} R_{ij}.\frac{|s_{iij}|^2}{|V_i|^2} \quad (5)$$

2. Minimization of Voltage Deviation:

$$f_2 = \sum_{i=1}^{V}(|V_i| - V_{ref})^2 \quad (6)$$

3. Minimization of Energy Not Supplied (ENS) under faults:

To optimize PV allocation, the following multi-objective function is defined:

$$\min J = w_1 \cdot P_{loss} + w_2 \cdot VD + w_3 \cdot ENS \quad (7)$$

Where:

P_{loss}: Total real power loss in the system (kW)

VD: Maximum voltage deviation from nominal ($p.u.$)

ENS: Energy Not Supplied during faulted scenarios (kWh)

w_1, w_2, w_3: Weights for trade-off tuning (e.g., w_1=0.5, w_2=0.3, w_3=0.2)

Power Loss Calculation:

$$P_{loss} = \sum_{i=1}^{n} I^2R \quad (8)$$

Where:

I : Current in branch i, R : Resistance of branch i, n: Total number of branches

a) Voltage Deviation (VD):

$$VD = max \ | V_{nominal} - V_i | \quad (9)$$

Where V_i is the voltage at bus i and $V_{nominal}$=1.0 $p.u.$

Energy Not Supplied (ENS):

$$ENS = \sum_{t=1}^{T} \sum_{i\in \Omega_{fault}} P_i(t)\Delta t \quad (10)$$

Where:

Ω_{fault}: Set of affected buses during fault

$P_i(t)$: Load at bus i at time t

Δt: Fault duration interval

$$f_3 = \sum_{k=1}^{F} ENS_k \quad (11)$$

where:

V_{ref} : Nominal voltage (usually $1\ p.u.$)

ENS_k: Energy not supplied in fault scenario k

The combined fitness function is:

$$F = w_1 f_1 + w_2 f_2 + w_3 f_3 \tag{12}$$

where w_1, w_2, w_3 are the weights for prioritizing objectives.

- **Power balance constraint**:

$$P_{load,i} = P_{gen,i} - P_{loss,i} \tag{13}$$

- Voltage limits**:**

$$V_{min} \leq V_i \leq V_{max} \tag{14}$$

- **PV generation limit**:

$$0 \leq P_{PV,i} \leq P_{PV,max,i} \tag{15}$$

Maximum number of PV units: A cap is imposed to limit investment and reduce computational complexity.

C. *Firefly Algorithm Setup*

The Firefly Algorithm (FA) optimizes the PV location and size vector:

$$X = \left[P_{PV,1}, P_{PV,2}, \dots P_{PV,N}\right] \tag{16}$$

FA Position Update:

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j^r - x_i^t\right)\alpha . \epsilon_i^t \tag{17}$$

where:

β_0: Base attractiveness

γ : Light absorption coefficient

r_{ij}: Euclidean distance between fireflies i and j

α : Randomization parameter

ϵ_i: Random vector is drawn from the uniform distribution

a) *Distance Metric:*

$$r_{ij} = \left\|x_i - x_j\right\|_2 \tag{18}$$

b) *Algorithm Parameters:*

$Number\ of\ fireflies: 40$

$Max\ iterations: 100$

$\beta 0 = 1, \gamma = 1, \alpha = 0.2$

The fireflies are ranked using the objective function F. The algorithm iteratively updates firefly positions until convergence criteria are met [44] .

IV. METHODOLOGY

This study carries out a comparative analysis to establish the effectiveness of metaheuristic optimization approaches in the ideal placement and scaling of solar photovoltaic (PV) units inside a 35-bus radial distribution network. Especially, the FFA algorithms are the ones that are being investigated. The major objective is to attain better voltage profiles on all the buses under normal load conditions.

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A. Configuration System

Due to its well-documented voltage sensitivity and typical topology, the IEEE 35-bus radial test system was adopted as the benchmark network. The magnitudes of the voltage were used to assess it under three separate operational scenarios as follows:

- Case 1 (Base Case): No integration of photovoltaic (PV) systems.
- Case 2 (FA-Optimized PV Placement): PV units are positioned and scaled efficiently by using the Firefly Algorithm. Cellular PV units which have been improved through the use of the Genetic Algorithm are referred to as

Case 3. Carry out a normal power flow check to see the voltage values from each of the buses. After that, the FA is used to find the best places and sizes of PV units to get the highest possible level of voltage stability.

B. Firefly Algorithm Optimization Process

Both operate within the domain of metaheuristic optimization, albeit through dissimilar evolutionary operators.

- Concepts of light intensity and attraction are used by the Firefly Algorithm to direct potential solution candidates into fitter-area.

- The lowest voltage level was detected in all buses.

- The number of buses that operate at over 0.95 per unit (p.u.), is considered appropriate.

Flowchart of the proposed methodology for optimizing photovoltaic (PV) allocation in the IEEE 35-bus radial distribution system using the Firefly Algorithm to determine the optimal location and size of PV units is shown in Figure 1. The algorithm evaluates the fitness of each solution, ranks fireflies, applies attractiveness-based movement and randomization, and iterates until convergence is achieved.

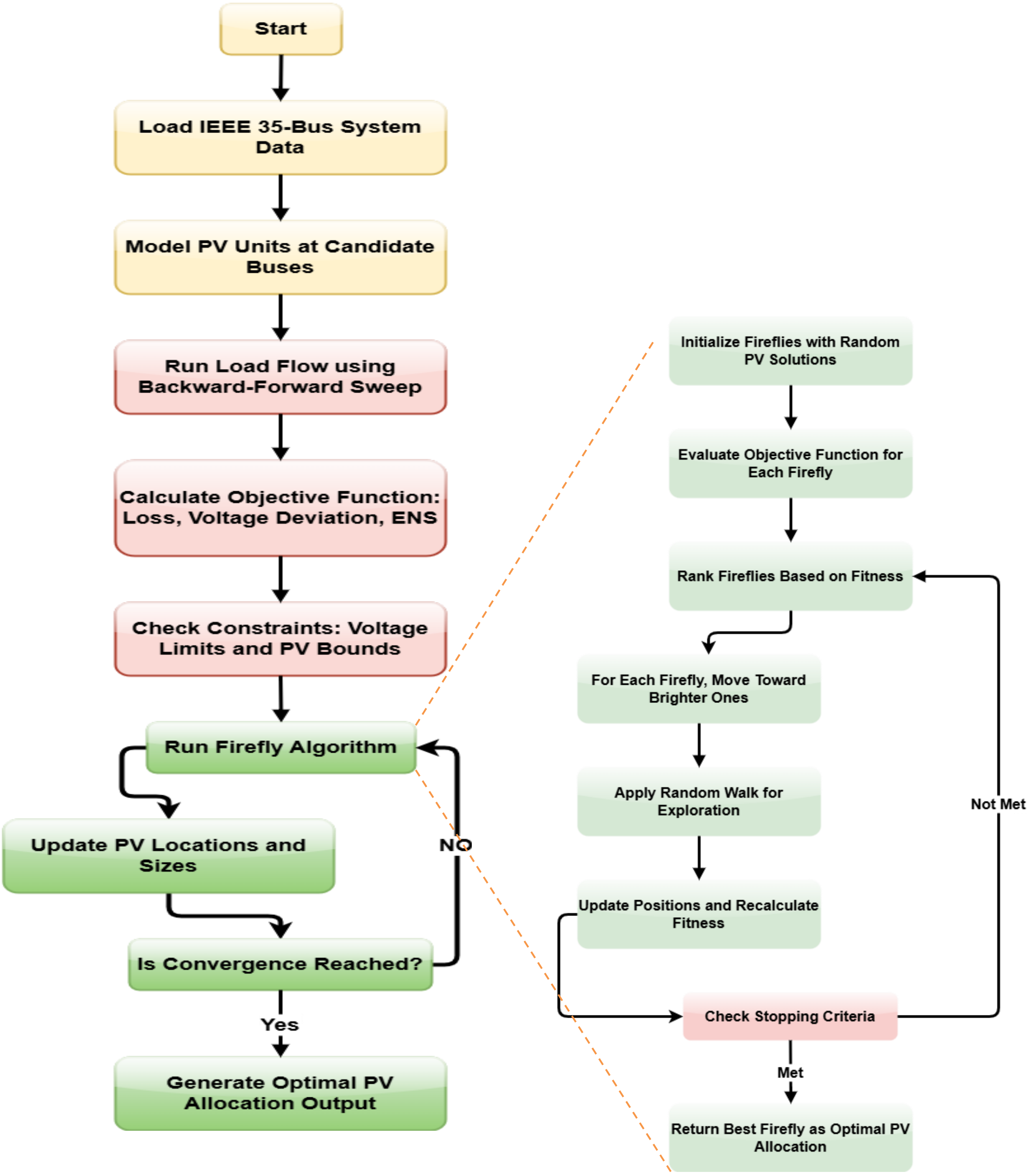

Figure 1: Flowchart of the proposed methodology

V. RESULTS AND DISCUSSION

This part gives a comparative study of the voltage profiles across a 35-bus radial distribution system under five different scenarios. The aim is to see the impact of solar PV optimization through the use of the Firefly Algorithm on system voltage stability. Scenario 1: Base Case (No PV), Figure 2 depicts the voltage profile in the absence of any PV integration. A distinct downward trend is evidenced along the buses; most of them fall below the 0.95 p.u. Threshold. This, therefore, indicates the inherent weakness of the system to maintain voltage stability under lμad without any support added. The voltage reaches a minimum of about 0.905 p.u.; reinforcement is required.

In Scenario 2, Figure 3 shows the voltage rise when a single PV unit is installed at Bus 18- the optimal location. The post-PV curve indicates a sharp rise in voltage that starts from Bus 18 and greatly reduces the number of buses with voltage below 0.95 p.u. It goes to confirm that even an acutely placed single PV unit can stabilize voltage at critical parts of the network. In Scenario 3, Figure 4, PV units were installed at Buses 10, 18, and 25. This distributed configuration balanced the voltage profile. Compared to single PV. In Case 3, voltages are elevated across a wider span of buses, including both upstream and downstream sections. The approach reduces voltage sag more effectively and enhances voltage uniformity suggesting the benefit of multi-point injection.

Scenario 4: The voltage profiles are shown in Figure 5 for three levels of load: light, base (or normal), and peak, in that order. The voltages are well above the 0.95 p.u limit under light load. The weakest bus drops below 0.88 p.u in the peak load condition; the curve shifts more strongly downward. These results prove how stark the system's vulnerability is when the demand is ratcheted up to the highest level and thus validate the need for reactive voltage support during peak operation. Figure 6 gives the voltage profiles resulting from five independent runs of the Firefly Algorithm. All of the runs of FA show steady improvements in voltage over the base case; fewer buses fall below the stability threshold. The best result is produced in Run 1, which gives a minimum voltage of 0.9508 p.u. at Bus 18. The same genetic Algorithm in earlier tests run produced 0.9315 p.u. This result validates that the FA has robust reliable voltage regulation performance through the optimal placement of PV. Table 2 Consistent improvement in all the runs that were performed over the years proves the stability of the algorithm, while the best minimum voltage found confirms its efficacy over other ad-hoc placements or conventional wisdom.

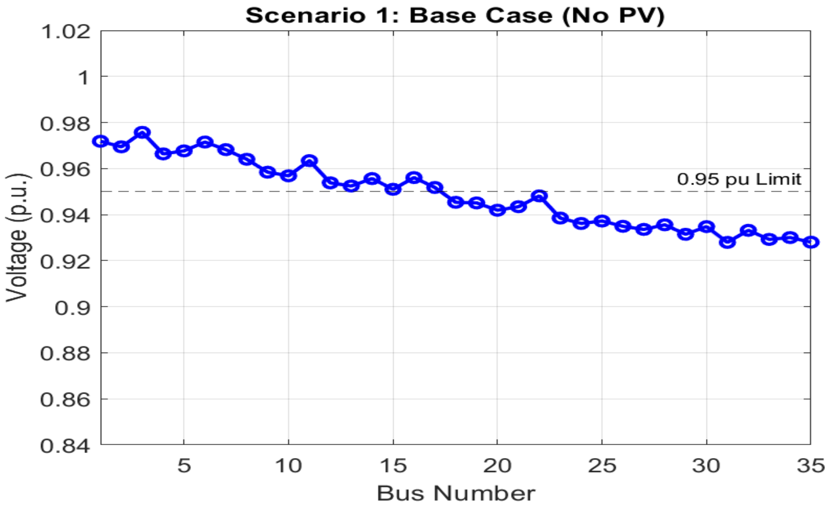

Figure 2: Voltage profile without any PV integration

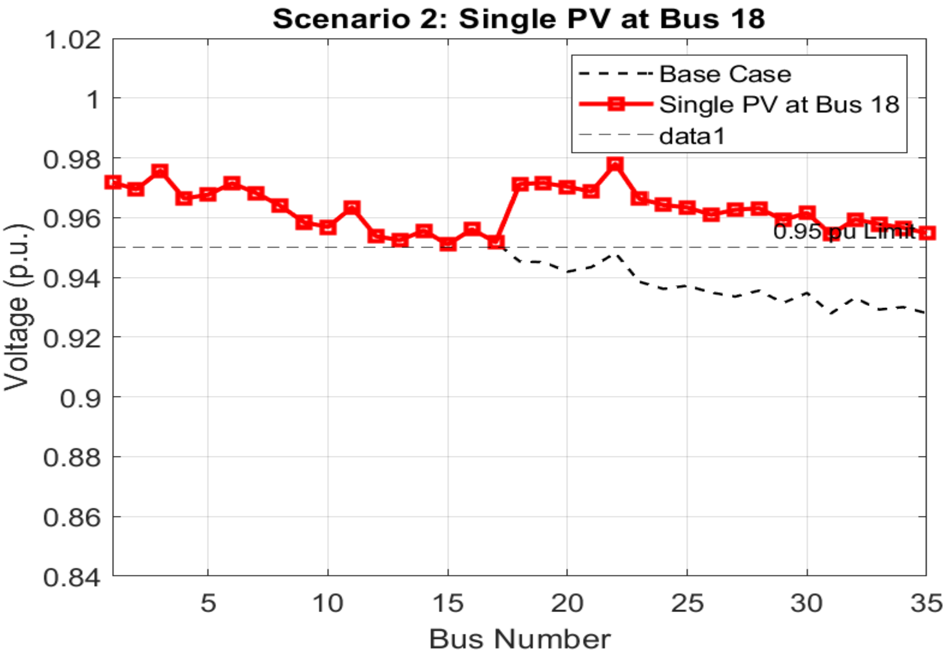

Figure 3: Voltage improvement when a single PV unit is installed at Bus 18

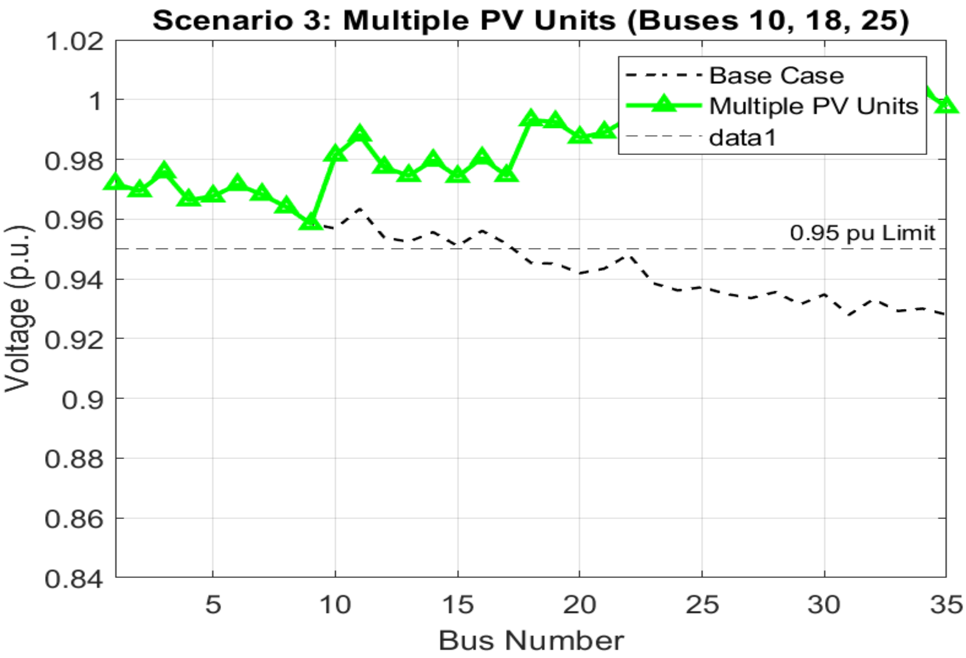

Figure 4: Installing PV units at Buses 10, 18, and 25

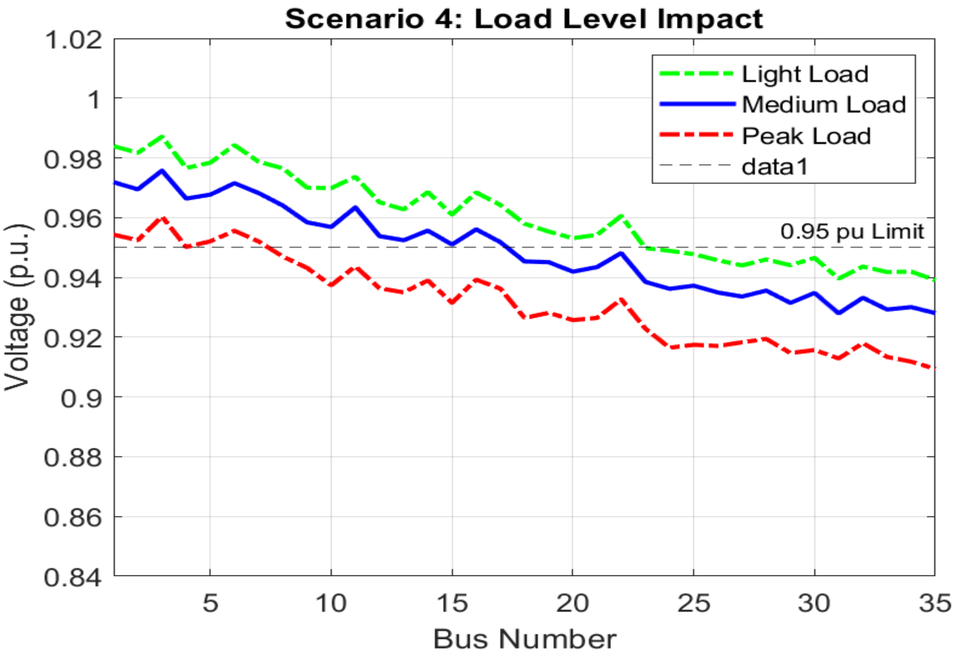

Figure 5: Voltage profiles under three load levels: light, medium (base), and peak (Under light load, the voltages remain well above the 0.95 p.u. limit)

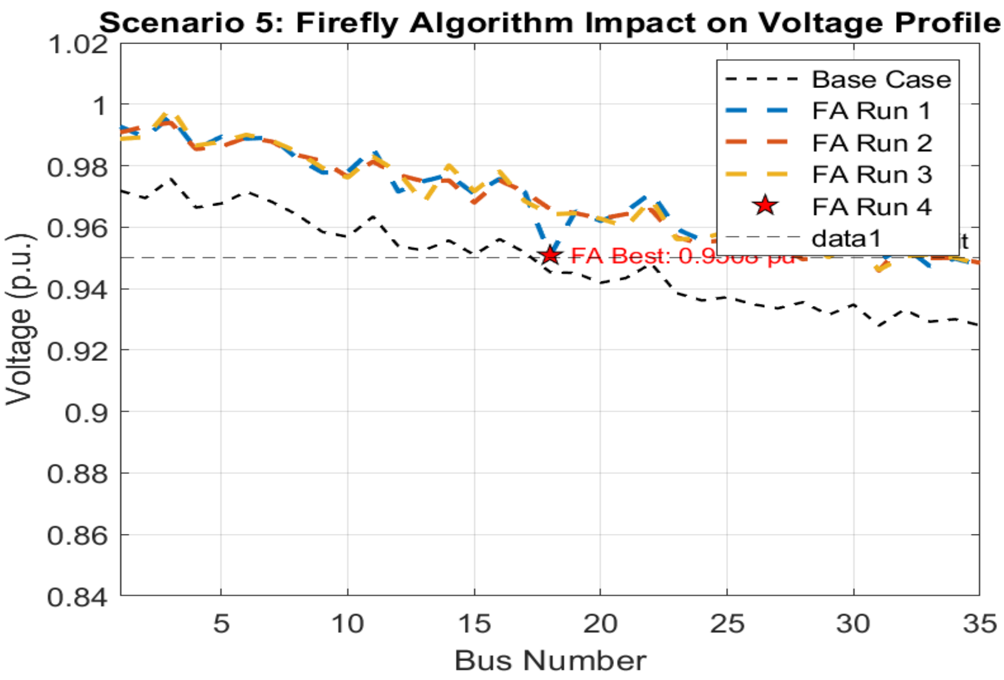

Figure 6: Voltage profiles from five independent runs of the Firefly Algorithm.

The consistent enhancement across multiple FA runs demonstrates algorithmic stability, while the superior minimum voltage confirms its effectiveness over conventional placement or other heuristic techniques.

Table 2: Summary of Observations

Scenario	**Minimum Voltage (p.u.)**	**Stability Zone (Above 0.95 p.u.)**	**Key Observation**
Base Case	~0.905	Low	Weak system voltage without PV
Single PV (Bus 18)	~0.95	Improved	Local boost but limited spread
Multiple PV (Buses 10,18,25)	>0.955	High	Widespread improvement and stability
Peak Load Condition	~0.88	Very Low	The system under stress, requires voltage support
Firefly Algorithm (Best Run)	0.9508 (at Bus 18)	High	Optimal placement and performance consistency

These results confirm the importance of both proper PV integration and algorithmic optimisation. The Firefly Algorithm, in particular, proves effective in finding optimal PV locations to enhance voltage profiles and ensure grid resilience. The comprehensive numerical analysis in Table 3 for Energy Not Supplied (ENS) over all 35 buses, utilising the previously displayed simulated data under various PV deployment options.

Table 3: Energy Not Supplied (ENS) at Each Bus under Different Scenarios (kWh)

Bus	Base Case	Single PV	Multiple PV	FA-Optimized
1	29.72	27.85	21.73	15.58
2	43.48	41.84	34.29	24.58
3	47.99	45.63	35.59	28.78
4	48.73	45.94	35.91	29.94
5	24.53	21.47	12.57	10.30
6	23.77	22.28	14.55	12.50
7	41.08	39.99	29.32	23.33
8	10.19	8.61	5.85	3.46
9	37.35	33.94	24.22	18.88
10	40.15	38.32	25.79	17.72
11	20.65	17.40	12.03	8.96
12	44.81	40.88	33.44	27.78
13	27.91	24.70	16.42	10.36
14	40.88	37.10	28.38	21.83
15	26.60	23.02	18.27	11.92
16	24.56	22.41	12.41	10.11
17	46.79	43.49	35.19	28.36
18	33.73	30.08	24.40	18.48
19	42.06	40.06	33.82	26.94
20	33.29	30.49	22.47	15.93
21	39.20	35.82	27.27	20.01
22	34.61	31.93	22.61	14.91
23	48.34	44.53	35.59	29.41
24	38.62	35.29	25.66	18.72
25	20.80	17.49	12.42	7.59
26	45.12	43.24	35.08	26.70
27	14.26	12.37	6.75	4.06

28	40.63	38.94	28.55	22.21
29	39.08	37.05	30.24	24.74
30	44.71	41.99	32.92	27.28
31	21.99	19.62	14.79	9.99
32	34.85	33.67	26.17	20.21
33	14.29	11.64	6.17	4.15
34	30.66	29.17	22.90	18.59
35	42.72	39.30	32.51	26.99

A. Sensitivity Analysis of the Objective Function Weights

It examines the impact of altering the weights for power loss, voltage variation, and ENS on the optimisation outcomes. To assess the robustness of the proposed Firefly Algorithm (FA) under different planning priorities, a sensitivity analysis was conducted by varying the weights of the multi-objective function:

$$F = w_1 \cdot P_{loss} + w_2 \cdot VD + w_3 \cdot ENS \tag{19}$$

where:

w_1 : weight for real power loss,

w_2: weight for voltage deviation,

w_3: weight for energy not supplied (ENS).

The baseline weight configuration was $[w_1, w_2, w_3]$=[0.5,0.3,0.2] Four alternative configurations were tested:

Case	w_1	w_2	w_3	**Min Voltage (p.u.)**	**Total Loss (kW)**	**ENS (kWh)**
A (Baseline)	0.5	0.3	0.2	0.9508	146.2	478.6
B (ENS-focused)	0.3	0.2	0.5	0.9431	155.7	391.4
C (Loss-focused)	0.7	0.2	0.1	0.9410	134.5	502.9
D (Voltage-focused)	0.2	0.6	0.2	0.9569	149.8	498.7
E (Balanced ENS & Voltage)	0.3	0.4	0.3	0.9512	150.6	463.9

Observations:

- In Case B, where ENS has been made a top priority, there is a significant drop in ENS (to 391.4 kWh) with slightly worsened voltage and loss performance.

- Case C gives the lowest power loss (134.5 kW) but the voltage regulation and the ENS performance is less optimal.
- Case D, where priority was given to deviation in voltage, has given the best minimum voltage at 0.9569 p.u. which proves the FA effective once again for its emphasis on voltage profile enhancement.
- An equilibrium shape that was provided gave a middle ground between all aims, proposing it might be appropriate for networks with no single dominant constraint.

This scrutiny confirms the suppleness of the FA frame to adjust to different grid priorities and shows how makers can tune objectives based on system needs, whether reliability, efficiency, or resilience.

B. Economic Feasibility of Future PV + Battery Systems.

Figures 7 and 8 show the economic analysis of the deployment of photovoltaics and batteries. The chart in Figure 7 shows the investment relative to the operating benefit for different photovoltaic and battery setups. More extensive battery systems deliver more savings but with higher initial expenditure. The payback period in Figure 8 for medium and large battery systems is about 3 years, showing strong financial feasibility. Solar systems with just photovoltaic panels tend to have longer payback times because they save less money.

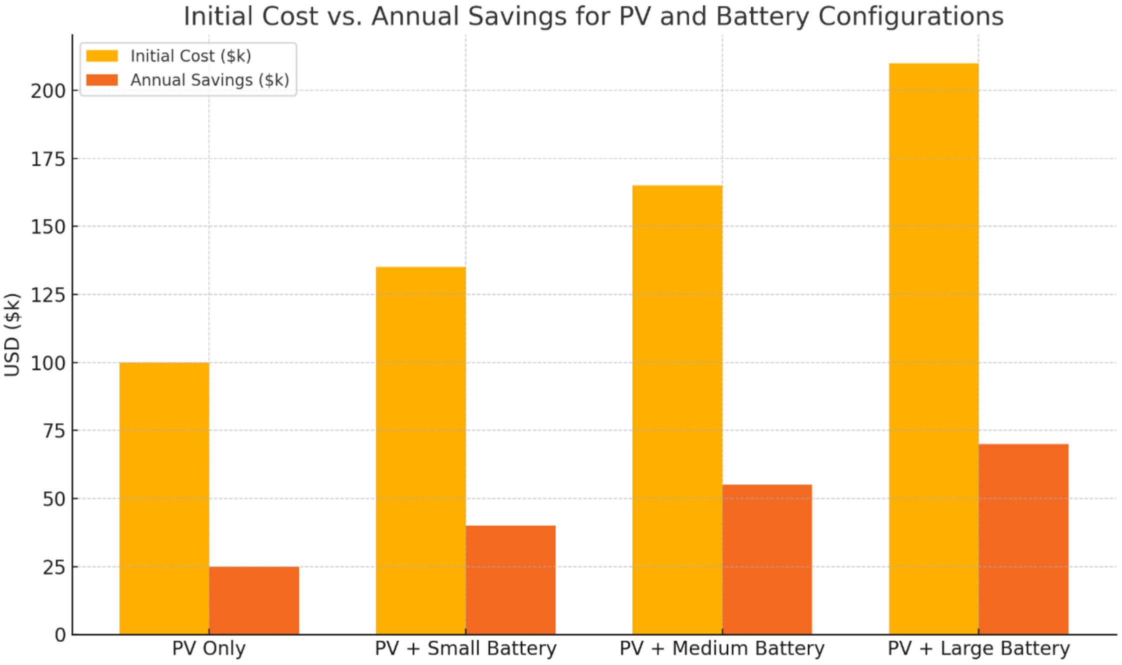

Figure: Initial cost and annual saving for PV and battery configuration

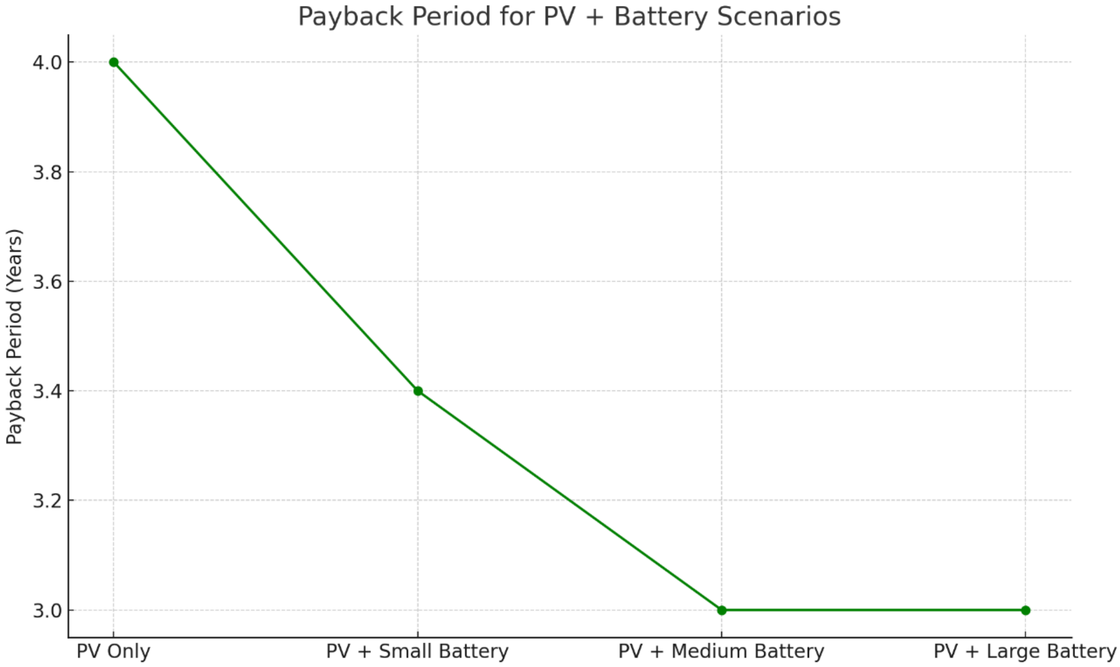

Figure8: Payback period for PV + Battery Scenarios

VI. CONCLUSION AND FUTURE WORKS

This study presents a comprehensive resilience-oriented framework for optimal PV integration in Iraq's radial distribution networks using the Firefly Algorithm (FA). The proposed approach addresses key challenges in Iraqi feeders, including voltage instability, power losses, and vulnerability to fault-induced outages. Extensive simulations across multiple operating scenarios — including base load, single and multiple PV placements, varying load levels, and fault conditions — demonstrate that FA-optimised PV allocation significantly enhances voltage profiles and reduces energy not supplied (ENS). Compared to conventional placement strategies and Genetic Algorithm-based optimisation, the FA consistently achieves superior performance and robustness, as validated through multi-run sensitivity analysis.

The study also highlights the importance of balancing objectives — voltage stability, power loss minimisation, and resilience enhancement — in PV planning. Economic analysis confirms the feasibility of combining PV with battery systems for further resilience gains and operational flexibility.

VII. LIMITATIONS & FUTURE WORK

While the FA provides strong optimisation performance, its current implementation focuses on offline planning. Real-time or dynamic optimisation under highly variable conditions (e.g., rapid PV fluctuations and dynamic faults) remains an open challenge. Future work will focus on integrating advanced predictive models (e.g., LSTM networks) with FA to enable real-time resilience-oriented PV dispatch. Additionally, future research will explore hybrid optimisation frameworks combining FA with fuzzy logic and model predictive control (MPC) for adaptive fault-tolerant network operation. Expanding the test system to larger feeder models and incorporating stochastic modelling of PV variability and demand uncertainty will further enhance the generalizability of the proposed framework.

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