Article

Not peer-reviewed version

A Weighted Mean of Vectors–Based Mathematical Optimization Framework for PV-STATCOM Deployment in Distribution Systems under Time-Varying Load Conditions

Ghareeb Moustafa * , Hashim Alnami , Badr M. Al Faiya , Sultan Hassn Hakmi *

Posted Date: 26 February 2026

doi: 10.20944/preprints202602.1385.v1

Keywords: distribution systems; weighted mean of vectors approach; energy losses minimization; allocation of PV-STATCOM

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 26 February 2026 doi:10.20944/preprints202602.1385.v1

Article

A Weighted Mean of Vectors–Based Mathematical Optimization Framework for PV-STATCOM Deployment in Distribution Systems Under Time-Varying Load Conditions

Ghareeb Moustafa *, Hashim Alnami, Badr M Al Faiya and Sultan Hassn Hakmi *

Department of Electrical and Electronics Engineering, Faculty of Engineering and Computer Science, Jazan University, Jizan 45142, Saudi Arabia

* Correspondence: gmoustafa@jazanu.edu.sa (G.M.); shhakmi@jazanu.edu.sa (S.H.H.)

Abstract

The increasing penetration of photovoltaic (PV) systems in distribution networks has introduced new challenges in voltage regulation and energy loss mitigation, particularly under time-varying loading conditions. This paper presents a constrained multi-objective mathematical optimization framework for the optimal allocation and sizing of PV-STATCOM devices in radial distribution systems. The problem is formulated as a nonlinear optimization model that simultaneously minimizes daily energy losses and voltage deviation indices over a 24-hour operating horizon while satisfying network operational constraints, inverter capacity limits, and renewable penetration restrictions. To efficiently solve the resulting non-convex optimization problem, a metaheuristic algorithm based on the Weighted Mean of Vectors (WMV) is employed. The WMV method integrates wavelet-based weighting mechanisms, mean-driven update rules, vector combination strategies, and a local refinement operator to balance global exploration and local exploitation within the feasible search domain. Constraint violations are handled through a penalty-based mathematical transformation of the objective function. The proposed framework is validated on the IEEE 33-bus and IEEE 69-bus distribution systems under realistic daily load variations. Numerical results demonstrate significant reductions in daily energy losses and voltage profile deviations compared to differential evolution, particle swarm optimization, artificial rabbits optimization, and golden search optimization algorithms. Furthermore, convergence analysis confirms the robustness and computational efficiency of the WMV approach in solving large-scale constrained power system optimization problems.

Keywords: distribution systems; weighted mean of vectors approach; energy losses minimization; **a**llocation of PV-STATCOM

---

1. Introduction

Fossil fuel consumption has long been identified among the primary contributors to climate change. One consequence of fossil fuel usage is that global warming is predicted to increase by 1.5 degrees Celsius by 2030 [1]. Moreover, progressive electrical distribution networks have required the development of new services and technologies to satisfy the growing demand for electrical energy produced by growing populations, advances in technology, and the improvement a better way of life [2]. Distributed generator (DG) integration technology has attracted plenty of attention in the decade preceding due to the reform of the energy sector and the worldwide scarcity of fossil resources [3]. DGs, especially solar distributed electricity production, have been gradually encouraging active power production in transmission networks. Power systems can profit greatly from the deployment of DGs, especially distribution systems with long power supply distances and a network structure that is brittle. For these positive advantages, DG placement is essential. Low DG investment

 doi:10.20944/preprints202602.1385.v1

utilization remains the result of inadequate DG placement and sizing. In severe situations, after DG integration, system indicators could be worse.

Research investigations on proper DG location and size have grown more and more crucial due to the rapid increase in DG installation in networks of distribution. A self-adaptive bonobo optimizer (SABOT) has been developed in [4] for optimal PV-DG integration has been validated on a real Nigerian feeder and IEEE 69-bus system, achieving significant emission and cost reductions. However, this study has not coordinated PV with reactive compensation devices, focused only on PV-DG placement, and lacks dynamic voltage control consideration. A Modified Gradient-Based Optimization algorithm has been manifested in [5] for DG and capacitor allocation to reduce losses in radial distribution systems, and validated on Egyptian 59-bus and 135-bus feeders with strong robustness improvements. However, the study has not been applied to emission or environmental objectives, and has limited stochastic/time-varying modeling.

It has been extremely challenging to fulfill the demand for reactive electricity. Flexible resources based on grid-connected inverters can be used to provide most of the reactive power requirements of distribution systems. Among all reactive compensation devices, flexible AC transmission devices (FACTS) are crucial for boosting the transmission line's adequate transfer capacity and controlling the flow of reactive power in the power system, both of which have an impact on the system electrical voltage uniformity and variability [6][7]. These FACTS include Distribution-Static VAR Compensator (D-SVC) [8], [9], Thyristor Controlled Series Capacitor (TCSC) [10] [11]. The STATCOM, which is just a shunt compensator, is one of the most commonly employed FACTs in contemporary power systems. Numerous applications for managing and controlling the electricity system are available in the STATCOM. PV-STATCOM, a photovoltaic inverter that serves as a FACT, carries out the tasks of a STATCOM controller, such as reactive power compensation, power factor enhancement, voltage regulation, and current harmonic suppression. It maintains a steady DC capacitor voltage and continuously injects or absorbs active and reactive power into the suggested system at the point of common connection to boost power quality both during the day and at night. By carrying out charging and discharging functions, it can also be used to balance power fluctuations in the suggested grid-connected system. With appropriate allocation and scale, PV-STATCOM's technical, economic, and environmental benefits can be optimized.

The voltage level of a distribution electrical network that uses solar energy sources is controlled by a PV-STATCOM, which is a solar system with a STATCOM [12][15]. Even at night, when the PV modules aren't actually producing any power, the PV inverters can nonetheless carry out that task. Throughout the day, voltage management is carried out to significantly enhance system functionality [13][17]. The reactive power provided by STATCOM regulates the level of voltage at the point of common coupling (PCC) [14]. The PV-STATCOM systems have been employed as extra damping controllers and voltage controls to improve transient stability [15]. In [16], PV-STATCOM has been implemented to control both steady-state and transient overvoltages in a practical distribution framework. In order to boost the functioning of distribution networks where voltage regulation may be offered under crucial operational demands, PV-STATCOMs have been deployed in [17]. In that study, a smart PV inverter has been employed to activate STATCOM in order to allow continuously reactive power compensation to occur.

In order to reduce energy consumption and voltage profiles at the same time, a novel artificial rabbits' algorithm (ARA) inspired by wild rabbit survival strategies has been developed in [18]. Even while this study demonstrates significant advantages in terms of reducing energy power losses and enhancing voltage profiles, it neglects to look at how the quantity of PV-STATCOMs installed affects the functioning of the distribution system. In principle, the PV-STATCOM could be of great benefit with appropriate integration to address a range of power system challenges [19]. Additionally, Ref. [20] examined the PV-STATCOM for supplying low voltage ride-through capacity and improving power quality with active and reactive injection of powers to increase the complete system voltages, taking into account grid-connected mode of operation under unpredictable grid conditions. Besides, the goal of PV-STATCOM's rapid reactive power control is to enhance the IEEE 33-bus distribution

 doi:10.20944/preprints202602.1385.v1

network's dynamic capability with regard to voltage recovery procedures in the event of a post-fault situation or voltage sag [21]. In order to improve the voltage profile and lower the overall losses of Northern Cyprus bus distribution network, Ref. [11] assigned the PV and STATCOM using the PSO approach.

Recently, Ahmadianfar et al. [22] created an entirely novel optimization approach identified as the Weighted Mean of Vectors (WMV) approach, which is inspired by the weight mean method. Three major operators—vector combining, rule updating, and local search operators—are used in the proposed WMV to change the population's placement (vectors) in the search domain. The updating rule stage employs a mean-based law and acceleration of convergence to generate new vectors. WMV revised its rules and vector combining steps to improve exploration and exploitation capabilities. The obtained vectors are combined with the updating rule in the vector combining stage to produce an appropriate solution. The weight of the vectors is determined by considering a wavelet function, which allows the method to identify the weighted mean of vectors by exploring the solution space globally. The WMV is a good choice for this application because of a number of important benefits. The capacity of WMV to successfully achieve a balance between exploration and exploitation throughout the optimization process is its main strength. Investigating potential regions of the search space is the main goal of the weighted mean computation. The weighted mean is more influenced by vectors with higher fitness (those which maintain a good balance among environmental and economic goals), which directs the search in these areas [23]. In order to avoid premature convergence to inferior solutions and to enable WMV to investigate numerous areas of the search space, vector integrating injects variation into the population. By its very nature, the weighted mean approach gives preference to options that are more advantageous for the economy and the environment [24].

WMV converges to optimal solutions more quickly when a convergence acceleration component is added to the weighted mean update procedure. This word speeds up the search by changing the current vector in the direction of the best solution discovered thus far. By altering the weighting technique employed in the weighted mean computation and the particular objectives under consideration, WMV can be tailored to various power system optimization issues. Because of its adaptability, it can manage a range of environmental and economic aspects pertinent to a certain power system situation [25]. Considering the unique features of WMV, the best possible PV-STATCOM placement for distribution system energy loss elimination is the main emphasis of this study. The proposed WMV is applied to reduce the daily voltage profile and daily energy losses when different 24-hour loadings are taken into account. The usual IEEE 33-node and 69-node distribution networks are used to illustrate their applicability. The following are the important contributions of the paper:

- Development of a constrained multi-objective mathematical model for optimal allocation and sizing of PV-STATCOM devices in radial distribution systems, simultaneously minimizing daily energy losses and voltage profile deviations over a 24-hour horizon.
- Integration of time-varying load modeling into the optimization framework, enabling realistic daily operational assessment rather than single operating-point evaluation.
- Application of the Weighted Mean of Vectors (WMV) algorithm to solve the resulting nonlinear, non-convex optimization problem, incorporating Wavelet-based weighted mean computation, Mean-driven rule update mechanism, Vector combining operator for diversity enhancement, and Local search refinement strategy for convergence acceleration.
- Implementation of a penalty-based constraint handling approach to incorporate voltage limits, thermal line constraints, inverter active/reactive power limits, and renewable penetration restrictions into the mathematical formulation.
- Comparative performance evaluation against established metaheuristic methods (PSO, DEA, AROA, GSOA), demonstrating improved convergence characteristics and superior compromise solutions in terms of loss minimization and voltage regulation.

 doi:10.20944/preprints202602.1385.v1

- Validation on benchmark IEEE 33-bus and 69-bus distribution networks, confirming the robustness and applicability of the proposed mathematical optimization framework for practical distribution system planning.

The next sections of the paper are as follows. While Section 3 presents the suggested design of the novel HPO, Section 2 highlights the preliminary form of the PV-STATCOM assignment challenge in distribution feeders. Additionally, Section 4 clarifies on the simulation results of the developed WMV in handling the PV-STATCOM assignment challenge taking into account two IEEE distribution feeders, while Section 5 formulates the work's concluding remarks,

2. PV-STATCOM Allocation Problem in Distribution Feeders

When deploying PV-STATCOM in distribution feeders, it is critical to minimize daily voltage changes and energy losses. As in Equation (1), both goals are handled using a single objective form (*OF*) that must be minimized.

$$OF = Min\left(\sum_{hr=1}^{24}\left(\sum_{Line=1}^{N_{Line}} R_{Line} \times I_{Line}^2 + \sum_{k=1}^{N_b}|V_k - 1|\right)\right) \tag{1}$$

where V_k signifies the voltage value at each distribution bus (k); N_b denotes the number of nodes; I_{Line} specifies the current flow in each line (Line); R_{Line} reflects the resistance of each line; N_{Line} describes the number of distribution lines in the system.

According to Equation (1), the provided model is concerned with 24-hour loading fluctuations per day, with the first term handling voltage deviation minimization and the second term addressing energy losses. In addition, the voltages throughout each distribution node and the current flow across each distribution branch must be maintained within acceptable levels at all times, as illustrated below [26]:

$$\left(V_{k,min} < V_k \le V_{k,max}\right)_{hr=1,2,....24;\ k=1:N_b} \tag{2}$$

$$\left(I_{Line} \le I_{Line,max}\right)_{hr=1,2,....24;\ Line=1:N_{Line}} \tag{3}$$

where $I_{Line,max}$ provides the distribution branch's thermal capacity; $V_{k,min}$ and $V_{k,max}$ indicate the voltage nodes' lower and upper limits, allowing for a 5% range.

When PV modules supply real or reactive power injections, the real component of the inverter current controls the DC voltage in the PV-STATCOM instruments for voltage control at the PCC. The present research takes into account the PV-STATCOM's ability to generate active power during the day as well as its potential to inject/absorb reactive power both during the day and at night. The overall balance limitations are changed hourly in order to integrate the PV-STATCOM system into the electrical distribution network. Therefore, the active and reactive power balance limitations can be characterized in the following manner [27]:

$$\left(\sum_{j=1}^{N_{PVS}} P_{PVS_j} + P_{Sub} = P_{losses} + \sum_{i=1}^{N_b} Pd_i\right)_{hr=1,2,....24} \tag{4}$$

$$\left(\sum_{j=1}^{N_{PVS}} Q_{PVS_j} + Q_{Sub} = Q_{losses} + \sum_{i=1}^{N_b} Qd_i\right)_{hr=1,2,....24} \tag{5}$$

where NPVS displays the entire number of PV-STATCOM components installed in the feeder; P_{Sub} and Q_{Sub} signify the substation's whole active and reactive power; *Pdi* and *Qdi* reflect the actual and reactive power consumption at node (*i*); *PPVSj* and *QPVSj* express the actual and reactive power injected through the PV-STATCOM that is located at node (*j*); *Plosses* and *Qlosses* illustrate the real and reactive system losses, respectively; and *hr* describes each hour of the day's horizon.

In this context, the PV-STATCOM's capacity to simultaneously inject and consume reactive power during the day and night, while also considering its ability to provide active power during the day, are taken into consideration. Therefore, the PV-STATCOM actual and reactive power injections that are to be installed at node (*j*) are required to be maintained not exceeding the following allowable limits:

$$\left(0 < P_{PVS,j} \leq P_{PVS,max,j}\right)_{hr=1,2,....24;\ j=1:N_{PVS}} \tag{6}$$

$$\left(0 < Q_{PVS,j} \leq Q_{PVS,max,j}\right)_{hr=1,2,....24;\ j=1:N_{PVS}} \tag{7}$$

where *PPVS,max* and *QPVS,max* reflect the prospective size's entire active and reactive power, respectively.

Additionally, as demonstrated in [28], the penetration limitations (*Kp*) of PV renewable DER resources must be properly considered so that it does not surpass 60% of the feeder's entire active power needs.

$$\left(\left[Pen_{\ Constraint} = \left(\sum_{k=1}^{N_{PVS}} P_{PVS,k} - K_P * \sum_{j=1}^{N_b} P_{d_j}\right)\right] \leq 0\right)_{hr=1,2,....24;\ \boldsymbol{max}\ peakdemand} \tag{8}$$

The objective function displayed in Equation (1) needs to be changed to greater values through incorporating some penalty terms for the violations in at least one of these conditions in order to properly manage the inequality constraints of Equations (2), (3), and (8). This resembles the following:

$$F = Min\left(\sum_{hr=1}^{24}\left(\sum_{Line=1}^{N_{Line}} R_{Line} \times I_{Line}^2 + \sum_{k=1}^{N_b} |V_k - 1|\right)\right) + Penalty \tag{9}$$

$$Penalty = K_A \times Viol_{penetration} + K_B \times Viol_{Line} + K_C \times Viol_{V,min} + K_D \times Viol_{V,max} \tag{10}$$

where K_A, K_B, K_C and K_D stand for penalty factors that have exceptionally high values.

$$Viol_{pen} = \begin{cases} Pen_{Co} & \text{if } Pen_{Con} > 0 \\ 0, & else \end{cases}, \qquad Viol_{Line} = \begin{cases} \max(I_{Line}) - I_{Line,\max} & if\ \ I_{Line,\max} < I_{Line} \\ 0, & else \end{cases} \tag{11}$$

$$Viol_{V,\min} = \begin{cases} V_{k,\min} - \min(V_k) & if\ V_{k,\min} > V_k \\ 0, & else \end{cases}, \qquad Viol_{V,\max} = \begin{cases} \max(V_k) - V_{k,\max} & if\ \ V_{k,\max} < V_k \\ 0, & else \end{cases} \tag{12}$$

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 26 February 2026 doi:10.20944/preprints202602.1385.v1

3. Proposed WMV for PV-STATCOM Allocation in Distribution Systems

The weighted mean of vectors (WMV) approach consists of three aspects: vector combination, rule adjustment, and local search procedures [29].

3.1. Population and Fitness Evaluation

WMV begins with an ensemble of vectors, each reflecting a possible solution in the search space. The solution vectors could only be produced within their allowable limitations. Throughout the iterations, every vector will be assessed on its level of fitness. The proposed WMV uses a (N_p) population vector and a (*Dim*) dimensional search domain ($Z^g_{q,j} = \{z^g_{q,1}, z^g_{q,2}, \ldots, z^g_{q,Dim}\}$, l = 1, 2, .., N_p). This phase exposes control settings for the WMV, including the scaling rate σ and weighted mean factor δ. The scaling rate is demonstrated to enhance the achieved vector using the modifying rule operator, which is facilitated by the search domain size. The scaling rate is quantified based on the issues' feasible search space and reduced using an exponential technique. Furthermore, this factor is employed to extend the vector's weighted mean. The two settings are adjusted gradually depending on the generation.

3.2. Weighted Mean Rule Update

In this step, the search space's vector position data are updated. WMV chooses a subset of vectors from the population for every iteration. A varied set encompassing potential regions of the search space is produced by selecting these vectors according to their level of fitness (the more suited ones are more probable to be chosen). WMV uses fitness scores as weights to compute a weighted mean for each chosen vector [30]. The current vector is essentially drawn towards greater potential areas in terms of economic and environmental goals by vectors with better fitness, which have a bigger influence on the mean. This weighted mean serves as the foundation for creating new vectors, together with a convergence rate term. The mean, which is determined by considering for each vector's fitness (wf_i), represents the average location of the vectors (z_i) in the collection. This method, in which solutions that have greater weight have greater implications on the weighted mean calculation, is selected due to its easy and straightforwardness of deployment.

Equation (13) specifies the calculation method for determining the weighted mean (*WMn*).

$$WMn = \sum_{i=1}^{N} wf_i \times z_i / \sum_{i=1}^{N} wf_i, \quad (13)$$

where N indicates the aggregate number of the vectors.

In Equation (13.1), *WMn* is explained with greater clarity:

$$WMn = (z_1 wf_1 + z_2 wf_2)/(wf_1 + wf_2), \quad (13.1)$$

A wavelet function (*WF*) is employed to determine the weight of each vector. By combining the translations and dilations of an oscillatory function with a defined period, like the mother wavelet, the wavelet offers a useful tool for analyzing seismic data. In order to provide effective variations, this function is evolved over the span of optimization. The definition of the mother wavelet is outlined as given below:

$$wf = \cos(z) \times \exp(-z^2 / \omega), \quad (14)$$

where the dilation parameter is expressed by the constant number denoted by ω.

Additionally, Equation (3) is capable of being utilized for designing the weighted mean of the vectors:

$$WMn = \frac{wf_1 \times (z_1 - z_2) + wf_2 \times (z_1 - z_3) + wf_3 \times (z_2 - z_3)}{wf_1 + wf_2 + wf_3}, \quad (15)$$

in which

$$wf_1 = exp\left(-\left|\frac{(f(z_1) - f(z_2))}{\omega}\right|\right) \times cos(\,(f(z_1) - f(z_2)) + \pi), \quad (15.1)$$

$$wf_2 = exp\left(-\left|\frac{(f(z_1) - f(z_3))}{\omega}\right|\right) \times cos(\,(f(z_1) - f(z_3)) + \pi), \quad (15.2)$$

$$wf_3 = exp\left(-\left|\frac{(f(z_2) - f(z_3))}{\omega}\right|\right) \times cos(\,(f(z_2) - f(z_3)) + \pi), \quad (15.3)$$

where $f(z)$ comprises the (z) vector's fitness function.

In the WMV, the updating rule operator promotes the variety of the population throughout the search process. To create new vectors, the operator generates the weighted mean of the existing vectors. There are two main components to this operator. In the first section, the weighted mean for an ensemble of random vectors is calculated in order to derive a mean-based rule. This rule uses the weighted mean data of a randomly assigned vectors' set to start with a random starting solution and proceed to the next solution. In the second section, the convergence acceleration enhances convergence speed and allows the WMV carry out effectively in order to find the best solutions.

Considering the better, best, and worst solutions, the *MeanRule* (*MR*), indicated in Equation (16), can be utilized to explain the increasing diversity of the population. In terms of the objective function value, it may be said that the best alternative is likely to be chosen at random from the top five solutions.

$$MR = rnd \times WMn1_l^g + (1-r) \times WMn2_l^g, q = 1,2,..,Np \tag{16}$$

$$WMn1_q^g = \delta \times \frac{(z_{a1}-z_{a2})\times wf_1 + (z_{a1}-z_{a3})\times wf_2 + (z_{a2}-z_{a3})\times wf_3}{wf_1+wf_2+wf_3+\varepsilon} + \varepsilon \times rnd, q = 1,2,...,Np \tag{16.1}$$

where

$$wf_1 = exp\left(-\left|\frac{(f(z_{a1})-f(z_{a2})}{\omega}\right|\right) \times cos(\,(f(z_{a1})-f(z_{a2})) + \pi), \tag{16.2}$$

$$wf_2 = exp\left(-\left|\frac{(f(z_{a1})-f(z_{a3})}{\omega}\right|\right) \times cos(\,(f(z_{a1})-f(z_{a3})) + \pi), \tag{16.3}$$

$$wf_3 = exp\left(-\left|\frac{(f(z_{a2})-f(z_{a3})}{\omega}\right|\right) \times cos(\,(f(z_{a2})-f(z_{a3})) + \pi), \tag{16.4}$$

$$\omega = max(\,f(z_{a1}), f(z_{a2}), f(z_{a3})), \tag{16.5}$$

$$WMn2_q^g = rnd \times \varepsilon + \frac{(z_{bs}-z_{bt})\times wf_1 + (z_{bs}-z_{ws})\times wf_2 + (z_{bt}-z_{ws})\times wf_3}{\varepsilon+wf_1+wf_2+wf_3} \times \delta, q = 1,2,...,Np \tag{16.6}$$

where

$$wf_1 = exp\left(-\left|\frac{(f(z_{bs})-f(z_{bt})}{\omega}\right|\right) \times cos(\,(f(z_{bs})-f(z_{bt})) + \pi), \tag{16.7}$$

$$wf_2 = exp\left(-\left|\frac{f(z_{bs})-f(z_{ws})}{\omega}\right|\right) \times cos(\,\left(f(z_{bs})-f(z_{ws})\right) + \pi), \tag{16.8}$$

$$wf_3 = exp\left(-\left|\frac{(f(z_{bt})-f(z_{ws})}{\omega}\right|\right) \times cos(\,\left(f(z_{bt})-f(z_{ws})\right) + \pi) \tag{16.9}$$

$$\omega = f(z_{ws}) \tag{16.10}$$

where *f*(*z*) indicates the value of the objective function, $a1 \neq a2 \neq a3 \neq l$ are multiple integers randomly selected from the domain of [1, *NP*]; ε has a very small constant value, *rndn* signifies a random value with a normal distribution, the symbol (*r*) represents a random number inside [0, 0.50], and w_1, w_2, and w_3 display three *WFs* to evaluate the weighted mean of the vectors, supporting the proposed WMV for investigating globally in the solution space. Among all vectors, the population's *g*th generation's best, worst, and enhanced outcomes are represented by z_{bt}, z_{bs}, and z_{ws}, respectively. After the results are categorized, these outcomes are created at each iteration.

The wavelet theory states that the purpose of the *WFs* is to diverge the *MR* space. There are two motivations to investigate the wavelet theory. The primary goal is to assist the WMV in finding the search space more effectively and achieving better results while applying the WMV technique by producing a powerful oscillation. The second objective is to create fine-tuning by modifying the dilation parameter displayed in the *WFs* in order to modify the *WF* amplitude. During the optimization procedure, the dilation parameter value is redirected in accordance with Equation (16.10). The scale factor is represented by the parameter (δ) in Equation (17), and β can be varied by utilizing the exponential function depicted in Equation (5.1):

$$\delta = \beta \times (2 \times rnd - 1) \tag{17}$$

$$\beta = 2\, exp\left(-4 \times g \frac{1}{max\, g}\right) \tag{17.1}$$

where *Maxg* indicates the largest number of generations. Additionally, the updating rule operator is enhanced with the convergence acceleration component (*CA*) to enable global search capacity. In the WMV, the closest outcome to global optima is the optimal solution. To verify that each vector in each generation has a varied step size, the *CA* obtained is multiplied by a random number (*rndn*) between [0,1] in Equation (18).

$$CA = rndn \times (z_{bs} - z_{a1}) \frac{1}{(\varepsilon - f(z_{a1}) + f(z_{bs}))}, \tag{18}$$

where rndn symbolizes a random number alongside a normal distribution.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 26 February 2026 doi:10.20944/preprints202602.1385.v1

Therefore, Equation (19) can be utilized used to evaluate the new vector:

$$Y_q^g = \sigma \times MR + z_q^g + CA \quad (19)$$

To identify suitable spaces in the search domain, the suggested WMV needs to perform a global search during the exploration phase. As a result, the updating rule that includes z_{bs}, z_{bt}, z_q^g, and z_{a1}^g is capable of being explained as appearing in the framework below:

If $rand < 0.5$

$$Y1_l^g = \sigma \times MR + z_l^g + rndn \times (z_{bs} - z_{a1}^g)\frac{1}{(1+f(z_{bs})-f(z_{a1}^g))};$$

$$Y2_q^g = \sigma \times MR + z_{bs} + rndn \times (z_{a1} - z_b^g)\frac{1}{(1+f(z_{a1}^g)-f(z_{a2}^g))}$$

Else

$$Y1_q^g = z_a^g + \sigma \times MR + rndn \times (z_{a2}^g - z_{a3}^g)\frac{1}{(1+f(z_{a2}^g)-f(z_{a3}^g))};$$

$$Y2_l^g = z_{bt} + \sigma \times MR + rndn \times (z_{a1}^g - z_{a2}^g)\frac{1}{(1+f(z_{a1}^g)-f(z_{a2}^g))}$$

End (20)

where the new vectors in the gth generation are represented by the symbols $Y1_q^g$ and $Y2_q^g$; the scaling rate of a vector can be observed by the parameter (σ), as explained in Equation (9). Besides, an exponential function that is demonstrated in Equation (21.1) is capable of being used for changing the parameter (α).

$$\sigma = \alpha \times (rnd \times 2 - 1) \quad (21)$$

$$\alpha = c\, exp\left(-d \times \frac{g}{Maxg}\right) \quad (21.1)$$

where the new vectors in the gth generation are indicated by the symbols $Y1_l^g$ and $Y2_l^g$. In this case, σ can be defined as depicted in Equation (21.2).

$$\sigma = rnd \times 2\alpha - \alpha \quad (21.2)$$

The following exponential function is able to be utilized for altering the factor α:

$$\alpha = c.\,exp\left(-\frac{g}{Maxg} \times d\right) \quad (21.3)$$

where c and d stand for the constants 2 and 4, respectively. It is evident that the current position can vary from the weighted mean of the vectors, indicating the exploration search, given that the variable σ has significant values. Conversely, when this parameter has small values, the current location support moves in the direction of the weighted mean of the vectors, which represents the exploitation search.

3.3. Vector Combining Stage

The vector merging operator is employed in WMV to avoid an early convergence to unsatisfactory solutions. This operator creates a new vector by combining two (or occasionally more) preexisting vectors from the population. A weighted average calculated according to a selected criterion, component averages, or other methods may be used in the combination. By adding diversity to the population, this procedure enables WMV to investigate various sections of the search space and possibly avoid becoming trapped in local optima, which are areas where only modest advances are feasible. In accordance with Equation (10), the two vectors ($Y1_q^g$ and $Y2_q^g$) are combined with vector x_l^g with regard to the criterion rnd < 0.5 to form the new vector u_l^g. This procedure is performed in order to increase the population's variety in WMV and improve local search potential to provide a new and desirable vector.

If $rnd < 0.50$

If $rnd < 0.50$; $u_q^g = \mu.\left|Y1_q^g - Y2_q^g\right| + Y1_q^g$

Else, $u_q^g = \mu.\left|Y1_q^g - Y2_q^g\right| + Y2_q^g$

End

Else, $u_q^g = z_q^g$

End (22)

where μ denotes 0.05× $rndn$ and u_q^g indicates the vector obtained using the vector amalgamation inside the gth generation.

3.4. Local Search for Refinement

WMV employs a local search process to find optimal solutions, even as the weighted mean and vector combining stages concentrate on exploration. This entails picking a potential vector—typically the best one discovered thus far or one selected at random from a favorable area. After that, a local search technique is used close to the selected vector. This approach may entail examining nearby solutions in the search space or making minor modifications to the vector's constituent parts. Finding even better options around the selected vector is the aim of the local search, which might accelerate convergence to ideal operating points that strike a compromise between environmental and economic goals. For boosting the convergence to global optima, search, and exploitation, the global position (z_{best}^{g}) and the mean-based criterion specified in Equation (13.1) are used to assess the local operator. In accordance to this operator, if $r < 0.5$, a novel vector could be formed around z_{best}^{g}:

If $rnd < 0.50$

If $rnd < 0.50, u_q^g = MR + z_{bs} + rndn \times (z_{bs} - z_{a1}^{g})$ (23.1)

Else, $u_q^g = z_{rnd} + rnd \times (rndn \times (v_1 \times z_{bs} - v_2 \times z_{rnd}) + MR)$

End

End (23.2)

In which

$z_{rnd} = ((1-\phi) \times \phi \times z_{bt} + \phi \times z_{avg} + (1-\phi)^2 \times z_{bs})$ (23.3)

$x_{avg} = (z_a + z_b + z_3)/3$ (23.4)

where ϕ stands for a random number between 0 and 1; and z_{rnd} exhibits an arbitrary combination of the z_{avg}, z_{bt}, and z_{bs} elements of the solutions that produce a new solution that creates the indeterminacy of the WMV for generating a superior search in the solution space. Two random numbers are represented by the two symbols υ_1 and υ_2, which are capable of being expressed in the following manner:

$$v_1 = \begin{cases} 2 \times rndifp > 0.5 \\ 1 otherwise \end{cases} \quad (23.5)$$

$$v_2 = \begin{cases} rndifp < 0.5 \\ 1 otherwise \end{cases} \quad (23.6)$$

where p provides a random number between 0 and 1. The random numbers υ1 and υ2 could potentially be used to boost the vector's significance of the optimal placement.

The number of iterations, vectors, and objects determines WMV's computational complexity, which may be evaluated as demonstrated in Equation (24):

$$O(CMV) = O(T \times (N \times d)) = O(TNd) \quad (24)$$

Figure 1 describes the suggested WMV's flowchart.

Simulation Results

IEEE 33-node and 69-node distribution feeders are used to validate the suggested WMV. The associated one-line diagram for the first feeder is displayed in Figure 2, where it consists of 32 distribution lines and 33 nodes, and demonstrate a typical voltage of 12.6600 kV. For the nominal loading condition, the total active (MW), reactive (MVAr), and apparent loads (MVA) are 3.7150, 2.3000, and 4.3690, respectively [31]. The networked one-line graph of the second feeder with a typical voltage of 12.66 kV can be seen in Figure 3, where it consists of 68 distribution lines and 69 nodes. The two entire system loads are 2.694 MVAr and 3.802 MW, respectively [32]. Furthermore, PV-STATCOM has a maximum reactive power threshold of ±1000 kVAr.

As illustrated in Figure 4 [33], the power factor of each load is maintained constant throughout the simulations, and the distribution nodes are expected to have the same loading curve.

doi:10.20944/preprints202602.1385.v1

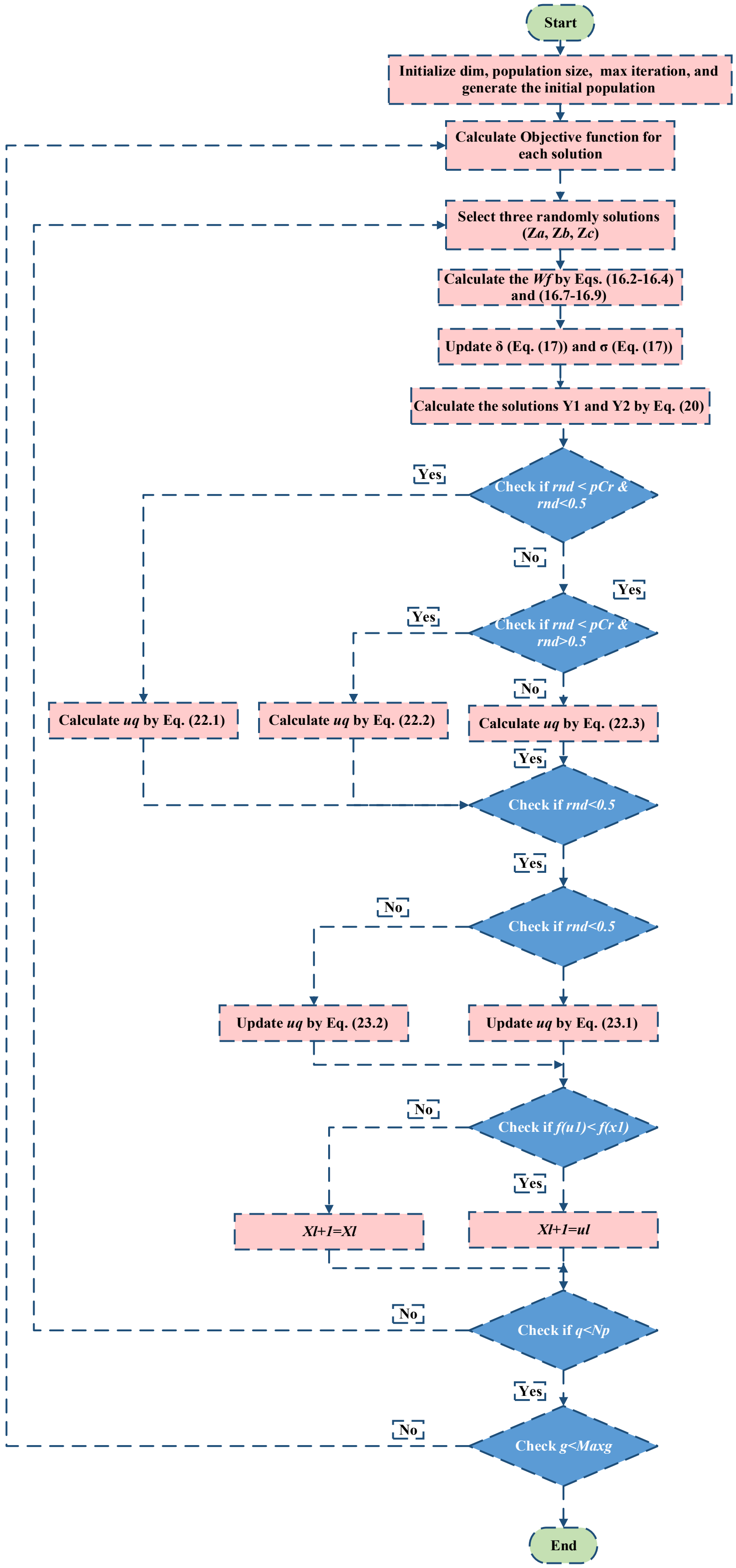


Figure 1. Main steps of the proposed WMV.

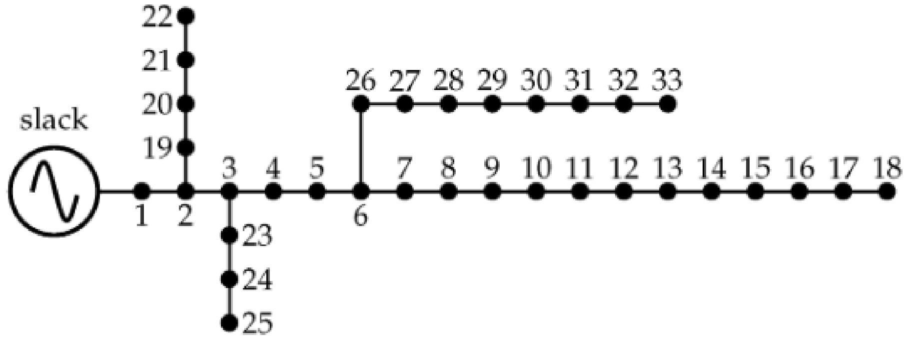


Figure 2. IEEE 33-distribution Feeder.

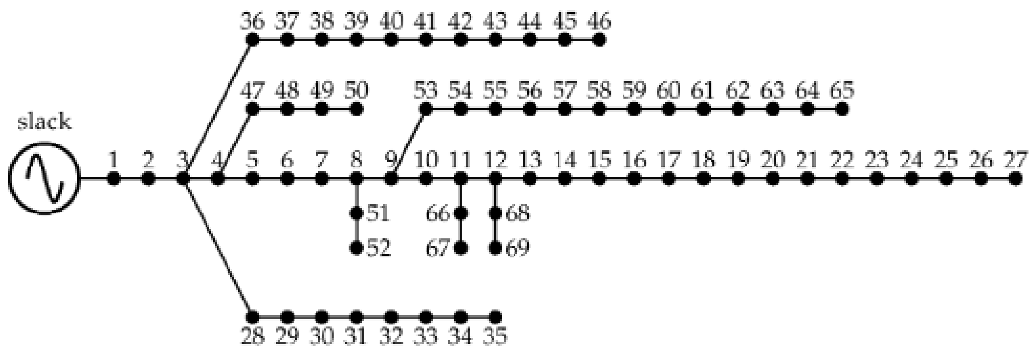


Figure 3. IEEE 69-distribution Feeder.

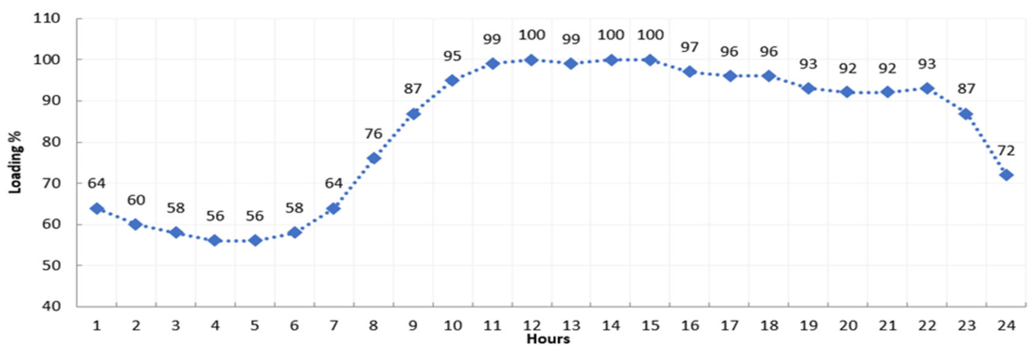


Figure 4. Hourly loading profile expressed as a percentage of the nominal state.

4.1. IEEE 33-Distribution Feeder

For PV-STATCOM allocation on the first system under examination, the proposed WMV is utilized in contrast to AROA, PSO, GSOA, HPOA and DEA in order to minimize energy losses and compromise voltage variations. There can only be three PV-STATCOM units in total. The results of the WMV, AROA [18], PSO [34], GSOA [34], HPOA [34] and DEA [18] for PV-STATCOM allocation are displayed in Table 1. In this table, the WMV define the installed buses that have the optimal allocation where the planned buses are 30, 13, and 29, and their associated PV sizes are 816, 999, and 660 kW, respectively. The accompanying STATCOM sizes at each of all three locations are ± 892, ±391, and ±618 kVAr, respectively. According to this data, the suggested WMV reduces energy losses from 10505.6 to 1398.029 with an improvement percentage of 86.69%, resulting in the least amount among other approaches. HPOA scores 1534.093 in the second rank, followed by AROA scores 1643.77 in the third rank, DEA in fourth place with 2132.16 and GSOA in fifth place with 2387.5. Consequently, PSO has 2909.081, which is the worst objective. Moreover, the hourly reactive power outputs of each PV-

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 26 February 2026 doi:10.20944/preprints202602.1385.v1

STATCOM using the proposed WMV algorithm for IEEE 33-distribution feeder are manifested in Figure 5.

Table 1. Allocations of PV-STATCOM for IEEE 33-distribution feeder.

Items		Initial	Proposed WMV	PSO	HPOA	DEA	GSOA	AROA
PV-STATCOM Devices	Installed nodes	-	30	2	11	10	31	7
		-	13	10	30	32	15	14
		-	29	28	26	33	8	31
	STATCOM Size (kVAr)	-	± 892	± 1000	± 1000	± 1000	953	862
		-	±391	±1000	±1000	±1000	965	769
		-	±618	±1000	±1000	±1000	842	838
	PV Size (kW)	-	816	451	840	1000	934	652
		-	999	1000	844	451	448	969
		-	660	1000	767	1000	716	830
Objective		10505.6	1398.029	2909.081	1534.093	2132.16	2387.5	1643.774

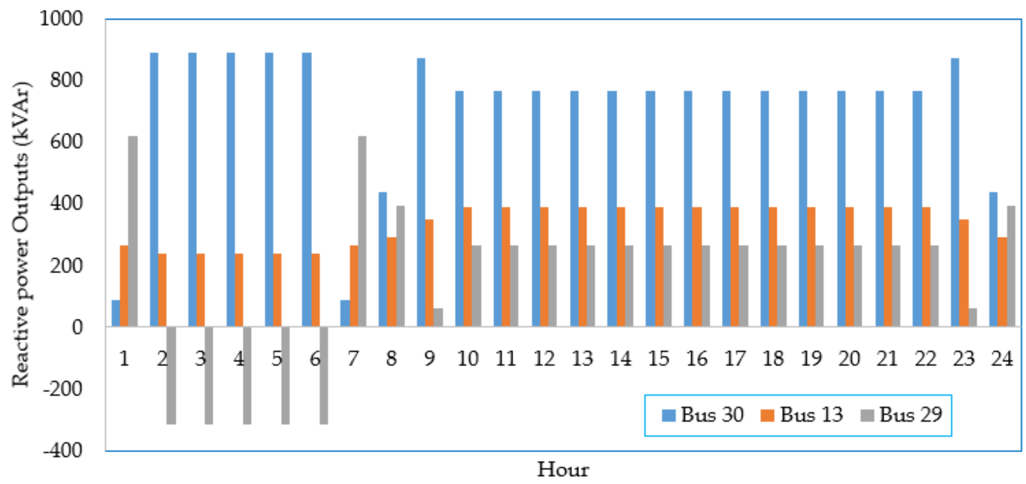


Figure 5. Hourly reactive power outputs of each PV-STATCOM using the proposed WMV algorithm for IEEE 33-distribution feeder.

Additionally, their pertinent convergence characteristics are displayed in Figure 6. As demonstrated from this figure that, the suggested WMV achieves the lowest trade-off of energy losses and voltage variations as compared to all other used methods, yielding outstanding convergence features. Beginning in the first 6% of iterations, the suggested WMV exhibits a quicker approach to the lower target values.

Figure 7 compares the hourly power losses of both of the most effective techniques, WMV and AROA, to the beginning instance in order to better illustrate the differences between them. It is evident that the suggested WMV significantly lowers power losses throughout the day in comparison to the original scenario. In comparison to the initial scenario, the WMV significantly reduces the energy losses from 3557.25 kW/day to 1398.0292 kW/day by 60.70%. When compared to AROA, the suggested WMV exhibits a notable decrease in power losses over the majority of hours. When using

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 26 February 2026 doi:10.20944/preprints202602.1385.v1

the WMV instead of AROA, the energy losses are reduced by 7.64%, from 1513.697 kW/day to 1398.0292 kW/day. Additionally, when using the WMV instead of AROA, the energy losses are reduced by 13.89%, from 1623.5602 kW/day to 1398.0292 kW/day. Furthermore, Figure 8 shows the associated hourly voltage deviations of WMV in comparison to AROA, HPOA and the initial scenario. Both AROA and HPOA achieve relatively similar advantages of 20.21 and 20.38 PU/day, respectively. It can be noticed that applying the WMV reduces voltage deviations from 35.643 PU/day to 16.13 PU/day, a 54.75% reduction over the initial scenario.

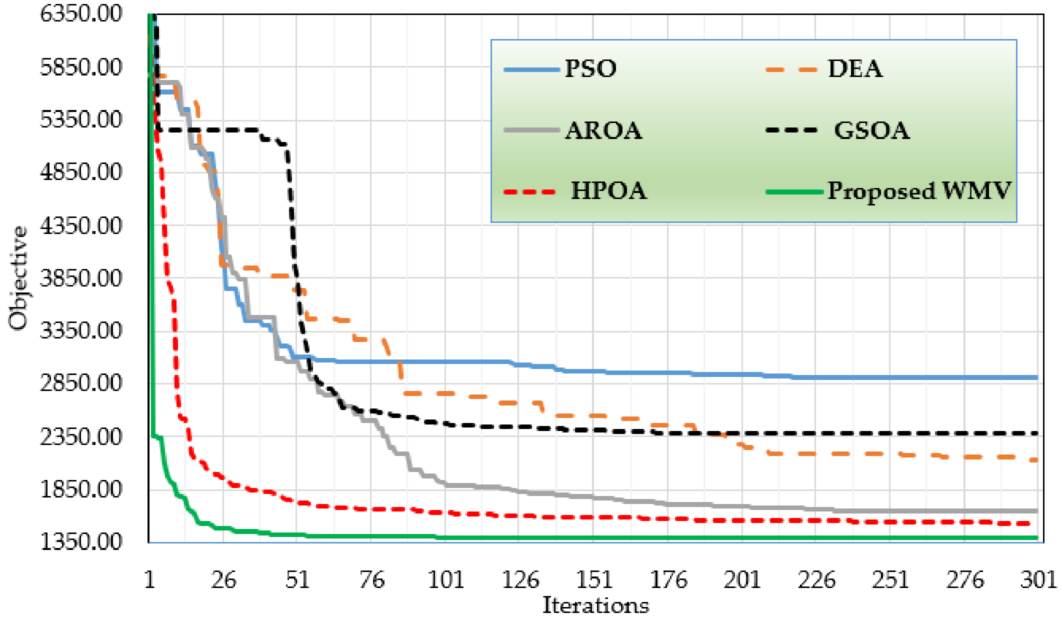


Figure 6. Convergence characteristics of the IEEE 33-distribution feeder applied techniques.

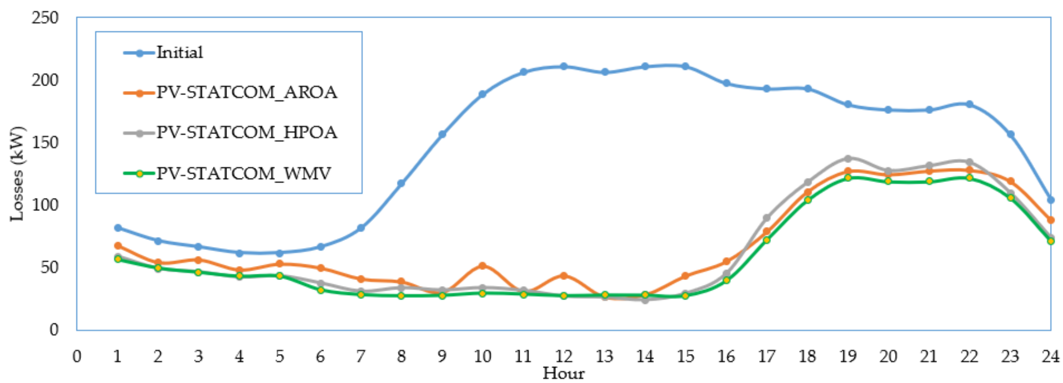


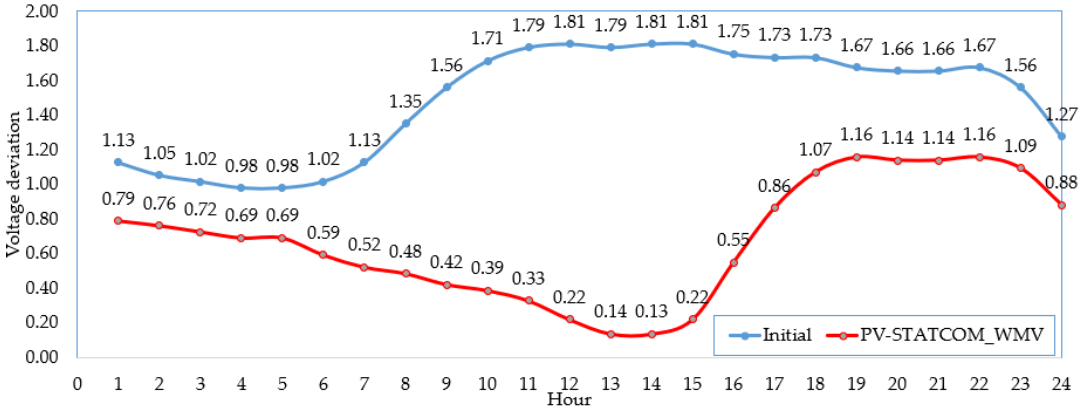
Figure 7. Hourly power losses based on the proposed WMV, AROA and HPOA versus the initial case for IEEE 33-distribution feeder.

4.2. IEEE 69-Distribution Feeder

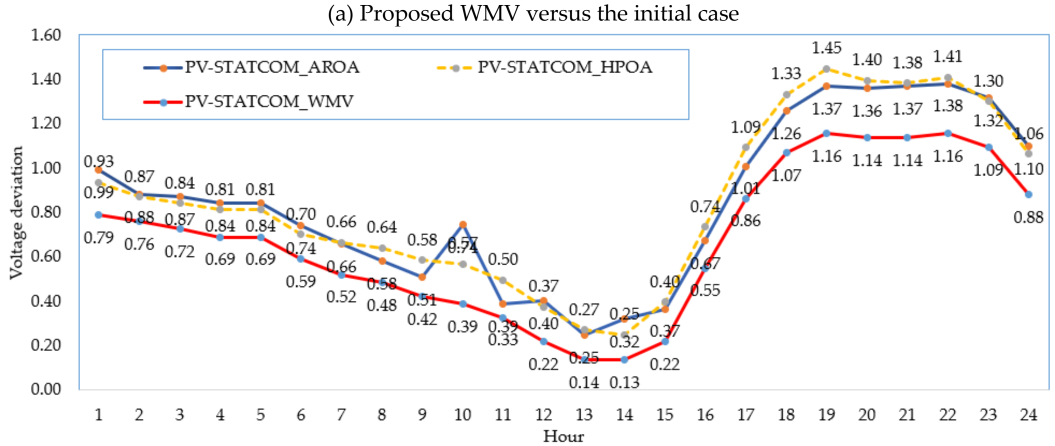
For PV-STATCOM allocation on the second system under examination, the proposed WMV is utilized in contrast to AROA, PSO, GSOA, HPOA and DEA in order to minimize energy losses and compromise voltage variations. There can only be three PV-STATCOM units in total. The results of the WMV, AROA [18], PSO [34], GSOA [34], HPOA [34] and DEA [18] for PV-STATCOM allocation are displayed in Table 2. In this table, the WMV define the installed buses that have the optimal allocation where the planned buses are 61, 12, and 9, and their associated PV sizes are 1000, 994, and

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 26 February 2026 doi:10.20944/preprints202602.1385.v1

540 kW, respectively. The accompanying STATCOM sizes at each of all three locations are ± 1000, ±420, and ±457 kVAr, respectively. According to this data, the suggested WMV reduces energy losses from 3821.42 to 1527.795 with an improvement percentage of 60.02%, resulting in the least amount among other approaches. HPOA scores 1616.607 in the second rank, followed by AROA scores 1622.933 in the third rank, DEA in fourth place with 1814.308 and GSOA in fifth place with 1952.972. Consequently, PSO has 2416.336, which is the worst objective. Moreover, the hourly reactive power outputs of each PV-STATCOM using the proposed WMV algorithm for IEEE 69-distribution feeder are manifested in Figure 9.



(a) Proposed WMV versus the initial case



(b) Proposed WMV versus AROA and HPOA

Figure 8. Hourly voltage deviations of IEEE 33-distribution feeder based on the proposed WMV against the initial case, AROA and HPOA.

Table 2. PV-STATCOM allocations for IEEE 69-distribution feeder.

Items		Initial	Proposed WMV	PSO	HPOA	DEA	GSOA	AROA
PV-STATCOM Devices	Installed nodes	-	61	63	63	61	64	61
		-	12	62	61	64	59	64
		-	9	61	2	69	62	62
	STATCOM Size (kVAr)	-	± 1000	± 1000	± 1000	± 1000	928	957
		-	±420	±1000	±1000	±1000	850	876
		-	±457	±1000	±1000	±1000	937	911

	PV Size (kW)	-	1000	508	1000	1000	967	737
		-	994	1000	1000	1000	488	964
		-	540	1000	10	498	806	774
Objective		3821.4161	1527.795	2416.336	1616.607	1814.308	1952.972	1622.933

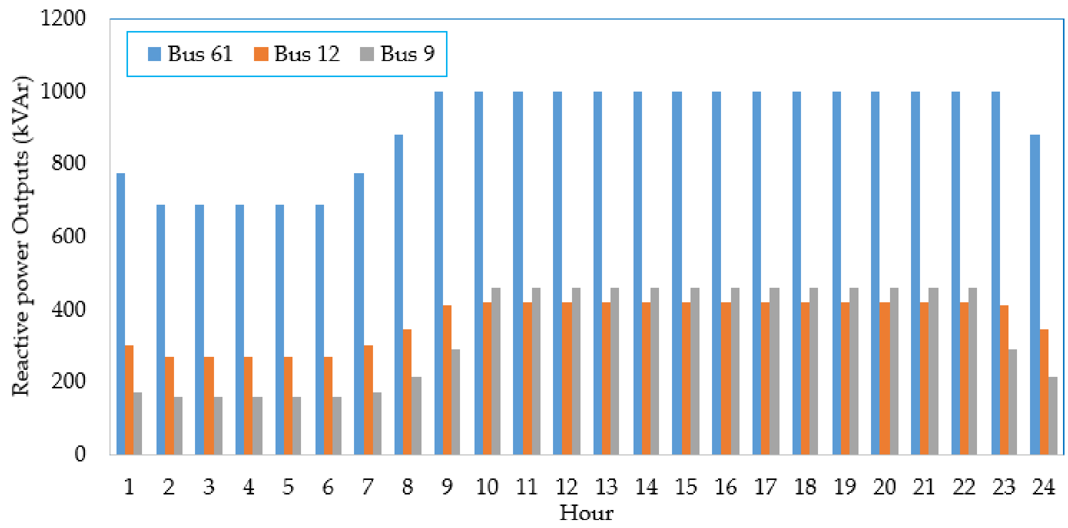
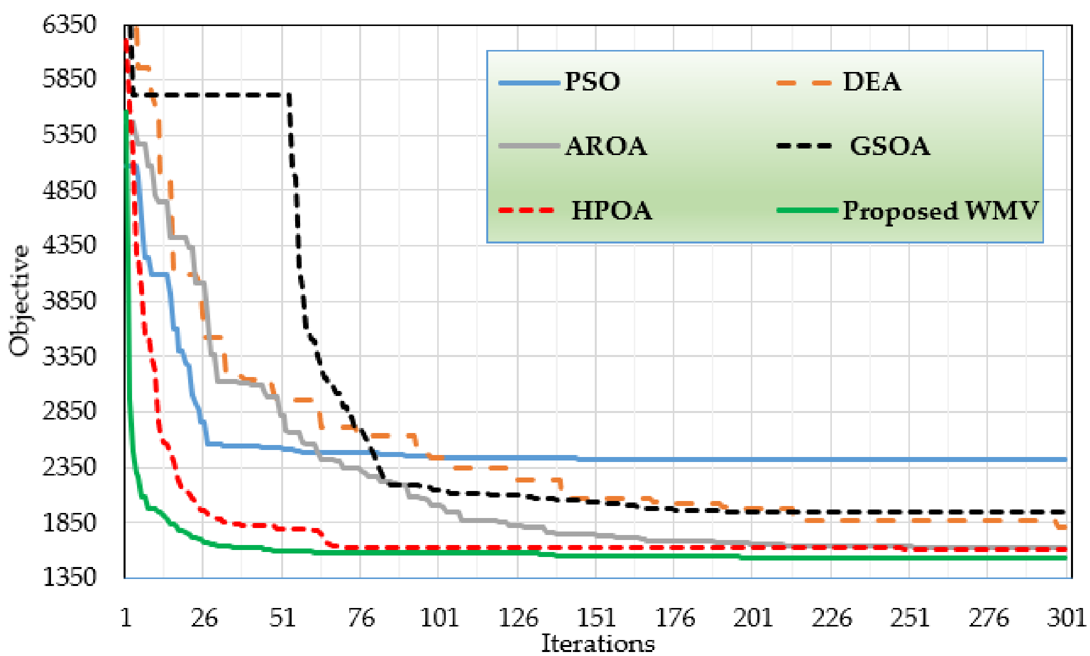


Figure 9. Hourly reactive power outputs of each PV-STATCOM using the proposed WMV algorithm for IEEE 69-distribution feeder.

Additionally, their pertinent convergence characteristics are displayed in Figure 10. As demonstrated from this figure that, the suggested WMV achieves the lowest trade-off of energy losses and voltage variations as compared to all other used methods, yielding outstanding convergence features. Beginning in the first 8% of iterations, the suggested WMV exhibits a quicker approach to the lower target values.



 doi:10.20944/preprints202602.1385.v1

Figure 10. Convergence properties of the applied algorithms for IEEE 69-distribution feeder.

Figure 11 compares the hourly power losses of both of the most effective techniques, WMV and AROA, to the beginning instance in order to better illustrate the differences between them. It is evident that the suggested WMV significantly lowers power losses throughout the day in comparison to the original scenario. In comparison to the initial scenario, the WMV significantly reduces the energy losses from 3784.5837 kW/day to 1527.7952 kW/day by 60.70%. When compared to AROA, the suggested WMV exhibits a notable decrease in power losses over the majority of hours. When using the WMV instead of AROA, the energy losses are reduced by 5.90%, from 1623.5602 kW/day to 1527.7952 kW/day. Additionally, when using the WMV instead of AROA, the energy losses are reduced by 4.13%, from 1593.6169 kW/day to 1527.7952 kW/day. Furthermore, Figure 12 shows the associated hourly voltage deviations of WMV in comparison to AROA, HPOA and the initial scenario. Both AROA and HPOA achieve relatively similar advantages of 21.65 and 22.99 PU/day, respectively. It can be noticed that applying the WMV reduces voltage deviations from 36.832 PU/day to 20.46 PU/day, a 44.54% reduction over the initial scenario.

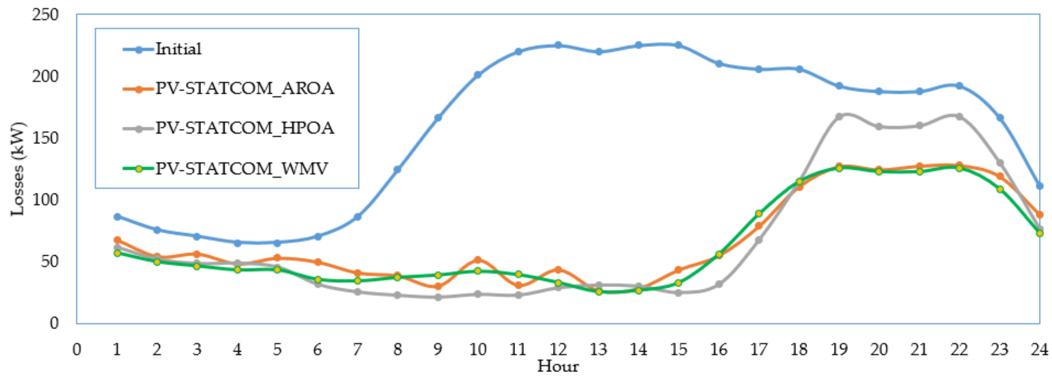
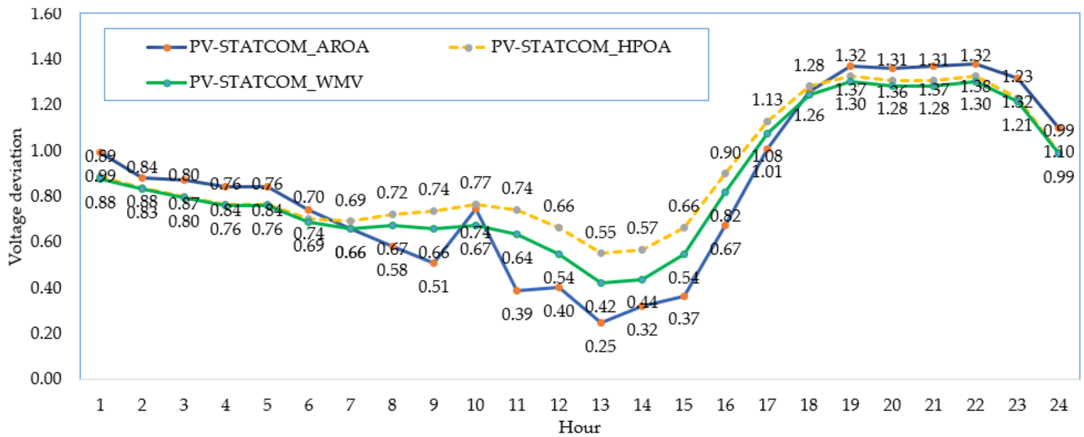
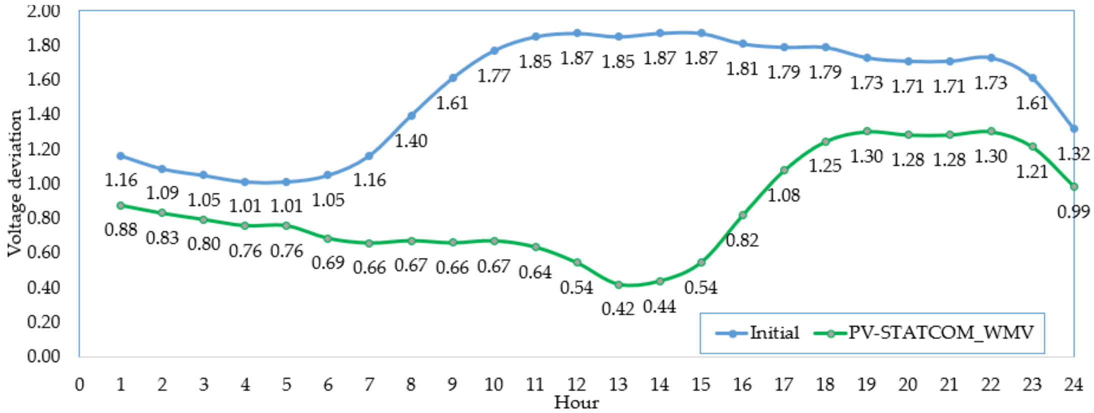


Figure 11. Hourly power losses of IEEE 69-distribution feeder based on the proposed WMV against the initial case, AROA, and HPOA.



(a) Proposed WMV versus the initial case



(b) Proposed WMV versus AROA and HPOA

Figure 12. Hourly voltage deviations of IEEE 69-distribution feeder based on the proposed WMV against the initial case, AROA and HPOA.

5. Conclusions

This paper presented a constrained mathematical optimization framework for the optimal allocation and sizing of PV-STATCOM devices in radial distribution systems under 24-hour load variations. The problem was formulated as a nonlinear, non-convex optimization model aiming to simultaneously minimize daily energy losses and voltage profile deviations while satisfying operational constraints, including voltage magnitude limits, branch thermal capacities, inverter active/reactive power limits, and renewable penetration restrictions. A penalty-based reformulation was adopted to effectively incorporate inequality constraints into the objective function. To solve the resulting optimization problem, the Weighted Mean of Vectors (WMV) algorithm was employed. The WMV optimizer integrates a wavelet-based weighted mean mechanism, a mean-driven rule update strategy, a vector combining operator to enhance population diversity, and a local search refinement process to improve convergence accuracy. This hybrid structure enables a balanced trade-off between global exploration and local exploitation within complex feasible search domains typical of power system planning problems.

The proposed mathematical framework was validated on the IEEE 33-bus and IEEE 69-bus distribution systems considering realistic daily loading profiles. Simulation results demonstrated substantial reductions in daily energy losses and voltage deviations compared to the initial operating conditions. Moreover, when benchmarked against established metaheuristic approaches, including PSO, DEA, AROA, and GSOA, the WMV algorithm consistently achieved superior compromise solutions with improved convergence characteristics and enhanced robustness. The analysis also confirmed that appropriate placement and sizing of multiple PV-STATCOM units significantly improve voltage regulation and system efficiency across all hourly operating conditions, maintaining voltage magnitudes within acceptable limits throughout the day.

Future work may extend the proposed formulation by incorporating stochastic modeling of solar generation uncertainty, investment cost considerations for techno-economic planning, multi-objective Pareto-based optimization, power reserve optimization [35] and hybridization of WMV with deterministic mathematical programming techniques. Additionally, integrating probabilistic load modeling and inverter capability curves could enhance practical applicability in real-world smart grid environments.

Acknowledgments: The authors gratefully acknowledge the funding of the Deanship of Graduate Studies and Scientific Research, Jazan University, Saudi Arabia, through Project number: (JU- 202503200 -DGSSR- RP -2025).

Data Availability Statement: Not Applicable.

Conflicts of Interest: The authors declare no conflict of interest. Non-financial competing interest.

 doi:10.20944/preprints202602.1385.v1

References

1. G. Fernández et al., "Optimal d-statcom placement tool for low voltage grids," *Energies (Basel).*, vol. 14, no. 14, 2021, doi: 10.3390/en14144212.
2. Z. M. Alves, R. M. Martins, G. Marchesan, and G. Cardoso Junior, "Metaheuristic for the Allocation and Sizing of PV-STATCOMs for Ancillary Service Provision," *Energies (Basel).*, vol. 16, no. 1, p. 424, Dec. 2022, doi: 10.3390/en16010424.
3. L. Luo et al., "Optimal siting and sizing of distributed generation in distribution systems with PV solar farm utilized as STATCOM (PV-STATCOM)," *Appl. Energy*, vol. 210, pp. 1092–1100, Jan. 2018, doi: 10.1016/J.APENERGY.2017.08.165.
4. M. H. Alqahtani, A. R. Ginidi, A. S. Aljumah, and A. M. Shaheen, "Cost-Effective and Low-Carbon Emission Deployment of PV-DG Integration in Distribution Networks Using Self-Adaptive Bonobo Optimizer," *International Journal of Energy Research*, vol. 2025, no. 1, 2025, doi: 10.1155/er/8830028.
5. A. M. El-Rifaie; et al., "Modified Gradient-Based Algorithm for Distributed Generation and Capacitors Integration in Radial Distribution Networks," *IEEE Access*, vol. 11, pp. 120899–120917, 2023, doi: 10.1109/ACCESS.2023.3326758.
6. G. Moustafa, M. A. Tolba, A. M. El-Rifaie, A. Ginidi, A. M. Shaheen, and S. Abid, "A Subtraction-Average-Based Optimizer for Solving Engineering Problems with Applications on TCSC Allocation in Power Systems," *Biomimetics*, vol. 8, no. 4, p. 332, Jul. 2023, doi: 10.3390/biomimetics8040332.
7. U. Shriya and S. H. Veena, "Increasing Grid Power Transmission Using PV-STATCOM," in *2021 6th International Conference for Convergence in Technology, I2CT 2021*, 2021. doi: 10.1109/I2CT51068.2021.9418077.
8. A. S. Aljumah, M. H. Alqahtani, A. M. Shaheen, and A. R. Ginidi, "Adaptive operational allocation of D-SVCs in distribution feeders using modified artificial rabbits algorithm," *Electric Power Systems Research*, vol. 245, p. 111588, Aug. 2025, doi: 10.1016/J.EPSR.2025.111588.
9. S. A. Ali, H. A. Mohammed, R. G. Ahmed, and M. S. Abdullah, "Improved Artificial Hummingbird Algorithm for Optimal Allocation of SVCs in Distribution Networks to Maximize Energy Efficiency," *Journal of Modern Power Systems and Clean Energy*, vol. 14, no. 1, pp. 261–272, 2026, doi: 10.35833/MPCE.2024.001380.
10. M. H. Alqahtani, S. Z. Almutairi, A. S. Aljumah, A. R. Ginidi, and A. M. Shaheen, "Enhanced power grid performance through Gorilla Troops Algorithm-guided thyristor controlled series capacitors allocation," *Heliyon*, vol. 10, no. 14, Jul. 2024, doi: 10.1016/J.HELIYON.2024.E34326/ASSET/6A5EA263-D595-4E82-AA96-31391146E01C/MAIN.ASSETS/GR2C.JPG.
11. R. Sirjani, "Optimal Placement and Sizing of PV-STATCOM in Power Systems Using Empirical Data and Adaptive Particle Swarm Optimization," *Sustainability 2018, Vol. 10, Page 727*, vol. 10, no. 3, p. 727, Mar. 2018, doi: 10.3390/SU10030727.
12. R. K. Varma, V. Khadkikar, and R. Seethapathy, "Nighttime application of PV solar farm as STATCOM to regulate grid voltage," *IEEE Transactions on Energy Conversion*, vol. 24, no. 4, 2009, doi: 10.1109/TEC.2009.2031814.
13. R. K. Varma, B. Das, I. Axente, and T. Vanderheide, "Optimal 24-hr utilization of a PV solar system as STATCOM (PV-STATCOM) in a distribution network," in *IEEE Power and Energy Society General Meeting*, 2011. doi: 10.1109/PES.2011.6039864.
14. S. Gasperic and R. Mihalic, "Estimation of the efficiency of FACTS devices for voltage-stability enhancement with PV area criteria," *Renewable and Sustainable Energy Reviews*, vol. 105, 2019, doi: 10.1016/j.rser.2019.01.039.
15. R. Sadiq, Z. Wang, C. Y. Chung, C. Zhou, and C. Wang, "A review of STATCOM control for stability enhancement of power systems with wind/PV penetration: Existing research and future scope," 2021. doi: 10.1002/2050-7038.13079.
16. R. K. Varma and E. M. Siavashi, "Enhancement of solar farm connectivity with smart PV inverter PV-STATCOM," *IEEE Transactions on Sustainable Energy*, vol. 10, no. 3, 2019, doi: 10.1109/TSTE.2018.2862405.
17. R. K. Varma and E. M. Siavashi, "PV-STATCOM: A New Smart Inverter for Voltage Control in Distribution Systems," *IEEE Transactions on Sustainable Energy*, vol. 9, no. 4, 2018, doi: 10.1109/TSTE.2018.2808601.

18. M. Elshahed, M. A. Tolba, A. M. El-Rifaie, A. Ginidi, A. Shaheen, and S. A. Mohamed, "An Artificial Rabbits’ Optimization to Allocate PVSTATCOM for Ancillary Service Provision in Distribution Systems," *Mathematics 2023, Vol. 11, Page 339*, vol. 11, no. 2, p. 339, Jan. 2023, doi: 10.3390/MATH11020339.
19. P. Kumar and A. K. Bohre, "Optimal allocation of Hybrid Solar-PV with STATCOM based on Multi-objective Functions using combined OPF-PSO Method," *SSRN Electronic Journal*, 2021, doi: 10.2139/ssrn.3882597.
20. L. N. Popavath and P. Kaliannan, "Photovoltaic-STATCOM with low voltage ride through strategy and power quality enhancement in a grid integrated Wind-PV system," *Electronics (Switzerland)*, vol. 7, no. 4, 2018, doi: 10.3390/electronics7040051.
21. L. Luo et al., "Optimal siting and sizing of distributed generation in distribution systems with PV solar farm utilized as STATCOM (PV-STATCOM)," *Applied Energy*, vol. 210, pp. 1092–1100, Jan. 2018, doi: 10.1016/J.APENERGY.2017.08.165.
22. I. Ahmadianfar, A. A. Heidari, S. Noshadian, H. Chen, and A. H. Gandomi, "INFO: An efficient optimization algorithm based on weighted mean of vectors," *Expert Syst. Appl.*, vol. 195, 2022, doi: 10.1016/j.eswa.2022.116516.
23. M. Elnagi, S. Kamel, A. Ramadan, and M. F. Elnaggar, "Photovoltaic Models Parameters Estimation Based on Weighted Mean of Vectors," *Computers, Materials and Continua*, vol. 74, no. 3, 2023, doi: 10.32604/cmc.2023.032469.
24. R. M. A. Ikram, R. R. Mostafa, Z. Chen, K. S. Parmar, O. Kisi, and M. Zounemat-Kermani, "Water Temperature Prediction Using Improved Deep Learning Methods through Reptile Search Algorithm and Weighted Mean of Vectors Optimizer," *J. Mar. Sci. Eng.*, vol. 11, no. 2, 2023, doi: 10.3390/jmse11020259.
25. X. Tang, H. Zhang, and B. Taheri, "Opimal design and 4E evaluation of a CCHP system using an improved version of weighted mean of vectors algorithm," *Int. J. Hydrogen Energy*, vol. 48, no. 43, 2023, doi: 10.1016/j.ijhydene.2023.01.027.
26. A. Nasef, A. Shaheen, and H. Khattab, "Local and remote control of automatic voltage regulators in distribution networks with different variations and uncertainties: Practical cases study," *Electric Power Systems Research*, vol. 205, p. 107773, 2022, doi: https://doi.org/10.1016/j.epsr.2022.107773.
27. S. A. Ali, H. A. Mohammed, R. G. Ahmed, and M. S. Abdullah, "Improved Artificial Hummingbird Algorithm for Optimal Allocation of SVCs in Distribution Networks to Maximize Energy Efficiency," *Journal of Modern Power Systems and Clean Energy*, vol. 14, no. 1, pp. 261–272, 2026, doi: 10.35833/MPCE.2024.001380.
28. A. M. Shaheen, A. M. Elsayed, R. A. El-Sehiemy, S. Kamel, and S. S. M. Ghoneim, "A modified marine predators optimization algorithm for simultaneous network reconfiguration and distributed generator allocation in distribution systems under different loading conditions," *Engineering Optimization*, pp. 1–22, Apr. 2021, doi: 10.1080/0305215X.2021.1897799.
29. Mohammed H. Alqahtani;, A. Draz;, A. M. Shaheen;, and A. El-Fergany, "Advanced Relay Coordination in Power Networks Considering Transformer Inrush and Motor Starting Currents via Weighted Mean Variance Optimizer," *IEEE Access*, vol. 12, pp. 184953–184975, 2024, doi: 10.1109/ACCESS.2024.3511698.
30. A. M. Shaheen, A. M. El-Rifaie, B. Al Faiya, G. Moustafa, and H. Alnami, "Economic and environmental optimization-dispatch in large-scale power systems using weighted mean of vectors algorithm," *Sustainable Computing: Informatics and Systems*, vol. 48, p. 101265, Dec. 2025, doi: 10.1016/J.SUSCOM.2025.101265.
31. A. Shaheen, R. El-Sehiemy, S. Kamel, and A. Selim, "Optimal Operational Reliability and Reconfiguration of Electrical Distribution Network Based on Jellyfish Search Algorithm," *Energies (Basel).*, vol. 15, no. 19, p. 6994, Sep. 2022, doi: 10.3390/en15196994.
32. A. Paz-Rodríguez, J. F. Castro-Ordoñez, O. D. Montoya, and D. A. Giral-Ramírez, "Optimal integration of photovoltaic sources in distribution networks for daily energy losses minimization using the vortex search algorithm," *Applied Sciences (Switzerland)*, vol. 11, no. 10, 2021, doi: 10.3390/app11104418.
33. A. El-Ela et al., "Renewable Energy Micro-Grid Interfacing: Economic and Environmental Issues," *Electronics (Basel).*, vol. 11, no. 815, 2022, doi: 10.3390/electronics11050815.

 doi:10.20944/preprints202602.1385.v1

34. D. Rekioua et al., "Optimal Allocation of PV-STATCOM Devices in Distribution Systems for Energy Losses Minimization and Voltage Profile Improvement via Hunter-Prey-Based Algorithm," *Energies 2023, Vol. 16, Page 2790*, vol. 16, no. 6, p. 2790, Mar. 2023, doi: 10.3390/EN16062790.
35. A. S. Aljumah, M. H. Alqahtani, A. R. Ginidi, and A. M. Shaheen, "Combined heat and power dispatch with reserve constraints using a mutated trochoid searching optimizer," *Electric Power Systems Research*, vol. 252, p. 112447, Jan. 2026, doi: 10.1016/J.EPSR.2025.112447.