An improved particle swarm optimization for optimal configuration of standalone photovoltaic scheme components

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Abstract
The hybrid energy system design problem needs efficacy tools to reach optimal results in remote areas. The metaheuristic optimization methods are the best choice to address complex problems. This article presents an improved approach based on an energy management strategy for optimal sizing and configuration of standalone photovoltaic scheme components. Improved particle swarm optimization for optimization and configuration of photovoltaic panel and battery system is applied using MATLAB and hourly solar radiation, ambient temperature data, and load demand. The objective of the optimization problem is to define the optimal sizing of the system components to meet the load demand to compose a cost-effective and reliable scheme. The optimized system results from the improved approach are compared with original particle swarm optimization and simulated annealing algorithms. So, the optimum design of the hybrid scheme is analyzed and compared based on different reliability values. The results show that the improved approach finds the optimal results easily with lower cost, faster convergence, and better reliability indexes in different reliability indexes in comparison with the other approaches. In this regard, for different reliability values (1%, 3%, and 5%), the improved particle swarm optimization shows approximately 22.9% cost saving in comparison with the simulated annealing, and improved particle swarm optimization shows approximately 0.35% cost saving in comparison with the particle swarm optimization. Also, show the reliability of the standalone hybrid photovoltaic system.

Keywords
improved particle swarm optimization, optimal configuration, reliability, standalone photovoltaic system
1 | INTRODUCTION

Many countries around the world are currently experiencing a power shortage, especially in remote areas. In these areas, fossil fuels, especially diesel generators, are commonly used to supply electricity. Due to fossil fuels reduction and severe environmental concerns, the choice of alternative methods and fuels is essential. Renewable energy resource especially solar energy, as an alternative source, has grown in recent years. Among the renewable energy resource, solar energy is the most attractive alternative source to meet the load demand due to its easier predictability compared to wind and availability in various areas.

The photovoltaic (PV) panel system is widely utilized to supply the required load demand independently or connected to the grid. In grid-independent systems, the use of a backup and storage system is essential. The battery storage unit is a common storage system. So, application of the hybrid PV system based on energy storage to supply the required load in remote areas is necessary. In recent years, the use of standalone photovoltaic systems based on energy storage has made rapid progress to cover the sporadic nature and uncertainty of solar energy sources. The primary objective of standalone photovoltaic studies is an improvement of the system performance based on economic and technical criteria. To have a cost-effective and reliable system, optimal configuration and design of standalone hybrid system are necessary. As a result, choosing a powerful optimization method will be required.

Several studies have focused on the investigation of optimization of standalone hybrid energy schemes. Also, several methods have been proposed for optimizing energy systems, including particle swarm optimization (PSO), simulated annealing (SA), genetic algorithm (GA), monarch butterfly optimization, improved harmony search, slime mold algorithm, moth search algorithm, hunger games search, harmony search optimization, Runge Kutta method, Harris hawks optimization, colony predation algorithm, and tabu search. Belouda et al used a model to optimally size a hybrid PV/wind/battery storage scheme for supplying a standalone application located in the north of Tunisia. Yu et al used marine predators algorithm for optimization of a hybrid photovoltaic/diesel generator/battery scheme for supplying the load demand of an isolated area in China. The obtained results were compared with the HOMER software. Altun and Kilic designed a hybrid standalone power scheme based on PV–wind–diesel–battery to meet the electricity demand of a building in Turkey. El-Sattar et al used two optimization algorithms, namely slime mold method and seagull optimization method for optimization and minimizing the energy cost of the hybrid PV/wind/biomass/battery scheme for supplying the load demand of an isolated area in Abu-Monqar, Egypt. It is found that the slime mold algorithm is better than other algorithms. Anoune et al used the GA for techno-economic analysis and optimization of the hybrid PV/wind/battery scheme using a time-series energy exchange during a typical week in each season for supplying the load demand in remote areas. Emad et al employed the grey wolf optimizer algorithm to find the optimal sizes of hybrid PV/wind/battery schemes to meet the load demand for remote areas in Egypt-Sinai. The obtained results were compared with the GA. Ferahtia et al proposed an energy management strategy based on the bald eagle search optimization method for optimization of hybrid PV/fuel cell/battery scheme that was designed for a one-day scheduling horizon. Liu et al used the harmony search algorithm to the optimal structure of a hybrid solar/battery scheme to meet the load demand in remote areas. It is found that, by increasing the reliability of the scheme, the total costs of the scheme are increased. Jiang et al investigated an optimal design of a hybrid PV–battery scheme with various PV panels and batteries under the smoothing scenario. Mohammed et al proposed a PSO method to optimize the power generated by a hybrid renewable energy scheme that consists of wind/solar/batteries to satisfy the energy demands of a remote area in Brittany, France. Junaid Khan et al used HOMER software for optimization of different hybrid systems based on solar/wind/diesel/battery for various cities in Punjab, India. Techno-economic analysis of the hybrid solar/wind schemes for supplying a load of industrial parks in remote areas of Ethiopia using HOMER software are presented by Azerefegn et al Naik et al used a hybrid algorithm based on the monarch butterfly and sine-cosine for optimization of the standalone microgrid system. The obtained results were compared with the PSO algorithm. Suman et al used a hybrid optimization algorithm based on PSO for optimization of the hybrid solar/wind/bio-generator/diesel/battery scheme for remote locations in Indian. Ghorbani et al applied an optimization algorithm based on PSO for the optimal sizing of a standalone house based on solar, wind, and battery. It was found that the PSO is one of the most powerful optimization methods. Almadhor et al presented a PSO algorithm for capacity configuration optimization of a hybrid solar/battery system. Sawle et al presented the optimal planning of hybrid solar, wind, battery bank, and diesel generator schemes to minimize the cost of energy as an objective function using the PSO algorithm. Azaza and Wallin used a PSO algorithm for the optimization of an off-grid hybrid microgrid scheme based on PV, wind, battery storage, and diesel in various locations. Stopato et al used an optimization model based on the PSO for the optimization of a hybrid PV–pump hydroenergy storage scheme for supplying load and water demand of a remote area in Nigeria.
Studies show that the PSO algorithm is one of the powerful and famous algorithms for the optimization of hybrid energy schemes. The PSO method is a stochastic optimization algorithm based on swarm and intelligence. PSO method simulates some animal's social behavior, such as insects, herds, birds, and fishes. The PSO algorithm has experienced a multitude of enhancements in different fields, and it is one of the powerful and famous algorithms. Researchers used PSO algorithms in different fields (scientific research and engineering use), especially in the optimization of hybrid renewable energy systems. Compared with the other heuristic algorithms, easy implementation, simple concept, computational efficiency, and robustness to control parameters are the advantages of the PSO algorithm. The disadvantages of the PSO algorithm are that the method has a low convergence rate in the iterative process and is easy to fall into local optimum in high-dimensional space, which causes to be less exact at the regulation of its speed and the direction.

In literature, different aspects of optimization of the standalone hybrid energy schemes have been proposed, and many optimization algorithms have been presented for providing the load demand. Results indicate that very few studies include the improved optimization algorithm based on particle swarm optimization and informative models for configuration and sizing of the standalone photovoltaic scheme components.

This article presents an improved optimization algorithm based on an energy management strategy for optimal sizing and configuration of standalone photovoltaic scheme components. In this regard, an improved PSO for the design of a standalone energy system with photovoltaic panels and battery storage subsystem is established to simultaneously minimize the lifetime cost and reliability index objectives. A standalone hybrid PV/battery system in a residential area is taken as a case study to determine the application of the suggested method. The optimized system results from the improved approach are compared by original particle swarm optimization and SA algorithms. So, the optimum design of the hybrid scheme is analyzed and compared based on different reliability values. The major contributions of this work are summarized as follows:

- An improved particle swarm optimization method is proposed to fill the gap in the field of optimal configuration of hybrid system components.
- Uncertainties related to meeting the load demand in standalone systems are correctly resolved by a hybrid PV panel and battery storage system based on an energy management strategy.
- Based on indicators such as the lifetime cost and reliability index, the features of the hybrid scheme components are compared and analyzed to determine the best hybrid system components selection.
- The optimized system results from the improved approach are compared by original particle swarm optimization and SA algorithms.
- Several comparative experiments are designed to verify the reliability of the proposed improved approach.
- Sensitivity analysis is conducted on the optimized hybrid system components to test the influence of various input reliability indexes.

The rest of the paper is organized as follows: the modeling of the hybrid scheme is described in Section 2. Optimization criteria are presented in Section 3. The proposed optimization algorithm is introduced in Section 4. Then, the results and discussion are presented in Section 5; and in Section 6, the finding results are concluded.
2 | MODELING OF THE HYBRID SCHEME

In this section, the standalone photovoltaic system components are considered for optimization. Figure 1 illustrates the graphical diagram of the proposed hybrid energy scheme, which involves a photovoltaic panel, a power conditioner unit, such as an inverter/convertor, batteries, load dumper, and charge controller. The PV panel and battery energy system are connected to the DC bus, where the PV panels provide the required load demand. The generated power by the PV panels and energy storage systems is converted through DC/AC inverter to supply the load demand.

2.1 | Photovoltaic

The generated power of the PV array \( p_{PV} \) based on solar radiation (SR) and the cell temperature \( T_c \) can be determined according to the following equations:\(^47\):

\[
p_{PV}(t) = P_{R,PV} \times (SR/\text{SR ref}) \times [1 + N_T (T_c - T_{ref})] \quad (1)
\]

\[
T_c = T_{air} + \left( \left( T_{NO} - 20 \right) / 800 \right) \times \text{SR} \quad (2)
\]

where \( P_{R,PV} \), \( \text{SR ref} \), and \( N_T \) refer to the rated power of the PV panel, reference solar radiation (1000 W/m\(^2\)), and panel temperature coefficient (\(-3.7 \times 10^{-3} \text{ (1/°C)}\)), and \( T_{ref}, T_{air} \) and \( T_{NO} \) denote the reference (25°C), ambient, and normal operating cell temperature, respectively.\(^48\) Based on the \( N_{PV} \) (number of PV panels), the total produced power of PV panels is \( P_{PV}(t) = N_{PV} \times p_{PV}(t) \).

2.2 | Storage system

The standalone photovoltaic system needs a storage system to charge excess energy through high-energy generation times to supply the electrical demand at lacking SR times. The energy storage level (ESL) of the battery bank is determined by employing the following equations:\(^49\):

In charging mode:

\[
\text{ESL}(t) = \text{ESL}(t-1) \cdot (1 - \sigma) + \left[ \left( E_{\text{PV}}(t) \cdot \eta_{\text{INV}} \right) - \frac{E_{\text{Load}}(t)}{\eta_{\text{INV}}} \right] \cdot \eta_{\text{BDC}} \quad (3)
\]

In discharging mode:

\[
\text{ESL}(t) = \text{ESL}(t-1) \cdot (1 - \sigma) - \left[ \frac{E_{\text{Load}}(t)}{\eta_{\text{INV}}} - \left( E_{\text{PV}}(t) \cdot \eta_{\text{INV}} \right) \right] / \eta_{\text{BDC}} \quad (4)
\]

where ESL \( (t) \) is energy storage level at time \( t \), \( \sigma \) denotes the rate of hourly self-discharge, \( \eta_{\text{INV}}, \eta_{\text{BDC}} \), and \( \eta_{\text{BDC}} \) are the efficiency of the inverter, charging, and discharging mode, respectively. \( E_{\text{Load}} \) represents demand of load at time \( t \).

3 | OPTIMIZATION CRITERIA

In optimal sizing and configuration of standalone photovoltaic scheme components to cover the load demand, researchers should evaluate the standalone photovoltaic scheme based on technical and economic constraints. An optimal standalone photovoltaic scheme is created with the optimal compromise between cost criteria and reliability index based on other limitations. In this paper, the loss of load supply probability (LLSP), as a reliability index, and the total net annual cost (TNAC), as cost criteria, are applied to find the ideal sizing of the hybrid scheme.

3.1 | Loss of load supply probability

In order to have a system with acceptable reliability, LLSP is applied, which shows how often the standalone photovoltaic scheme is inefficient in supplying electrical power. Mathematically, LLSP for 1 year (8760 h) is expressed as:

\[
\text{LLSP} = \frac{\sum_{t=1}^{T} \text{LLS}(t)}{\sum_{t=1}^{T} E_{\text{Load}}(t)} \quad (5)
\]

Here, LLS denotes the loss of load supply whenever the energy demand is more than the energy produced \( (E_{\text{Gen}}) \).

\[
\text{LLS}(t) = E_{\text{Load}}(t) - E_{\text{Gen}}(t) \quad (6)
\]

3.2 | Total net annual cost

TNAC includes the annual operation and maintenance cost \( (O&M) \) and annual capital and replacement cost \( (C&R) \). In the optimization process, the TNAC must be minimized as an objective function.

\[
\text{Minimize. TNAC} = \sum (C \& R + O \& M) \quad (7)
\]

By recognizing the project lifetime, replacement periods, annualized O&M costs, and annualized C&R costs for each component of the standalone photovoltaic scheme, the TNAC value can be determined according to the following equations:

\[
C \& R = CRF \cdot \left[ N_{PV} \cdot C \& R_{PV} + N_{BAT} \cdot C \& R_{BAT} + N_{INV} \cdot C \& R_{INV} \right] \quad (8)
\]
where $N_{\text{INV}}$ and $N_{\text{BAT}}$ denote the number of inverter and battery, $C\&R_{\text{PV}}$ is the PV panel unit cost, and CRF represents the capital recovery factor, which is defined by the following equation based on the interest rate ($i$) and project lifespan ($n$):

$$\text{CRF} = \frac{i(1+i)^n}{(1+i)^n - 1} \quad (9)$$

Based on the battery lifetime (here 5 years) and its replacement periods, present worth of battery ($C\&R_{\text{BAT}}$) by utilizing the single payment present worth factor is expressed according to the following equation:

$$C\&R_{\text{BAT}} = P_{\text{BAT}} \cdot \left(1 + \frac{1}{(1+i)^5} + \frac{1}{(1+i)^{10}} + \frac{1}{(1+i)^{15}}\right) \quad (10)$$

where $P_{\text{BAT}}$ denotes the battery price.

Similarly, based on the inverter/converter lifetime (here 10 years), the present worth of converter/inverter ($C\&R_{\text{INV}}$) based on its price ($P_{\text{INV}}$) is derived as:

$$C\&R_{\text{INV}} = P_{\text{INV}} \times \left(1 + \frac{1}{(1+i)^{10}}\right) \quad (11)$$

The O&M cost of the components of the hybrid system is expressed according to the following equation:

$$O\&M = N_{\text{PV}} \cdot O\&M_{\text{PV}} + N_{\text{BAT}} \cdot O\&M_{\text{BAT}} + N_{\text{INV}} \cdot O\&M_{\text{INV}} \quad (12)$$

Here, $O\&M_{\text{PV}}$, $O\&M_{\text{BAT}}$, and $O\&M_{\text{INV}}$ are the O&M costs of the PV panel, battery, and inverter/converter unit, respectively.

### 3.3 Constraints

The optimization algorithm is working according to the highest allowable value of LLSP (RI), and other limitations of the decision variables:

$$\text{LLSP} \leq \text{RI} \quad (13)$$

$$0 \leq N_{\text{PV}} \leq N_{\text{PV-Max}} \quad (14)$$

$$0 \leq N_{\text{BAT}} \leq N_{\text{BAT-Max}} \quad (15)$$

$$\text{ESL-Min} \leq \text{ESL} \leq \text{ESL-Max} \quad (16)$$

$$\text{ESL-Min} = (1 - \text{DOD}) \cdot S_{\text{BAT}} \quad (17)$$

where $N_{\text{BAT-Max}}$ and $N_{\text{PV-Max}}$ refer to the maximum number of PV panels and batteries, ESL$_{\text{Min}}$ and ESL$_{\text{Max}}$ are the minimum and maximum energy storage level of the battery bank, and $S_{\text{BAT}}$ and DOD are the nominal capacity of battery and depth of discharge, respectively.

### 3.4 Operation strategy

The operation strategy used in the proposed standalone photovoltaic system can be determined according to the following steps:

- When the energy generated from the standalone photovoltaic system satisfied the load demand, the required load is supplied without the use of the storage system (battery).
- When the energy generated from the standalone photovoltaic system exceeds the load demand, it will feed the storage system.
- When the energy generated from the standalone photovoltaic scheme is insufficient to meet the load demand, the energy storage unit is used to make up for the shortage in power generation.

### 4 Particle Swarm Optimization

The particle swarm optimization is an evolutionary algorithm based on the movement of organisms in a fish school or bird flock, which was presented by Kennedy and...
Eberhart. The PSO was simplified to optimization and can search very large spaces of candidate solutions. PSO solves an optimization problem by having particles in the search space based on the particle’s position and velocity, which is updated in the following manner:

\[ x_{i}^{k+1} = x_{i}^{k} + v_{i}^{k+1} \]  
\[ v_{i}^{k+1} = \omega \cdot v_{i}^{k} + c_{1} \cdot r_{1} \cdot (p_{\text{best}}^{k} - x_{i}^{k}) + c_{2} \cdot r_{2} \cdot (g_{\text{best}}^{k} - x_{i}^{k}) \]  

The values \( x_{i}^{k} \) and \( v_{i}^{k} \) represent the \( i \)th particle position and velocity in iteration \( k \), respectively, and \( g_{\text{best}} \) is the swarm’s best-known position and \( p_{\text{best}} \) is the particle’s best-known position, \( \omega \) is the inertia weight, and \( r_{1} \) and \( r_{2} \) represent random numbers (between 0 and 1).
FIGURE 4  Yearly load profile

FIGURE 5  Yearly Solar insolation profile

FIGURE 6  Yearly ambient temperature profile
4.1 | Improved particle swarm optimization

With PSO, the degree to which the particle remembers its prior velocity is controlled by an inertial constant $w$, which is started from a $w_0$ and decreases during the iterations by $w_{k+1}$. This concept suggests modifications to the basic PSO algorithm that lead to improved particle swarm optimization (IPSO). The inertia weight $w$ is expressible as

$$w_{k+1} = \alpha \cdot w_k$$  \hspace{1cm} (20)

The velocity of each particle is updated in the following manner:

$$v_{k+1} = w_k \cdot v_k + c_1 \cdot r_1 (p_{\text{best}}^k - x_k^k) + c_2 \cdot r_2 (g_{\text{best}}^k - x_k^k)$$ \hspace{1cm} (21)

where $w_0$ is a positive initial value and $\alpha$ is the inertia weight damping ratio (here 0.99, which is set by trial and error). The pseudo-code and flowchart of the IPSO algorithm are presented in Figures 2 and 3.

5 | RESULTS AND DISCUSSION

In this study, a remote area in Davarzan is selected for optimization. Davarzan is a county in Razavi Khorasan Province in Iran. The latitude and the longitude of the selected area are 36°21′06″ N and 56°52′42″ E, respectively. The system minimum load value used for simulation is 1.6 kW and the peak value is 7.5 kW. Monthly data of load power over 1 year are shown in Figure 4. For the proposed case study, hourly average solar radiation and ambient temperature during 1 year are presented in Figures 5 and 6, respectively. Some of the assumptions used in this study are as follows:

- The time step for the analysis is considered as 1 h.
- The hourly average solar radiation, ambient temperature, and load demand during 1 year (8760 h) are considered.
- The specifications of the proposed system components and the prices of the components are presented in Table 1.

5.1 | Comparison of optimization algorithms

An improved PSO (IPSO) algorithm is proposed in this study for designing the standalone photovoltaic scheme. The suggested algorithm results are compared with those obtained by the original PSO and SA algorithms in order to affirm the suggested IPSO’s efficacy in achieving the maximum reliability and minimum cost. The studied optimization methods are coded and implemented using MATLAB software on a computer PC (core-i7, 6 GB RAM, ...
and 2.3 GHz CPU). For heuristic algorithms, 30 independent runs are conducted, and the results are recorded to compare the algorithms’ accuracy. The relevant parameters of algorithms were listed in Table 2, which are set by trial and error.

Table 3 indicates the results of the optimal configuration of the standalone photovoltaic scheme for different RI by IPSO, PSO, and SA algorithms. These results include the best, mean, standard deviation (SD), and worst values of TNAC, and the best, mean, and worst values of simulation time (ST) in 30 independent runs. In RI = 1%, the IPSO has the best TNAC with $179,987 followed by PSO with $180,721 and SA with $252,921. The best ST value is 9.375 s, which is obtained by IPSO. In this case, the convergence curves for the best implements using IPSO and PSO for RI = 1%; (B) zoom part.
implements using IPSO and PSO are shown in Figure 7. As seen from this figure, IPSO has the best results in achieving the minimum TNAC value and best simulation time, outperforming PSO and SA. In RI = 3%, the best TNAC, which refers to the minimal select, is $146,205, which is obtained by IPSO followed by PSO with $146,296 and by SA with $235,341. The mean and worst values of TNAC are $146,205 and $146,205, which is obtained by the IPSO. Figure 8 shows the convergence curves for the best implements using IPSO and PSO in RI = 3%, which shows the superiority of the proposed algorithm over PSO. Due to the obtained results in RI = 5%, the IPSO reached to a lower TNAC ($112,366) than PSO ($113,008) and SA ($114,660); and also a lower ST value in different indexes. The simulation time in the minimum state is 9.375 s. The convergence curves for the best implements using IPSO and PSO in RI = 5% are shown in Figure 9. As a result, it can be noticed that the IPSO is characterized by the fast convergence properties, the minimum TNAC, and the minimum ST, compared with the PSO and SA algorithms. And it is shown that the TNAC value reduces by increment in the value of RI. In this regard, the convergence curves for the best implements for different RI using IPSO, PSO, and SA algorithms are presented in Figure 10. The best value of TNAC for different RI using IPSO, PSO, and SA algorithms are presented in Figure 11. In RI = 1%, it can be seen that IPSO shows approximately 28.8% cost saving in comparison with the SA, and IPSO shows approximately 0.4% cost saving in comparison with the PSO. Also, in RI = 3%, the IPSO shows approximately 37.9% cost saving in comparison with the SA, and IPSO shows approximately 0.06% cost saving in comparison with the PSO. And in RI = 5%, the IPSO shows approximately 2% cost saving in comparison with the SA, and IPSO shows approximately 0.6% cost saving in comparison with the PSO. Also, Figure 12 shows the best value of simulation time for different RI using IPSO, PSO, and SA algorithms. As a result, it can be seen that the IPSO algorithm is faster than the PSO and SA algorithms and offers better results in terms of the lowest cost.

5.2 Sensitivity analysis

In this section, the sensitivity analysis is conducted on the optimized hybrid system components and the prices of the components to test the influence of various input reliability indexes. The optimal cost, reliability,
and combination of the standalone photovoltaic system for different RI (1%, 3%, and 5%) using proposed algorithms (PSO, IPSO, and SA) are presented in Table 4. In this Table, the optimal value of TNAC of hybrid system obtained by the SA algorithm is the basis, and the TNAC obtained by IPSO and PSO algorithms is compared with it for cost saving. Based on the IPSO, in RI = 1%, the optimum size of essential PV panels and batteries is 104 and 1912 units, to meet the load demand in the case study, when the estimated LLSP value is 0.9067%. The economic analysis displays that the value of TNAC of the system is $179,987, the values of the C&R and O&M cost of the hybrid system are $159,574 and $20,413, respectively. It can be seen that IPSO shows approximately $734 cost saving in comparison with the PSO.

In RI = 3%, the optimal number of PV panels and batteries are 96 and 1547 units, which is obtained by IPSO. Also, the optimal values of TNAC and LLSP are $146,205, and 2.994%, respectively. The economic analysis displays that the values of the C&R and O&M cost of the hybrid system are $129,538 and $16,667, respectively. Based on the PSO, the optimal values of TNAC, LLSP, $N_{PV}$, and $N_{Batt}$ are $146,296, 2.9926$, 96, and 1548, respectively. Also, when using the SA algorithm, the optimal values of the $N_{PV}$ and $N_{Batt}$ are 94 and 2519, respectively. And the optimal values of TNAC and LLSP are $235,341 and 2.0081$, respectively. It can be seen that IPSO shows approximately $91 cost saving in comparison with the PSO, and approximately $89,136 cost saving in comparison with the SA algorithm. Also, it is shown that the TNAC value reduces from $179,987 to $146,205 by increment in the value of RI from 1% to 3%. In this regard, the optimal number of PV panels and batteries are reduced from 104 & 1912 to 96 & 1547, respectively. So, the value of the LLSP is increasing from 0.9067% to 2.9940%.

FIGURE 9 (A) The convergence curves for the best implements using IPSO and PSO for RI = 5%; (B) zoom part
As seen from this table, in RI = 5%, the IPSO has the best TNAC with $112,366 followed by PSO with $113,008 and SA with $114,660. It can be seen that IPSO shows approximately 0.6% cost saving in comparison with the PSO, and approximately 2% cost saving in comparison with the SA algorithm. It also shows that the optimal values of the $N_{PV}$ and $N_{ Batt}$ are 89 and 1181, respectively. By comparing the results provided in the table, it can be noticed that with increasing the amount of RI from 1% to 5%, the value of the TNAC is decreased by 38% and shows that the value of the LLSP is increased from 0.9067% to 4.9994%. Also, the optimal numbers of PV and storage systems are decreased by 14.5% and 38.2%, respectively. For better analysis of results, the hourly energy storage...
level of the battery bank and generated power of the PV panels during the year (8760 h) using IPSO for different RI (1%, 3%, and 5%) are presented in Figure 13. It can be seen that by increasing the amount of RI from 1% to 5%, the energy storage level of the battery bank and generated power of the PV panels during the year are decreased. Additionally, the highest hourly power production of PV panels is in the month of May because of the appropriate temperature and abundance of solar radiation. The highest hourly energy storage level of batteries is in the month of Jun because of the availability of appropriate temperature, a good amount of solar radiation, and relatively low load compared to other months. In this regard, the battery storage system absorbs surplus energy generated by the PV and discharging occurs at night time in the absence of solar energy. For better understanding, for each RI, the hourly performances of energy storage level of the battery, PV power, and LLS during the year using IPSO are shown in Figure 14. According to the obtained results, the excess power from PV panels is used to save on battery. It can be seen that by increasing the amount of RI from 1% to 5%, the loss of load supply during the year is increased, which shows how often the standalone photovoltaic scheme is inefficient to supply the electrical power. In this regard, whenever the energy demand is more than the energy produced, the LLS occurs. For example, when RI is 1%, 99% of the load during the year is supplied by the standalone photovoltaic/battery scheme, and 1% of the load during the year is not supplied (Figure 14A). In RI = 3%, 97% of the load during the year is supplied by power generated of the PV panels and battery energy storage system, and 3% of the load during the year is not supplied (Figure 14B). In this regard, 95% of the load during the year is supplied by a hybrid system, and 5% of the load during the year is not supplied for RI = 5% (Figure 14C).

Table 5 indicates the cost results of the standalone photovoltaic system for different RI by IPSO, PSO, and SA algorithms. These results include the NAC values of the optimal PV panels, storage system, inverter, and the O&M cost values of the PV panels, storage system, and inverter in the optimal condition of the hybrid system. It can be seen in RI = 1%, for the IPSO, the batteries denote the highest annual section cost with $175,478 of the total cost of the hybrid scheme, followed by PV panels with...
$3691, then inverter with $818. In this regard, when the SA algorithm is used, the optimal NAC of the PV panels and batteries are $3478 and $248,624, respectively. In RI = 3%, for the IPSO, the NAC values of the optimal PV panels, storage system, and inverter are $3407, $141,979, and $818, respectively, which shows that the batteries are the highest annual section cost with 97% of the total cost of the hybrid scheme. Also, it is shown that the NAC value of the optimal PV panels reduces from $3691 to $3407 by increment in the value of RI from 1% to 3%. Consequently, the NAC value of the storage system is reduced by 19.1%.

For the RI = 5%, in IPSO, the batteries denote the highest annual section cost with 96% of the total cost of the hybrid scheme, followed by PV panels with 3%, and then inverter with 1%. It can be noticed that by increasing the RI from 1% to 5%, the value of the NAC of PV panels decreases by 14.4% and shows that the value of the NAC\textsubscript{BAT} decreases by 38.2%. The results from the IPSO, PSO, and SA algorithms for different RI showed that the NAC of the batteries denotes the largest portion of all units. In this regard, Figure 15A shows the NAC values of the optimal PV panels, storage system, and inverter for different RI using the IPSO algorithm.

The results from RI = 1% show that the O&M cost of the batteries accounts for the largest portion with $19,120, followed by the PV panels with $1248, and the inverter representing the lowest O&M cost value with $45, which they found by IPSO algorithm. In SA and PSO algorithms, the O&M cost of the batteries is $27,090 and $19,200, respectively. It can be seen that IPSO shows approximately $80 cost saving in comparison with the PSO, and approximately $7970 cost saving in comparison with the SA algorithm. In RI = 3%, for the IPSO, the O&M cost of the PV panels, batteries, and inverter are $1152, $15,470, and $45, respectively. It is shown that the O&M cost of the optimal PV panels reduces from $1248 to $1152 by increment in the value of RI from 1% to 3%. Also, the O&M cost of the storage system is reduced by $3650.

In RI = 5%, results show that the O&M cost of the batteries accounts for the largest portion with 92%, followed by the PV panels with 8%. It can be noticed that by increasing the amount of RI from 1% to 5%, the value of the O&M\textsubscript{PV} decreases by $180 and shows that the value of
the NACBAT decreases by $7310. The O&M cost values of the PV panels, storage system, and inverter in the optimal condition of the hybrid system for different RI using the IPSO algorithm are shown in Figure 15B. It can be seen that the O&M cost of the batteries is the largest portion of all units for different RI.
In this paper, an improved optimization approach called improved particle swarm optimization algorithm has been developed for optimal sizing and configuration of standalone photovoltaic system components with the aim of meeting the load demand of a small remote area in Davarzan, Razavi Khorasan Province in Iran. This hybrid power system is based on PV panels and battery energy storage systems. The aim of this research is to determine the optimal sizing of the system components to reduce the TNAC, while maintaining high values of reliability. The optimized system results from the improved approach are compared with original particle swarm optimization and simulated annealing algorithms. Then, the optimum design is analyzed and compared based on different reliability values. The simulation results demonstrate the effectiveness of the improved optimization approach for finding the optimal capacities of the photovoltaic panels and battery energy storage units in the proposed standalone photovoltaic system for different reliability indexes. In this regard, for different reliability values (1%, 3%, and 5%), the IPSO shows approximately 22.9% cost saving in comparison with the SA, where IPSO shows approximately 0.35% cost saving in comparison with the PSO. Additionally, by increasing the amount of RI from 1% to 5%, the value of the TNAC is decreased by 38% and shows that the value of the LLSP is decreased from 0.9067% to 4.9994%. Furthermore, the optimal number of PV panels and batteries are decreased by 14.5% and 38.2%, respectively. Finally, by increasing the amount of RI from 1% to 5%, energy storage level of the battery bank and generated power of the PV panels during the year are decreased.

In future studies, the hybrid optimization algorithm can be used to the optimal configuration of the standalone photovoltaic scheme. Furthermore, other hybrid energy technologies based on renewable energy can be studied. Also, the IPSO method can be further developed to be compatible with the large-scale multi-objective optimization of the hybrid energy system.

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**TABLE 5** The cost results (in $) of the standalone photovoltaic system components for different RI using algorithms

| RI (%) | Method | NAC\(_{PV}\) | NAC\(_{BAT}\) | NAC\(_{INV}\) | O&M\(_{PV}\) | O&M\(_{BAT}\) | O&M\(_{INV}\) |
|--------|--------|--------------|--------------|--------------|--------------|--------------|--------------|
| 1      | PSO    | 3691         | 176,212      | 818          | 1248         | 19,200       | 45           |
|        | IPSO   | 3691         | 175,478      | 818          | 1176         | 27,090       | 45           |
|        | SA     | 3478         | 248,624      | 818          | 1152         | 15,480       | 45           |
| 3      | PSO    | 3407         | 142,071      | 818          | 1152         | 15,470       | 45           |
|        | IPSO   | 3407         | 141,979      | 818          | 1152         | 15,470       | 45           |
|        | SA     | 3336         | 231,187      | 818          | 1128         | 25,190       | 45           |
| 5      | PSO    | 3159         | 109,031      | 818          | 1068         | 11,880       | 45           |
|        | IPSO   | 3159         | 108,389      | 818          | 1068         | 11,810       | 45           |
|        | SA     | 3159         | 110,683      | 818          | 1068         | 12,060       | 45           |

**FIGURE 15** (A) the NAC values of the optimal PV panels, storage system, and inverter; (B) the O&M cost values of the PV panels, storage system, and inverter in the optimal condition of the hybrid system for different RI using IPSO algorithm

6 | CONCLUSION

In this paper, an improved optimization approach called improved particle swarm optimization algorithm has been developed for optimal sizing and configuration of standalone photovoltaic system components with the aim of meeting the load demand of a small remote area.
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