Metaheuristic searching genetic algorithm based reliability assessment of hybrid power generation system

Ahmed N Abdalla1, Muhammad Shahzad Nazir2, MingXin Jiang1, Athraa Ali Kadhem3, Noor Izzri Abdul Wahab4, Suqun Cao1 and Rendong Ji1

Abstract
Generating systems are known as adequately reliable when satisfying the load demand. Meanwhile, the efficiency of electrical systems is currently being more influenced by the growing adoption of the Wind/Solar energy in power systems compared to other conventional power sources. This paper proposed a new optimization approach called Metaheuristic Scanning Genetic Algorithm (MSGA) for the evaluation of the efficiency of power generating systems. The MSGA is based on a combination of metaheuristic scanning and Genetic Algorithm. The MSGA technique is used for evaluating the reliability and adequacy of generation systems integrated with wind/Solar energy is developed. The usefulness of the proposed algorithm was tested using Reliability Test System 'IEEE-RTS-79' which include both of wind power and solar power generation. The result approve the effectiveness of the proposed algorithm in improving the computation time by 85% and 2% in comparison with the particle swarm optimization (PSO) and differential evolution optimization algorithm (DEOA) respectively. In addition, the proposed model can be
used to test the power capacity forecasting scheme of the hybrid power generation system with
the wind, solar and storage.

**Keywords**
Reliability, genetic algorithm, wind power generation, solar power generation, power supply planning

**Introduction**
The shortage of energy and the demand for energy-saving and emission reduction have
urged the power grids of countries around the world to actively develop low-carbon
power technologies (Nazir et al., 2020a). With the deepening of research on the use of
renewable energy worldwide and the reduction of power generation costs, more and more
different types of renewable energy power generation are connected to the power system.
Since, obviously, various energy sources complement one another in time and location
(Nazir et al., 2020b; Zhang et al., 2020) Combined generation of renewable energy forms
will offset intermittent energy losses and increase the resilience of the grid to intermittent
renewable energies (Ahmed et al., 2019; Cai et al., 2020). It is necessary to evaluate the
utilization value of complementary power generation using multiple energy forms.

Many researchers have introduced various models and algorithms to assess the reliability of
the power system to guide system design and operation by quantitatively evaluating the reli-
bility of the power system (Maleki, 2018; Zhang et al., 2019). The main methods currently used
are analytical (Da Silva et al., 2014) and Monte Carlo simulation (MCS) (Jayatheertha and
District, 2012). The analytical method applies to small power systems with a simple structure
because the amount of calculation and the size of the system are exponential. Da Silva et al.
(2014) Focused on analytical methods of assessing the reliability of generating systems in multi-
site wind farms. The MCS approach allows the reliability matrixes to be estimated accurately.
The MCS may be helpful for this purpose by involving several system states for the penetration
of wind energy into operating systems, and there is a need for large computational inputs which
could be time-efficient if efficient convergence is paramount. Solomon et al. (2014) applied the
Israeli actual power grid to analyze the matching problem of large-scale wind power and pho-
tovoltaic power generation systems. By comparing the wind and solar single and complemen-
tary operation modes, the wind and solar complementary power generation model was
obtained, which improved the power penetration of intermittent energy into the power grid.
Madani et al. (2012) and Denholm (2012) has established a generation reliability evaluation
model for wind power, photovoltaic power generation, and energy storage systems, and pro-
posed a new coordinated scheduling strategy. Billinton et al. (2012) pointed out that wind-solar
resources are highly complementary and have better stability, reliability, and economy when
analyzing the distributed generation system of wind-solar-biogas mixed renewable energy.
Consequently, the un-concentrated supply of wind power sources further complicates the reli-
bility evaluation process (Billinton et al., 2012; Madaeni et al., 2012; Zhang et al., 2019).
Therefore, new equipment are required for assessing generation systems with a large penetra-
tion of wind energy sources (Shahzad et al., 2017; Zhang et al., 2019; Nazir et al., 2020).

Meta-heuristic algorithms, such as genetic algorithm and ant colony algorithm, etc., have
become more and more effective methods for solving complex optimization problems (Bonabeau
et al., 2000; Dorigo et al., 1996). Most meta-heuristic algorithms are derived from the simulation of biological behavior or physical properties or chemical processes, for example, Ant colony algorithm is to simulate the actual ant colony foraging process (Gambardella and Dorigo, 1997), particle swarm algorithm is derived from the bird and fish groups (Benidris and Mitra, 2014; Green et al., 2010, 2012; Hadow et al., 2010; Huang and Liu, 2013), Evolutionary Computation (EC) and Smart State Space Pruning (ISSP). Despite the series of researches on the reliability of generation system, more appropriate techniques are needed which are computationally scalable and more practical to reflect the soundness of power generation (Almutairi et al., 2015; Kadhem et al., 2017; Athraa et al., 2017). Each algorithm has its advantages and disadvantages, such as: If the cooling process is slow enough, the simulation process is long enough, the simulated annealing algorithm can almost ensure that the optimal solution is found. However, slight adjustments to the parameters will affect the convergence of the algorithm.

The need for models for the simulation of the stochastic characteristics of power generating system behavior is not a new problem for generally population-based intelligent research methods. However, it becomes a serious issue when considering the integration of wind resources with power systems. This paper is attempted to propose a new algorithm called Metaheuristic Searching Optimization Algorithm (MSGA) for the reduction of the computational resources in the MCS and intelligent algorithms. The proposed MSGA optimize output probability model of hybrid power sources of wind turbines and solar generators are established. Then, based on the suitable capacity, a credible capacity and complementary indicators of the wind-solar combined power generation system is proposed to discuss the effects of different energy storage ratios and wind/solar installed ratios on the credible capacity of the combined power generation system, and when the wind-solar combined access Complementary benefits.

**Related work**

**Wind/solar output characteristics**

The output characteristics of wind turbines are generally expressed by a piecewise function. If the wind farm has the number of wind turbines with the same parameters, and the wind speed difference of different wind turbines is ignored, the output power of the wind farm can be described by the following piecewise function (Nazir and Abdalla, 2019):

$$P_W(v) = \begin{cases} 
0, & v \leq v_{ci} \\
\frac{v^3}{v^3_{R} - v^3_{ci}} P_r - \frac{v^3_{ci}}{v^3 - v^3_{ci}} P_r, & v_{ci} \leq v \leq v_r \\
\frac{v^3}{v^3_{R} - v^3_{ci}} P_r, & v_r \leq v
\end{cases}$$

(1)

Where: $P_W(v)$ represent the wind farm output power at the wind speed is $v$; $v_{ci}$ represent is the cut-in wind speed; $v_{co}$ is represent the cut-out wind speed; $v_r$ represent the rated wind speed; and $P_r$ represent the rated output power of a single wind turbine.

The hourly solar irradiance is obtained, the power output of the photovoltaic power generation system can be obtained according to the performance parameters of the photovoltaic panel, as follows (Nazir et al., 2020b; Temiz and Javani, 2020):

$$P_{PV} = \eta_{c} S_{C,A} I_{\beta}$$

(2)
Where \( S_{CA} \) is the cell area; \( I_\beta \) is the photovoltaic panel with a dip angle \( \beta \) per unit area of solar radiation received per hour.

The battery energy conversion efficiency can be described by

\[
\eta_{ct} = \begin{cases} 
\eta_c(I_\beta/I_k) & 0 \leq I_\beta \leq I_k \\
\eta_c & I_k \leq I_\beta 
\end{cases}
\]  

(3)

Where: \( \eta_{ct} \) is the battery energy conversion efficiency under standard test conditions; \( I_k \) is a certain incident light irradiance value.

In general, the battery conversion efficiency remains constant and no longer changes with the incident irradiance change after exceeding the value 150 W/m².

The power output \( P_h \) of the wind-solar combined power generation system is also a random variable as follows

\[
P_h = P_W + P_{Solar}
\]  

(4)

Where \( P_W \) present the wind turbine and the output, \( P_{Solar} \) represent the photovoltaic power generation unit.

Assuming that \( P_W \) and \( P_{Solar} \) are independent of each other, the density function of the output of the wind and solar power generation system as follows:

\[
f_{P_h}(P_h) = f_{P_W}(P_W) + f_{P_{Solar}}(P_{Solar})
\]  

(5)

On the other hand, because the output of the wind-solar combined power generation system is affected by the light intensity and wind speed, \( P_h \) per hours can be substituted for the calculation. According to the generator location the probability density function of the wind-solar combined power system output varies as follows:

\[
f_{P_h}(P_h) = \int_{\min(P_h,P_R)}^{\max(0,P_R - P_{Solar}(k_\mu))} f_{P_{Solar}}(P_h - P_W) f_{P_W}(P_W) dP_W
\]  

(6)

Where: \( P_R \) is the rated power of the wind turbine; \( k_\mu \) is the upper limit of the sky clearness coefficient per hour.

The output range of the wind turbine is \( 0 \leq P_W \leq P_R \), the output range of the photovoltaic power unit is \( 0 \leq P_{Solar} \leq P_{Solar}(k_\mu) \), and the output range of the wind and solar power generation system is \( P_{h\min} \leq P_h \leq P_{h\max} \). Where the maximum output value of combined power generation as \( P_{h\max} = P_R + P_{Solar}(k_\mu) \), and the minimum value of \( P_{h\min} \) is about 0.

**Power generation system reliability evaluation indicators**

The reliability evaluation methods mainly include network method, state-space method, state enumeration method, Monte Carlo simulation method, etc. (Dąbrowska, 2020). In the reliability evaluation of independent power generation systems with wind complementarity, the commonly used reliability evaluation indicators are Loss of load probability
LOLP), Expected energy not serviced (EENS), and Loss of load expectation (LOLE) (Söder et al., 2020). Since LOLP is closely related to the reliability of the power generation and transmission system, it can more realistically and directly reflect the supply and demand of the power market, and it can also more intuitively quantify the risks caused by the loss of system capacity, which is mainly divided into the following six types (Söder et al., 2020):

**Loss of load probability (LOLP).** The load probability that the system cannot meet the power demand within a certain period evaluated by:

\[
\text{LOLP} = \sum_{i \in S} P_i \tag{7}
\]

Where: \(S\) represent the set of all unsatisfied states; \(P_i\) represent the probability of the system in state \(i\).

**Loss of load frequency (LOLF).** The load frequency is the number of times that the system cannot meet the demand of supply load.

\[
\text{LOLF} = \sum_{i \in S} F_i \tag{8}
\]

In the formula, \(F_i\) represents the frequency of the system in state \(i\).

**Loss of load expectation (LOLE).** The load expectation that the system cannot meet the expected time value of the power demand evaluated by:

\[
\text{LOLE} = T \times \text{LOLP} = T \times \sum_{i \in S} P_i \tag{9}
\]

Where \(T\) is the given time expressed in \(h/a\) or \(d/a\), the unit is \(h\) (hour) or \(d\) (day).

**Loss of load duration (LOLD).** In a certain period, the system cannot meet the average duration of the supply to meet the demand.

\[
\text{LOLP} = \text{LOLE} / \text{LOLF} \tag{10}
\]

**Expected energy not serviced (EENS).** In a certain period, the system cannot meet the expected value of the load power reduction caused by the supply load demand.

\[
\text{EENS} = \sum_{i \in S} C_i F_i D_i = T \sum_{i \in S} C_i P_i \tag{11}
\]

Where \(D_i\) represents the duration of state \(i\); \(C_i\) is the power reduction for the load in state \(i\).

**Expected of load curtailments (ELC).** The load curtailment within a certain time, the system was unable to meet the expected value of power reduction due to supply meeting demand which
can evaluated by:

\[ ELC = \sum_{i \in S} C_i F_i \] (12)

**The proposed methodology**

**Principle of the MSGA**

Figure 1, shows the proposed MSGA optimization algorithm which has a simple procedure and outstanding performance. The four steps of the MSGA comprise initialization, selection, mutation, and crossover. In the MSGA, the mutation operator is employed for the selection step, while the machine state-space search function is used to guide the search to potential failure conditions in the feasible region.

The selection of numerical values in the MSGA for \( f \), CR, and NP (the control parameters) is mainly dependent on the issue at hand (Qin et al., 2008). Factors such as the population size (pop size) must not be too small for resisting local optima, though a larger pop size requires additional computation input. The crossover constant \( \text{CR} \in [0, 1] \) impacts a beneficial attribute to the search process. It is suggested that a CR value of 0.5 be used (Vitaliy, 2006), while the differentiation constant \( f \) should relate closely to the convergence speed.

**Implementation procedures for reliability assessment**

In this paper the MSGA optimize the available unit output cannot meet the load demand and there is a power difference, and the remaining available capacity of the energy storage device cannot meet this difference. This paper mainly refers to the LOLE indicator for the

![Figure 1. Proposed MSGA technique.](image-url)
calculation of equal reliability, to estimate the credible capacity of the wind-solar storage power generation system.

The steps to solve the credible capacity of hybrid power generation system are as follows:

**Step 1:** Random generate the output probability density function of the wind turbine and the photovoltaic generator according to the local data and the parameters of the selected unit.

**Step 2:** Through MSGA, the reliability index $f_{\text{LOLE}}$ are calculated. The LOLE can be evaluated as follows:

$$f_{\text{LOLE}} = p\left\{ \left[ P_c(t - 1) + P_h(t) + P_g(t) \right] < P_L(t) \right\} T$$  \hspace{1cm} (13)

Where $T$ represent period which can be a day, as the daily load curve, a load curve of 8760 h; $P_L(t)$ is the current load, its value fluctuates with the annual load curve; $P_h(t)$ is the power output of the combined wind-solar power generation system; $P_g(t)$ is the output of the conventional unit currently available; $P_c$ is the maximum available energy storage capacity of the device.

**Step 3:** The reliability index remains unchanged. The capacity of the conventional unit $C_{\text{un}}$ to be accessed when the computing system reaches the same reliability.

**Step 4:** Return to **Step 2 and 3** to calculate the reliability index and the wind unit capacity $C_{\text{Wind}}$ reach required for equal reliability when the wind power is connected to the system alone.

**Step 5:** Return to **Step 2 and 3** calculate the reliability index when photovoltaic power generation is connected to the system alone and the solar unit capacity $C_{\text{Solar}}$ reach required for equal reliability.

**Step 6:** Use the obtained results to calculate the complementary gain capacity $G$ as follows.

$$G = C_m/C_{\text{eq}}$$  \hspace{1cm} (14)

Where $C_m$ is the complementary capacity of the hybrid power generation system;

$$C_m = C_{\text{eq}} - C_{\text{Solar}} - C_{\text{Wind}}$$  \hspace{1cm} (15)

Where $C_{\text{PV}}$, present the installed capacity of the photovoltaic power generation system; $C_{\text{Wind}}$ present the installed capacity of wind power generation, and $C_{\text{eq}}$ present the equivalent unit capacity is. It is clear that the complementary gain capacity $C_m$ is greater than 0, it means that the system benefits from complementary characteristics.

The calculation of the reliability indicator for LOLE was based on the achieved state array and the sum of the hourly load values. Usually, it is modelled as a random variable with a random variable model using time series approaches such as Weibull distribution. The rating changes over time, but for a given interval, can be regarded as a constant value and this was considered for reliability calculation in this study.

Several criteria are employed for the termination of the algorithm while computing its results and stopping criterion corresponds to the number of generations (Green et al., 2011).

**Results and discussion**

This paper focuses on developing and testing an approach for assessing reliability generating systems using IEEE-RTS-79 which contain renewable resources. These test systems were deployed to validate the performance of the MSGA developed for the reliability assessment.
The IEEE-RTS-79 test system contains 32 generating units; its unit capacity ranges from 12 to 400 MW, with a total system power output of 3405 MW at a peak load of 2850 MW (Subcommittee, 1979). Having published the IEEE-RTS-79 system, it has become a vital tool for assessing various models of reliability and for evaluating methodologies in various research fields. The rated wind capacity used is 2 MW, and the rated wind velocities are 2.5, 12 and 18 m/s respectively. The maximum power output of the solar array used in the solar power plant is 280 W under standard test conditions, the capacity factor is 14.3%, and the battery area is about 2 m². The electric utility industry is experiencing few changes to accommodate a multi-area RTS design through the incorporation of additional data.

Case 1: Evaluation of MSGA performance for the IEEE-RTS-79 system

The parameter values of the MSGA control settings were recorded as pop size = 60 and CR = 0.6. The boundary variables that limit the obtainable state-space were identified as L = 0.1 and H = 0.6, while the data previously reported by (Jabr, 2013) were used for the reliability parameters for the unit settings for generation. The set to 1e-15. For producing the hourly values the load period curve and the load model were used. For each year, that gives a total of 8736 individual values. The maximum number of generation (set at 100) was the deployed stop criterion for MSGA (Green et al., 2010).

To show the accuracy of the MSGA algorithm, MCS and Differential Modified Simple Genetic Algorithm (DEAO) benchmarked its output against those. These algorithms for the benchmarking were also developed for similar problems. The MSGA stop criteria were when it created 100 individual generations. The MSGA results were compared with those of other previously reported algorithms (Li, 2013; Samaan and Singh, 2002) as shown in Table 1. The findings were compared according to their indexes of reliability. Using MSGA and DEAO (Kadhem et al., 2017) the absolute values used for this analysis were extracted from a single sprint. The MSGA was therefore discontinued because no significant change in the fitness value was observed for consecutive 100 generations.

For verification of the MSGA’s confidence and strength, the algorithm was executed under similar conditions for 100 consecutive runs as discussed earlier. Table 2 displays

| Reliability Indices | MSGA (Mean) | Analysis Method [34] | Error (%) |
|---------------------|-------------|-----------------------|-----------|
| LOLE (h/year)       | 9.372       | 9.394                 | 0.234%    |
| LOEE (MWh/year)     | 1132        | 1176                  | 3.74%     |
the consequences of executions. The MSGA findings that were obtained were correlated with those reported by (Allan et al., 1986).

The calculation effort of the proposed approach has also been evaluated and compared with those of MSGA, MCS, and DEOA, as shown in Table 3. The measurement effort of the proposed method has been found to depend on the desired precision. However, when the degree of the coefficient of variance was reached 5 per cent (Pradhan et al., 2020), the simulation evaluation will be stop. This distinction was made with absolute values that were derived from a single run of MSGA and DEOA (Kadhem et al., 2017). The MSGA computation time was shorter compared with the other approaches, as can be seen in Table 3.

Case 2: Reliability indices for IEEE-RTS-79 using MSGA with WPG

For traditional generating units, the reliability parameters (for, μ, ӯ) previously given by (Li, 2013) were used, while it was taken as 1e-15. The LDC model was used to produce the annual load values which for one year comprise 8736-h values. For the algorithm, the stop criterion was called the maximum number of iterations needed to achieve 100 generations (Green et al., 2010).

The reliability indexes for RTS-79 with a peak load of 2850 MW and a WPG of 170 MW evaluated by the proposed MSGA, MCS, and particle swarm optimization (PSO) as shown in Table 4. The despite its simplicity, the MSGA showed the slightest computation time compared to the benchmarking PSO algorithm. Besides, MCS algorithm could be assumed to be at its worst convergence time, based on the LOLE index.

Table 5 summarizes the findings of a comparison between the reliability indices of five models previously published in the literature (Soleymani et al., 2015) and MSGA’s. Both techniques used the MCS method to measure the reliability indexes of various wind speed models (such as Normal distribution, Markov method, ARMA time series model, Weibull distribution, and real wind speeds). It became clear that the findings obtained using MSGA had values of reliability indices that were similar to those obtained using real wind speed data in the MCS process.

Table 3. Computational time comparison between MCS, MSGA, and DEOA algorithms.

| Techniques | Monte Carlo | MSGA No. of Generations = 100 | DEOA No. of Generations = 100 |
|------------|-------------|-------------------------------|-------------------------------|
| LOLE (h/year) | 9.541 | 9.42 | 9.37 |
| Time (s) | 372 | 3.92 | 4 |

Table 4. Comparison between MCS, BPSO, and the proposed MSGA method.

| Methods | LOLE (hour/year) | LOEE (MW/h/year) | Time (s) |
|---------|------------------|------------------|----------|
| Proposed MSGA | 7.48 | 1248.24 | 3.92 |
| PSO | 7.43 | 823.78 | 8.979 |
| MCS | 7.55 | 941.07 | 64.641 |
Case 3: Reliability indices under the combined wind and solar power generation system

The efficiency of the proposed MSGA was ensured through a careful selection of the control parameters used in this study. The analysis of the impact on the reliability of the system when combined wind and solar power generation. In this case, the fixed wind power access capacity is 100 MW, which gradually increases the access capacity of solar power generation. Figure 5 shows LOLE during combined wind and solar power generation. Figure 2 shows that when the energy storage is connected, the system reliability can be better improved as the capacity of the wind-solar combined power generation system is the size of the conventional unit. Figure 3 shows the total installed capacity of Wind/Solar energy to 300 MW, and considers the situation of different installed proportions of wind and solar, and calculates the capacity ratio of the combined wind and power system. It can be observe that the installed capacity of wind power is larger than that of solar power, the capacity ratio is more ideal. This is due to the local climate resources, the wind type used, and the specific parameters of the solar power generation device, which need to be considered in the specific power optimization.

Case 4: Evaluation of the complementary benefit of installation capacity ratio

The complementary gain capacity is present the power generation benefits brought the combined power generation system. When the proportion of installed wind power and

**Table 5.** Comparison between the proposed MSGA method and suggested methods in the literature.

| Techniques                      | LOLE (hour/year) | LOEE (MWh/year) |
|---------------------------------|------------------|-----------------|
| Actual data with MCS           | 7.45             | 908.70          |
| Proposed MSGA                  | 7.48             | 1248.24         |
| Markov model with MCS          | 7.47             | 918.10          |
| Normal model with MCS          | 6.95             | 858.50          |
| Weibull model with MCS         | 7.78             | 976.70          |
| ARMA method with MCS           | 7.12             | 884.90          |

**Figure 2.** LOLE combined wind and solar power generation.
installed solar capacity is different, the complementary gain capacity will also be different. Figure 4 shows the evaluation of the complementary gain capacity under different wind-solar ratios, in which the total wind/solar capacity are 300 MW. It can observe that the complementary gain capacity is greatly affected by the energy storage access capacity, and has different performances at different installed ratios. Therefore, the complementary benefits are better if the installed capacity of wind power is larger than the installed solar capacity.

The evaluation of the installed ratio of wind/solar energies under the same rate capacity. To obtain the same reliability, the capacity of a single unit is should be identified. However to obtain the same reliability, in the case of multiple types of power supply access, there can
be different sets of unit capacity ratio. Figure 5 lists the combinations of wind and solar power units with size capacities of 20, 30, and 40 MW. The combination of wind and solar power units with equal reliable capacity is affected by local climate resources and the parameters of the selected units. In addition, the combination resources of wind/solar units used to simplify power planning when different new energy sources are connected.

Conclusions
This paper proposed a new Weibull-based MSGA model for reliability evaluation of generation systems with a Wind/Solar energy sources. The suggested intelligent algorithm for evaluating the reliability index of the power generation system will be provided to evaluate the reliability indices of non-chronological systems as a feasible alternative to the non-MCS. This algorithm reduced the calculation time used to measure the reliability indexes. In addition, this algorithm shows significant improvement the complementary gain capacity which greatly affected by the energy storage access capacity, and has better performances at different installed ratios. The combination of wind and solar power systems with enough resources will speed up the integration of various sources of renewable electricity.

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ORCID iD
Muhammad Shahzad Nazir  
https://orcid.org/0000-0001-9877-9590
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