Novel Design of Slim Mould Optimizer for the Solution of Optimal Power Flow Problems Incorporating Intermittent Sources: A Case Study of Algerian Electricity Grid

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This work was supported by the Taif University Researchers Supporting Project, Taif University, Taif, Saudi Arabia, under Grant TURSP-2020/34.

ABSTRACT Nowadays, electrical power grids are facing increased penetration of renewable energy sources (RES), which result in increasing level of randomness and uncertainties for its operational quality. In addition, emerging need for efficient solutions to stochastic optimal power flow (OPF) problem has attracted considerable attention to ensure optimal and reliable grid operations in the presence of generation uncertainty and increasing demand. Therefore, this paper proposes an efficient Slime Mould-inspired Algorithm (SMA) that aims to minimize overall operating cost of main grid by managing the power flow among different generating resources. The problem is formulated as large-scale constrained optimization problem with non-linear characteristics. Its degree of complexity increases with incorporation of intermittent energy sources, making it harder to be solved using conventional optimization techniques. However, could be efficiently resolved by nature-inspired optimization techniques without any modification or approximation into the original-formulation. The objective function is the overall cost of system, including reserve cost for over-estimation and penalty cost for under-estimation of both PV-solar and wind energy. The SMA performance is evaluated on the IEEE 30-bus test system and Algerian power system, DZA 114-bus. The SMA is compared with four optimization algorithms: i) The well-studied meta-heuristics, i.e., Gorilla troops optimizer (GTO), and Orca predation algorithm (OPA), ii) Recently developed meta-heuristics, i.e., Artificial ecosystem optimizer (AEO), Hunger games search (HGS), and Jellyfish search (JS) optimizer, iii) ad high-performance meta-heuristics, Success-History based parameter adaptation for differential evolution method. The overall simulation results reveal that the SMA ranked first among the compared algorithms, and so, over and so, over different function landscapes.

INDEX TERMS Optimal power flow (OPF), emission, renewable energy sources, uncertainty, gorilla troop optimizer, orca predation algorithm, slime mould algorithm.

LIST OF ABBREVIATIONS

| Symbol | Description |
|--------|-------------|
| $P_{\text{loss}}$ | The Total Power Losses. |
| TVD | Total Voltage Deviation. |
| $\delta_{ij}$ | The voltage angle difference between i and bus j. |
| $q_{ji}$ | The phase angle of term $F_{ji}$. |
| $V_{Gi}$ | Voltage Magnitude for Generator at Bus i. |
| $N_{\text{PV}}$ | The number of PV. |
| $N_{\text{PQ}}$ | The number of PQ buses (Load buses). |
| $g_k$ | Conductance of $k^{th}$ branch connected between i & j. |
V_i, V_j  Voltage magnitude for load bus i & j.
V_{L,N_{PQ}}  Voltage Magnitude for Load Bus i.
|Y_{ij}|  The Elements of Bus Admittance Matrix.
S_i  Apparent Power Flow of Branch i.
P_{D,i}  Active Power Load Consumption at Bus i.
Q_{D,i}  Reactive Power Load Consumption at Bus i.
P_{G_i}/Q_{G_i}  Active/Reactive Power Generation at Bus i.
V_i^{\text{max}}  Maximum Bus Voltage Magnitude at Bus i.
V_i^{\text{min}}  Minimum Bus Voltage Magnitude at Bus i.
P_{G_i}/Q_{G_i}  Active/Reactive Power Generation at Bus i.
P_{D_i}/Q_{D_i}  Active/Reactive, Load Consumption at Bus i.
P_{L,N_{PQ}} , Q_{L,N_{PQ}}  Active and reactive power at each load bus.
Q_{G_i}^{\text{min}}, Q_{G_i}^{\text{max}}  Limits Value of Reactive Power Generation.
NLB  Number of Load Buses.
NG  Number of Generators Buses.
\lambda_V, \lambda_Q, \lambda_i  The penalty factors.
SMA  Slime Mould Algorithm.
OPA  Orca Predator Algorithm.
AEO  Artificial Ecosystem Algorithm.
GTO  Gorilla Troops Optimizer.
HGS  Hunger Games Search.
RES  Renewable Energy Sources.
TG  Thermal Generator.
WG  Wind Generator.
SG  Solar Generator.

I. INTRODUCTION
Optimal power Flow (OPF) is one of primordial tools of electric power systems, offering electric power at minimum-cost and high quality. In short, is therefore the backbone tool of electric grids due to the important role which plays to maintain reliable and economical system operation. OPF Master Objective is to specify the optimal adjustment of control variables so that a selected objective function is optimized while satisfying different physical and operational-constraints inflicted by electric power grids (equality and inequality constraints). The most commonly objective-function is minimization of overall generation cost. However, other functions are minimization of gas emission, real power loss, voltage stability-index (VSI), and bus voltage-deviation [1]. While used control-variables are: active power of generators outputs, generator voltages magnitudes, positions of the transformer taps, and contributions of the compensators in terms of reactive power. These variables are mixture between discrete and continuous ones; parallel compensators and taps changer transformer are discrete variables, while remaining ones are continuous.

In traditional electric grids, the study of OPF considers conventional power generators run on fossil-fuels. However, under electricity market liberalisation, and integration of renewable energy sources (RES), study of OPF is becoming more complicated leading in increase the complexity of its objectives significantly. This is due to the diverse functions based on the variability and uncertain used in its problem formulation. The prime objective behind incorporation of renewable generators (WT+PV) in the grids is to reduce the transmission line losses and improving the reliability and quality of electric grids. Also they reduce environmental pollution. [1] In addition, with increasing of injected power from RES, specifying optimal contribution of each generator in the system is necessity. Thus, energy management and optimal scheduling of different resources could facilitate diverse missions of electric power system operator, ultimately reducing total generation electricity cost.

In the few past decades, numerous conventional optimization techniques have been applied to solve different versions of OPF problem. The conventional solvers are the Newton method [2] [3], non-linear programming (NLP) [4] and interior point methods [5]. Despite the fact that some of abovementioned methods have excellent convergence characteristics and some of them are usually suitable for industry applications. However, they have some weaknesses, which are summarized as follows:

1) Sensitivity to the initial search point, i.e., they might converge easily to local solutions as may converge to global ones.
2) Lack of flexibility with respect to practical systems, i.e., each method is suit for a specific problem formulation in its proper objectives and/or constraints.
3) Besides the inflexibility aspect, they also encounter a huge difficult to set of uncertain and stochastic problems, such as OPF with application of renewable generation.

Therefore, developing new and effective optimization methods is necessity in effort to overcome the shortcomings of the traditional optimization techniques’. [6] Thanks to the computational intelligence schemes and open access to optimization techniques have liberated considerable researches in the field of meta-heuristic algorithms to solve complex optimization problems during first decade. These optimizers have ability to provide near-global solutions and capability to escape local ones, avoiding in premature convergence. Many meta-heuristic optimization algorithms have been implemented to cope with classical OPF problem like improved version of PSO [7], moth swarm algorithm (MSA) [8], improved bacterial forging method (IBF) [9], teaching-learning-based optimization (TLBO) technique [10], backtracking-search algorithm (BSA) [11], improved colliding-bodies optimizer (ICBO) [12], adaptive multiple teams perturbation-guiding Jaya (AMTPG-Jaya) algorithm [13], and Differential Evolution [14] While
In the past few years, a system with mixed resources involving thermal, wind and solar generators has been studied in quest of providing electrical energy at minimum generation-cost with high-quality. As mentioned earlier, electricity market allows the incorporation of renewable energy sources into the electricity grids in order to minimize the environmental problems and enhancement of load relief on a transmission lines as well system voltage profile control by transmission line active power losses reduction. In that context, a few works have been published in literatures. For instance in [15] modified Jaya algorithm is applied to solve OPF incorporating RES considering four different objective functions to improve recorded results against other optimizers while the RES is modeled as a negative load, but any forecasting technique was not employed to forecast wind and solar photovoltaic power output. The results show outperforms of MJAYA on the basic Jaya as well on other existing algorithms. Partha Biswas et al. [16] proposed an adaptive version of differential evolution-based technique (SHADE) to solve OPF problem in a system involving renewable power generators. To forecast wind power and solar photovoltaic production, authors used Weibull and lognormal probability distribution functions (PDF). In addition, the feasibility of results was discussed and checked that all control variables fell inside the allowed limits. Thus, findings clearly show the efficacy of the proposed model, but, unfortunately, it was applied only on medium-sized test system IEEE 30-bus. In another publication [17], Ehab E. Elattar proposed modified version of the moth swarm algorithm to solve OPF problem of combined heat and power system with presence stochastic wind farm. The model is well presented and results were discussion but only for IEEE 30-bus system in which feasibility of solution of large-scale test system IEEE 118-bus were not discussed. As well, application of suggested model on a practical power grid was not conducted. Zia Ullah et al. [18] provide a new hybrid optimization algorithm PPSOGSA for OPF solution considering renewable energy generators. The model of stochastic behavior is based of PDF scheme. The results amply show the superiority of proposed hybrid method against basic PPSO and GSA. Again, however, the algorithm was not examined by applying it to real/large-sized power system. In Yu-Cheng Chang et al. [19], evolutionary particle swarm optimization (EPSO) algorithm was used for solving OPF problem in a wind-thermal power system. The suggested wind model is based on the up-spinning and down-spinning reserves of the production units. But, the approach was also evaluated only on modified IEEE 30-bus system and large-scale power systems were not taken into consideration when validating the proposed model. A modified cuckoo search optimization technique employed for OPF solution incorporating wind power was proposed in Chetan Mishra et al in [20]. Authors in [21] proposes a new strategy for the optimal scheduling problem taking into account the impact of uncertainties in RES and load demand forecasts. GA is used to test the effectiveness of the suggested optimal scheduling strategy by applied on the medium and large-scale test system IEEE 30-bus and 300-bus. In overall obtained results were good and promising too.

In view of aforementioned works, published results are promising and encouraging. But bear in mind that in spite of all efforts carried out in this area since half-a-century ago, topic remains open for research and also worthy of further attention. On the other hand, despite the success of many optimization methods in realizing satisfactory results, but still suffer from some limitations and shortcomings as far as their susceptibility of falling into local optima and the difficulty of tuning the main intrinsic parameters. More precisely, none of them can guarantee finding the optimal solution for all optimization problems.

Moreover, application of these algorithms on larger scale or real-sized electric grids is uncommon. Consequently, these gaps give an opportunity to suggest or develop effective metaheuristics techniques able deal different OPF formulations.

In this paper, a SM algorithm is proposed to deal with OPF problem in the presence RES and different objective functions. The proposed SMA is examined on the medium-large test system IEEE 30-bus, and a real-sized DZA114-bus power system. In addition, superiority of feasible solutions (SF) method is used herein to handle constraints of stochastic OPF problem. Slime Mould Algorithm (SMA) is a novel stochastic optimization algorithm nature-inspired proposed by Shimin Li et al. in 2020 [22], which simulates the behavior of Physarum polycephalum and morphological changes of slime mould while searching food. Its structure is very simple, which makes it easier to implement for various optimization problems [22]. Also, it has excellent randomness properties, makes it search for all optimal solutions in the search-space, hence effectively avoiding local-optimum. In addition, the following points summarize precisely master benefits of proposed SMA and also serving as motivational factors for selecting this optimizer.

1) Adaptive variation of weight allows the SMA to keep a certain perturbation-rate while warranting fast convergence, thus preventing search-process in confined regions (local optima).

2) It has an important parameter of vibration $V_{b}$ allows the individual position of SM to contract in a specific method, which guaranteeing early exploration and the accuracy of the exploitation process.

3) The position updating decision parameter $DS$ and three different position updating schemes guarantee better capability of the SMA in different search-phases.

4) The numerical results of engineering optimization problems in real life showed that SMA is more efficiency than the compared optimization techniques.

Remainder of this paper is organized as follows. Section 2 introduces the problem definition, objectives and mathematical formulation of OPF problem including applicable constraints. The description of proposed algorithm is presented in Section 3. Section 4 presents various numerical results on a test system IEEE 30-bus and Algerian DZA.
114-bus in order to show the capabilities of the developed algorithm. Finally, this paper is concluded with Section 5.

II. PROBLEM FORMULATION

The primary objective of OPF is to find the optimal settings of control-variables so that the specified objective-function is minimized while satisfying all constraints imposed (equality and inequality). Mathematically is formulated as follows:

\[
\begin{align*}
\text{Minimize} \quad & F_{\text{obj}}(x, u) \\
\text{S.t.} \quad & g(x, u) = 0 \\
& h(x, u) \leq 0
\end{align*}
\]

where \( F_{\text{obj}}(x, u) \) is the objective function, \( g(x, u) \) defines equality constraints, \( h(x, u) \) inequality constraints. \( x \) and \( u \) are the vector of dependent variables and the vector of control variables, respectively. For obtaining the optimality and guarantee the feasibility of solutions, dependent variables also should be within the allowable limits, which play an essential role in the security of electric power system

A. OBJECTIVE FUNCTIONS

In this work, three objectives will be minimized, cost, power loss, and gas emissions of thermal units.

- **Thermal power only units:**

  Fuel cost of thermal units can be described as [17]:

  \[
  C_T(P_{TG}) = \sum_{i=1}^{N_{TG}} a_i + b_i P_{TG_i} + c_i P_{TG_i}^2
  \]

  For more realistic pattern and precise modelling valve-point effect scheme is considered. Equation (3) is modified by adding an additional sine term to account for the valve effects in this manner:

  \[
  C_T(P_{TG}) = \sum_{i=1}^{N_{TG}} a_i + b_i P_{TG_i} + c_i P_{TG_i}^2 + |d_i \times \sin(e_i (P_{min} - P_{TG}))|
  \]

  where \( a_i, b_i, c_i, d_i, \) and \( e_i \) are the cost coefficients of the \( i \)-th thermal generators producing power output \( P_{TG_i} \). \( N_{TG} \) is the number of thermal generating and \( P_{min} \) is the minimum of power of conventional thermal generator. The cost and emission gas coefficients for the conventional units used here are provided in [16].

  Since wind and solar generators does not require any fuel like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms. The first norm like conventional thermal generators, cost-function evaluation of the wind and solar obey of some norms.

  Since wind and solar power plant is less than the estimated-values, this scenario called as overestimation of power, herein the system operator needs to the spinning reserve to ensure uninterrupted supply to the consumers. The cost of committing the reserve production units to meet overestimated quantity is named as reserve-cost [1]. The reserve cost for wind and solar power units is written with following equations:

  \[
  \begin{align*}
  \text{Cost}_{RW,j}(P_{WS,j} - P_{Av,j}) = K_{RW,j}(P_{WS,j} - P_{Wav,j}) \\
  & = K_{RW,j} \int_{0}^{P_{WS,j}} (P_{WS,j} - P_{W,j}) f_{W} \, dP_{W,j} \\
  \text{Cost}_{RS,k}(P_{SS,k} - P_{SAv,k}) = K_{RS,k}(P_{SS,k} - P_{SAv,k}) \\
  & = K_{RS,k} f_{S}(P_{SAv,k} < P_{SS,k}) \* \left[ P_{SS,k} - E(P_{SAv,k} < P_{SS,k}) \right]
  \end{align*}
  \]

  where \( K_{RW,j} \) denotes coefficient of reserve-cost pertaining to wind power plant, \( P_{WA,j} \) is the actual available-power from the same plant. \( f_{W} \) is the Wind power PDF for \( j \)-th power plant where and more detail is given in [1]. \( K_{RS,k} \) is the coefficient of reserve-cost for \( k \)-th Solar-Generator. \( P_{SAv,k} \) is the actual available power from the same power-plant. \( f_{S}(P_{SAv,k} < P_{SS,k}) \) is the probability of solar power-shortage occurrence than the scheduled power \( P_{SS,k} \). \( f_{S}(P_{SAv,k} > P_{SS,k}) \) is the expectation of solar-power above \( P_{SS,k} \).

  Contrary to overestimation, the second scenario called the under estimation of wind/solar power plant. In this scenario under estimation of wind/solar power plant. In this scenario the actual power produced is higher than the estimated one, yielding the surplus power. This situation requests introduce the penalty cost against each surplus amount of power, where expressed by the following equations:

  \[
  \begin{align*}
  \text{Cost}_{W,j}(P_{Wav,j} - P_{WS,j}) = K_{PW,j}(P_{Wav,j} - P_{WS,j}) \\
  & = K_{PW,j} \int_{P_{WS,j}}^{P_{Wav,j}} (P_{W,j} - P_{WS,j}) f_{W} \, dP_{W,j} \\
  \text{Cost}_{PS,k}(P_{SAv,k} > P_{SS,k}) = K_{PS,k}(P_{SAv,k} > P_{SS,k}) \\
  & = K_{PS,k} f_{S}(P_{SAv,k} > P_{SS,k}) \* \left[ E(P_{SAv,k} > P_{SS,k}) - P_{SS,k} \right]
  \end{align*}
  \]

  where \( K_{PW,j} \) is the penalty cost coefficient for the \( j \)-th wind power plant, \( P_{Wf,j} \) is the rated output-power from the same wind-farm. \( K_{PS,k} \) is the coefficient of penalty-cost for \( k \)-th solar PV plant. \( f_{S}(P_{SAv,k} > P_{SS,k}) \) is the probability of solar power surplus i.e, actual power above the scheduled power \( P_{SS,k} \). \( f_{S}(P_{SAv,k} > P_{SS,k}) \) is the expectation of solar power above \( P_{SS,k} \).
It is important to indicate that the cost evaluation for wind generator and solar PV unit are depends on the wind Weibull probability-distribution-functions (PDF) and solar radiation by lognormal PDF respectively [23].

Case 1: In the first objective function, OPF is formulated with presence of RES, whereby all the cost-functions aforementioned are included. This objective minimizes the generation cost without including emission cost. Mathematically can be expressed as:

\[ F_{Obj}^1 = C_T(P_{TG}) + \sum_{i=1}^{N_{WG}} \left[ C_{W,i} (P_{WS,i}) + C_{RW,i} (P_{WG,i} - P_{WW,i}) \right] + \sum_{k=1}^{N_{SG}} \left[ C_{S,k} (P_{SS,k}) + C_{RS,k} (P_{SG,k} - P_{SA,k}) \right] \]

where \( N_{WG} \) and \( N_{SG} \) denote the number of wind generators and PV solar in the grid.

Case 2: Emission gases and Carbon tax: Conventional thermal power generators emit harmful gases into the environment such as SOX, NOX, and CO2, which pollute the atmosphere. To reduce emission of greenhouse gases, the carbon tax was imposed as penalty. This end can be achieved through minimization of generation and emission cost which can be expressed as follows:

Second objective function Minimize-

\[ F_{Obj}^2 = F_{Obj}^1 + C_{tax} \times E \]

\[ E = \sum_{i=1}^{N_{TG}} \left[ (\alpha_i + \beta_i P_{TG,i} + \gamma_i P_{TG,i}^2) \times 0.01 + \omega_i \exp(\mu_i P_{TG,i}) \right] \]

where \( \alpha_i, \beta_i, \gamma_i, \omega_i, \mu_i \) are the emission-coefficients corresponding to the \( i^{th} \) generator and \( C_{tax} \) is the carbon tax, which is equal to 20 (\$/h).

**B. SYSTEM CONSTRAINTS**

- **Equality-constraints:** are the power flow equations which are given below:

\[ P_{Gi} - P_{di} - \sum_{j=1}^{N_B} \left[ |V_i| \times |V_j| \times Y_{ij} \right] \times \cos \left( \theta_{ij} - \delta_i + \delta_j \right) = 0 \]

\[ Q_{Gi} - Q_{di} - \sum_{j=1}^{N_B} \left[ |V_i| \times |V_j| \times Y_{ij} \right] \times \sin \left( \theta_{ij} - \delta_i + \delta_j \right) = 0 \]  

- **Inequality constraints:** represent the limits applied on the following variables

\[ P_{min}^{TG,i} \leq P_{TG,i} \leq P_{max}^{TG,i}, \quad i = 1, 2, \ldots, N_{TG} \]  

\[ P_{min}^{WG,j} \leq P_{WG,j} \leq P_{max}^{WG,j}, \quad j = 1, 2, \ldots, N_{WG} \]

\[ Q_{min}^{TG,i} \leq Q_{TG,i} \leq Q_{max}^{TG,i}, \quad \text{for} \quad i = 1, 2, \ldots, N_{TG} \]  

\[ Q_{min}^{WG,j} \leq Q_{WG,j} \leq Q_{max}^{WG,j}, \quad \text{for} \quad j = 1, 2, \ldots, N_{WG} \]  

\[ Q_{SG,k} \leq Q_{SG,k} \leq Q_{max}^{SG,k}, \quad k \in N_{SG} \]  

\[ Q_{Ci} \leq Q_{Ci} \leq Q_{max}^{Ci}, \quad i = 1, 2, \ldots, N_{C} \]  

\[ V_{Gi} \leq V_{Gi} \leq V_{max}^{Gi}, \quad \text{for} \quad i = N_{C} \]  

\[ V_{Li} \leq V_{Li} \leq V_{max}^{Li}, \quad \text{for} \quad i = N_{NL} \]  

**Security constraints**

\[ T_{k_{min}} \leq T_k \leq T_{k_{max}} \in NT \]  

\[ S_i \leq S_i^{max} \in N_{TL} \]

Eqs, (15) – (17) are the active power limits of conventional power-plants, wind and solar power generators, respectively. Eqs, (18) – (21) are the reactive power capabilities of conventional power-plants, wind- and solar generators and shunt reactive power sources. Eq. (22) shows the constraints applied at the generators busbar, whereas Eq. (23) represents the voltage limits constraining load-buses, \( N_L \) being the number of load-buses.

Security-Constraints of: tap changing transformer and line capacity are given by Eqs, (24) (25), respectively. \( N_{TL} \) is the number of lines in the electric grid.

In handling constraints, one of the first widely adopted approaches employed is static-penalty function method which is commonly based on trial and error. However, improper selection of penalty-coefficients may sometimes lead to violation of system constraints. To this purpose, constraint handling technique, superiority of feasible solutions (SF) is employed for guaranteeing the feasibility of solutions.

- **Superiority of feasible solutions (SF)**

This approach was first proposed by Powell and Sklonick in 1993 to deal infeasible solutions, afterwards Deb in [24] propose similar technique which transform the equality constraints to inequality constraints with aid of a tolerance factor epsilon \( \epsilon \) by using Eq. (26). Mathematically described as follows:

\[ \text{fitness} (x) = \begin{cases} \frac{f(x)}{|g_i(x)|^2} & \text{if } h_i(x) \geq 0, \quad h_i(x) = 1, 2, \ldots, N \\ f_{worst} + \max_{i=1}^{N} h_i (x) & \text{otherwise} \end{cases} \]

\[ |g_i(x)| - \epsilon \leq 0 \]

where \( f_{worst} \) is the objective function value of the worst feasible solution in the population and if there are no feasible solutions in the population, then \( f_{worst} \) is set to zero. \( \epsilon \) is a tolerance parameter for the equality-constraints. Other mathematical expression of SF method is presented as follows:

\[ T_i (x) = \begin{cases} \max \{h_i(x), 0\} & \text{if } i = 1, \ldots, N \\ \max \{|g_i(x)| - \epsilon, 0\} & \text{if } i = N + 1, \ldots, M \end{cases} \]
Therefore, the aim is to minimize a desired objective function \( F_i (X) \) so that the optimal solution subjected to all inequality constraints \( T_i (X) \). The overall constraint violation for an infeasible individual is a weighted mean for all the constraints, which is presented as:

\[
v_i (x) = \frac{\sum_{i=1}^{N} w_i [T_i (x)]}{\sum_{i=1}^{N} w_i}
\]

(29)

when we compare two solutions \( X_i \) and \( X_j \), \( X_i \) is said superior to \( X_j \) under the following conditions:

1) A feasible point is preferred over an infeasible one
2) Between two feasible solutions, solution having a smaller objective-value in a minimization case (greater objective value in case of maximization) is preferred.
3) Between two infeasible solutions, the one that has a smaller constraint violation is chosen.

More detail on different constraint-handling techniques for meta-heuristic optimization can be found in [25], [26].

C. STOCHASTIC WIND/SOLAR AND UNCERTAINTY MODELS

Since wind speed is a random variable, its distribution is obtained by Weibull Probability Density Function (PDF) with shape factor \( k \) and scale factor \( c \). Mathematically given by:

\[
f_w (S) = \left( \frac{k}{c} \right) \left( \frac{S}{c} \right)^{k-1} \exp \left( - \frac{S}{c} \right)^{k} \text{ for } 0 < S < \infty
\]

(30)

- **Wind power model**
  
  The output wind power from a wind turbine is a function of wind speed, expressed by the following equation: [16]

\[
P_w (\nu) = \begin{cases} 
0, & \text{for } \nu (\nu_{in} \text{ and } \nu) \nu_{out} \\
 \frac{P_{wr}}{\nu_{in}} \left( \frac{\nu - \nu_{in}}{\nu_{out} - \nu_{in}} \right), & \text{for } \nu_{in} \leq \nu \leq \nu_{r} \\
 \frac{P_{wr}}{\nu_{in}} \left( \frac{\nu - \nu_{in}}{\nu_{r} - \nu_{in}} \right), & \text{for } \nu_{r} \leq \nu \leq \nu_{out}
\end{cases}
\]

(31)

where \( \nu_{in} \), \( \nu \), and \( \nu_{out} \) are respectively the turbine cut-in, rated and cut-out wind speeds. \( P_{wr} \) defines the rated output power of the wind turbine.

- **Wind power probability for different wind speeds**
  
  From eq. 32, we can note that if \( \nu \) is less than \( \nu_{in} \) and above \( \nu_{out} \), the power output is zero. Also, the wind turbine produces \( P_{wr} \) for the condition \( \nu_{r} \leq \nu \leq \nu_{out} \).

For these discrete zones, the probabilities can be written by the following equations:[27]

\[
f_w (P_{wr}) [P_{wr} = 0] = 1 - \exp \left[ - \left( \frac{\nu_{in}}{\alpha} \right)^{\beta} \right]
\]

(32)

\[
f_w (P_{wr}) [P_{wr} = P_{wr}] = 1 - \exp \left[ - \left( \frac{\nu_{out}}{\alpha} \right)^{\beta} \right] + \exp \left[ - \left( \frac{\nu_{in} + P_{wr}}{\alpha} \right)^{\beta} \right]
\]

(33)

Unlike the discrete zones, the output wind power is continuous for the condition \( \nu_{in} \leq \nu \leq \nu_{r} \). Hence, the probability for this region is described as follows: [27]

\[
f_w (P_{wr}) = \frac{\beta (\nu_{r} - \nu_{in})}{\alpha \beta P_{wr}} \left[ \nu_{in} + \frac{P_{wr}}{\nu_{r} - \nu_{in}} \right]^{\beta - 1} \times \exp \left[ - \left( \frac{\nu_{in} + P_{wr}}{\nu_{r} - \nu_{in}} \right)^{\beta} \right]
\]

(34)

Also, the solar irradiance to energy conversion for the PV plant also can be given by

\[
P_{s} (G) = \begin{cases} 
P_{sr} \left( \frac{G^2}{G_{std}^2} \right), & \text{for } 0 \leq G \leq R_c \\
P_{sr} \left( \frac{G}{G_{std}} \right), & \text{for } G \geq R_c
\end{cases}
\]

(35)

where \( G_{std} \) is the solar irradiance in standard environment, \( R_c \) is a certain irradiance point, \( P_{sr} \) is the rated output of the PV power plant. Further details about uncertainty model of RES can be found in Ref [1].

III. SMA-BASED PROPOSED METHOD

Slime Mold Algorithm is a novel stochastic optimization technique proposed by Li et al. in 2020 [22], that has tried to mimics the behavior of Physarum polycephalum and the bio-oscillation mode of the slime in nature. SMA used the weights to simulate the negative and positive feedback produced by slime mold during foraging-process, forming three kinds of morphotype. The latter is regarded as a new idea involves creating a differentiation in search-space for obtaining new possible solutions. One of the most interesting characteristics of slim mould is the unique pattern, allowing to SM custom several foodstuff sources simultaneously, forming a venous network joining them. This pattern allows exploring different regions of search-space and avoids falling into local optima. Based on the quality food-stuff, slime mould can well-being dynamically adapt or adjust their search schemes efficiently. When the quality of food sources is positive (high-quality), the slim mould utilizes the region-limited search-technique, herein slim mould focuses only on the achieved food sources. Otherwise, in case of quality of food sources that have been found is negative (low-quality), they abandon the food source in order to explore new ones in the area. According of the negative, positive feedback responses, slime mould can develop the optimum food-path to tie food in a relatively more best way. The mathematical model of some mechanisms and characteristics of the slime mould will be illustrated in the subsequent sections.
A. MATHEMATICAL MODELING OF THE SLIME MOULD ALGORITHM

1) APPROACH-FOOD

SM can easily reach food through the odour in the air. This behavior of contraction is modeled mathematically Eq.(30)

\[
\hat{X}(t+1) = \begin{cases} \hat{X}_B(t) + \nu_b. \left( \vec{W}.X_A(t) - \hat{X_B}(t) \right), & r < p \\ \nu_c.X(t), & r \geq p \end{cases}
\]

(36)

where \( \nu_b \) is a parameter within range \([-a, a] \), \( \nu_c \) decreases linearly from 1 to 0. \( t \) represents the current iteration. \( \hat{X}_B \) indicates the individual position associated with highest odour-concentration currently found. \( \hat{X} \) represents the position of SM, \( \hat{X}_A \) and \( \hat{X}_B \) are two randomly generated individuals from the population. \( W \) is the weight of slime mould. The \( p \) formula expressed by Eq. 38

\[
p = \tanh |S(i) - DF|
\]

(37)

where \( S(i) \) is the fitness value of \( \hat{X} \), whereas \( DF \) is the best fitness obtained in all iterations. \( \nu_b \) is defined as follows:

\[
a = \arctanh \left( - \left( \frac{\text{iter}}{\text{max} - \text{iter}} \right) + 1 \right)
\]

(38)

The formula of \( W \) in Eq. (1) can be given by

\[
\vec{W} = \begin{cases} 1 + r.\log \left( \frac{bF - S(i)}{bF - wF} + 1 \right), & \text{Condition} \\ 1 - r.\log \left( \frac{bF - S(i)}{bF - wF} + 1 \right), & \text{others} \end{cases}
\]

(39)

Eq. 34 simulates the negative and positive feedback created between the concentration foods explored with the vein width of the SM.

\[
\text{SmellIndex} = \text{sort}(S)
\]

(40)

where \( r \) is a randomly generated number with a range of \([0, 1]\) and \( bF \) represents the optimum fitness-value obtained in the current-iteration. The worst fitness-value realized in the iterative process currently is \( wF \). \( \text{SmellIndex} \) defines the sequence of fitness-values sorted. \( \log \) is introduced to ease the change-rate of numerical value, in which the contraction frequency value does not change significantly.

2) WRAP-FOOD

A slime mould will update its location with the following formula:

\[
X^* = \begin{cases} \text{rand.}(ub - lb) + lb, & \text{rand} < z \\ \hat{X}_B(t) + \nu_b. \left( \vec{W}.X_A(t) - \hat{X}_B(t) \right), & r \geq p \\ \nu_c.\hat{X}(t), & r < p \end{cases}
\]

(41)

where \( ub \) and \( lb \) are the upper and lower bounds of search-space, respectively.

3) GRABBLE-FOOD

The success of SM mainly depends on their oscillation parameters \( \nu_b \) and \( \nu_c \), were used to introduce stochastic nature in the model, helping to guide individuals towards food position having high concentration. Detailed characteristics about slime mould algorithm is given in [22]. SMA is like other meta-heuristic techniques start the process of optimization by distributing individuals in the search-space as first solutions. Each individual in a population represents a possible solution of the optimization problem, and then all generated solutions have been evaluated by selected objective-function and select the minimal value with minimization and maximum value in case of maximization.

Afterwards, at each iteration the individuals update their coordinates according to some equations movement of slime mould in nature along with some parameters.

In the next step, the updating process is repeated till a terminal criterion is satisfied. Last step, the optimal-solution that corresponds to the best-individual achieved so far is memorized. Table 1 describes the steps of the proposed SMA in solving OPF problem considering WT and PV generation with SF constrain approach. The flowchart of proposed algorithm is presented in Fig 2.

IV. NUMERICAL RESULTS AND DISCUSSION

To validate the potential and feasibility of the proposed SMA in solving stochastic OPF problems incorporating wind power generators and solar photovoltaic, SM algorithm was examined on the modified IEEE 30-bus test system and Algerian electricity grid DZA 114-bus under different objective functions. The modification is to insert two wind generators at buses #5 and #13 along with one solar generator at bus #1. All data ca be retrieved in [23] and Zimmerman et al. [28]. All algorithms have been coded and solved under MATLAB R2014a platform and run on an Intel®Core™i5-4300U 2.50 GHz 4.00 GB RAM personal computer. The population size is selected using empirical tests by running the SMA several times with different population sizes like 20, 40, 60 and 80. The test results are...
TABLE 1. SMA for stochastic optimal power flow (OPF) problem.

| Step | Description |
|------|-------------|
| 1    | Read data of test system and SMA-SF input |
| 2    | Read input data of test system configuration: Bus-data, Line-data, transformers data, and generation units-data. |
| 3    | Dimension of the problem, dim (dim =12 for IEEE 30-bus, 30 for DZA 114-bus) |
| 4    | Number of population, \( N_p \) (\( N_p = 30 \) for IEEE 30-bus and 60 for DZA 114-bus, Selected) |
| 5    | Stopping criteria is the Max-number of iterations |
| 6    | Minimum and Maximum value of control (decision) variables, in vector like \( X_{\text{min}} \) and \( X_{\text{max}} \) \( X_{\text{max}} = [X_{\text{min}}, X_{\text{max}}, ..., X_{\text{max}}] \) |
| 7    | Specify the desired objective function to be optimized (\( F_{\text{min}}^1 \), \( F_{\text{min}}^2 \), or \( F_{\text{min}}^3 \)) |
| 8    | Calculate the forecasted-output power of wind turbine and PV units. |
| 9    | Generate initial population of size \( N_p \) individuals uniform spreading in the range \( [X_{\text{min}}, X_{\text{max}}] \) |
| 10   | Run power-flow for each updated individual in the population and calculate the fitness of all individual. Then, evaluate constraint function and constraint violation using Equations (27) – (30). |
| 11   | Apply the SMA operators and equations of update to create a new population of individuals’ (i.e., obtaining Improved solutions of the problem). |
| 12   | In selection phase, individuals for next population are replaced with new individuals if give better value of objective function according to rules of SF method. After each updating process, the new individual is considered better if it yields negligible constraint violation or zero constraint violation than the respective old population individual. Otherwise, previous individual is retained. |
| 13   | Repeat steps 5-7 until the stopping criteria is reached, i.e., until max-iteration achieved |
| 14   | Report the optimal results that corresponds with the best pathfinder and its fitness value (objective-function value) |

FIGURE 2. Flowchart of SMA.

not reported herein, we therefore, indicate only the population size which resulted in achieving best outcomes. To this end, in all simulation cases, number of population size is specified as 30 individuals for IEEE 30-bus, 60 for DZA 114-bus and maximum number of iterations is fixed 300 for IEEE 30-bus and 400 for practical power system. For the purpose of a fair comparison, all control variables of test systems were considered as continuous. Table 2 provides PDF parameters of wind power and solar PV plants. Table 3 reports description of all test-systems characteristics used in this article.

A. RESULTS OF MODIFIED IEEE 30-BUS TEST SYSTEM

To show the efficiency of the SMA, the deterministic OPF cases for the modified system configuration, i.e., without WT generators and PV units are considered. Four cases are studied herein, with the objective functions mentioned in section above, namely: Case 1 – minimization of basic fuel cost; Case 2 – optimized cost against reserve-cost; Case 3 – minimization of total generation-cost with carbon-emission tax; Case 4 – optimized cost against penalty-cost. The optimal results obtained for each examined case are presented in Table 4.

1) CASE 1 – MINIMIZATION OF TOTAL GENERATION-COST

In this case, the objective-function is minimization of the total cost of generation. Obtained findings by using proposed algorithm SMA are based on the Weibull PDF parameters. Figures 3-5 represent Weibull fitting and wind distribution obtained from the simulation of 8000 Monte Carlo scenarios, while the stochastic power-output of solar photovoltaic unit is illustrated by Fig 6.

Optimal locations of the wind farm and PV power generation depend on several factors such as wind speed and solar radiation, respectively [29].

In this paper, the locations of wind and PV units are selected as in [30] for IEEE 30-bus test system with the aim of comparing the obtained results with those mentioned in [30]
and from company of electricity SONELGAZ for Algerian power system.

As shown, from obtained findings the SMA, given in Table 4 is achieved the minimum value of generation cost compared with other optimizers. The optimal generation cost achieved by SMA is 781.078 MW, while for other optimization techniques, PSO (784.3400 $/h), TLBO (782.6767 $/h), SHADE-SF (782.50 $/h), jellyfish (781.6387 $/h), artificial ecosystem optimizer (781.5219 $/h), and hunger games search (781.86 $/h) as well as vs. a recently optimization technique which introduced October 1, 2021 entitled, orca predation algorithm (782.0760 $/h) and gorilla troops optimizer GTO (781.26 $/h). It is worth to note that PWG1 and PWG2 indicate the scheduled powers from wind generators #WG1 and #WG2, respectively. The emission rate is calculated by using the optimal scheduled power of thermal generators, where reserve is assumed an alternate source that does not add to the emission.

Based on the results obtained in the literature regarding solution of classical OPF problem and the results given in Table 4, it can state that with insertion of renewable energy sources, the total generation-cost decreased from 800.00 $/h as a reference cost to 781.07 ($/h), i.e., around 18.9 $/h. More precisely, if every hour can save the cost of 18.9 $, and the operating time per-year is supposed as 7500 h, then operating time from the propose optimizer SMA can save 141975 Dollars in total every year. Consequently, the

insertion of wind generators and solar power plant significantly contributes on the reduction on total generation cost compared with the original system configuration (i.e., without RES). The comparison and statistical- results of SMA with other algorithms are listed in Table 5. Fig. 7, illustrates a comparison between the convergence of SMA and other applied algorithms.

2) CASE 2—MINIMIZATION OF TOTAL GENERATION-COST WITH CARBON-EMISSION TAX

In this case, the quadratic total cost of generation and emission functions in (13) were minimized considering the
TABLE 4. Optimal results comparison for different algorithms for IEEE 30-bus, Case 1.

| Variables | Min  | Max   | PSO 23 | TLBO 32 | SHADE-SF 1 | JS [30] | OPA | AEO | HGS | GTO | SMA |
|-----------|------|-------|--------|---------|------------|---------|-----|-----|-----|-----|-----|
| $P_{G1}$ | 50   | 140   | 134.907| 134.843 | 134.908    | 134.905 | 134.91 | 134.908 | 134.907 | 134.907 | 134.91 |
| $P_{G2}$ | 20   | 80    | 28.037 | 29.0639 | 28.564    | 29.0226 | 27.0785 | 27.7985 | 28.8317 | 28.1779 | 29.4961 |
| $P_{G1}$ | 0    | 75    | 43.744 | 44.045  | 43.774    | 43.9696 | 43.0040 | 42.9166 | 42.8527 | 43.2909 | 42.2527 |
| $P_{G3}$ | 10   | 35    | 10.000 | 10.0606 | 10        | 10.0066 | 10.0003 | 10.0057 | 10.0000 | 10.0000 | 10.0034 |
| $P_{G2}$ | 0    | 60    | 37.193 | 36.6258 | 36.949    | 37.0193 | 36.4374 | 35.9806 | 35.3547 | 36.5917 | 37.1432 |
| $P_{G1}$ | 0    | 50    | 35.303 | 34.5823 | 34.976    | 34.2532 | 37.7603 | 37.9418 | 37.2989 | 36.1438 | 35.3402 |

FIGURE 6. Real power distribution (MW) of solar PV at bus 13.

The carbon tax (Ct) imposed on the thermal power plants. Herein, the carbon-tax value is equal to 20 $/ton [1]. It is obvious that with existence of the Carbon-Tax the penetration level from RES is raised, and this can be visualised within simulation results. The ratio of penetration of RES in the scheduled of optimum generation is based on the volume of emission rate with the imposed carbon-tax value. Main objective here is to schedule more power among the renewable energy so that the volume of emission is kept at minimum level.

3) CASE 3 – OPTIMIZED COST AGAINST RESERVE-COST
In third case, all parameters are retained the same as in first case except reserve-cost-coefficients. The coefficients of wind generators and solar photovoltaic unit are varied by a discrete-step of 1 starting from 4 to 6, i.e., $K_r = 4$, (case3-a), $K_r = 5$, (case3-b) = 6, (case3-c). The penalty-cost-coefficients for all intermittent sources are remain the same as the first case. The optimal power scheduled of generators is presented by bar graph in Fig.8 and compared with those found for the base case (case 1). For clarification purpose, Case 3-a describes case when reserve coefficient $K_r = 4$, case 3-b represents for $K_r = 5$, and case 3-c represents $K_r = 6$. In this case study, when the coefficient of reserve cost increases, the

TABLE 5. Statistical results of different optimizers for Case 1.

| Algorithms | Min ($/h$) | Max ($/h$) | Mean ($/h$) | Std |
|------------|------------|------------|-------------|-----|
| GOA [23]   | 785.7109   | 823.4751   | 804.01685   | 9.52e+00 |
| BWOA [23]  | 784.8148   | 795.4683   | 788.247149  | 5.83e+00 |
| GWO [23]   | 781.6645   | 783.3359   | 783.041118  | 2.75e-01 |
| ALO [23]   | 781.6562   | 791.9234   | 784.325274  | 2.49e-00 |
| PSO [23]   | 781.9047   | 794.4220   | 784.904776  | 2.52e-00 |
| GSA [23]   | 782.2237   | 794.8995   | 785.860254  | 2.44e-01 |
| MFO [23]   | 781.6928   | 783.9304   | 782.491975  | 4.77e-01 |
| BMO [23]   | 781.6519   | 783.5283   | 781.818671  | 3.44e-01 |
| AEO        | 781.3979   | 782.8744   | 781.8199    | 3.095e-01 |
| HGS        | 781.86     | 782.9445   | 782.4106    | 3.649e-01 |
| GTO        | 781.2626   | 782.7022   | 782.082     | 3.77e-01 |
| SMA        | 781.07     | 782.990    | 781.9726    | 4.53e-01 |
TABLE 6. Optimal results of case 2 for modified IEEE 30-bus test system.

| Variables | SHADE-SF [23] | MFO [23] | BMO [23] | JS [30] | OPA | HGS | GTO | AEO | SMA |
|-----------|---------------|----------|----------|--------|-----|-----|-----|-----|-----|
| P_{G1}    | 123.020       | 123.637  | 123.127  | 123.572| 123.914 | 123.315 | 123.372 | 123.394 | 123.6670 |
| P_{G2}    | 33.047        | 33.2996  | 31.947   | 33.1626| 34.5124 | 32.6554 | 32.7853 | 32.6331 | 33.5199 |
| P_{G3}    | 46.021        | 46.1099  | 45.402   | 46.0866| 46.6065 | 45.7569 | 45.8351 | 45.8296 | 46.2945 |
| P_{G4}    | 10.000        | 10.0000  | 10.000   | 10.000 | 10.000 | 10.000 | 10.000 | 10.000 | 10.000 |
| P_{G5}    | 38.748        | 38.8443  | 38.270   | 38.8011| 39.1231 | 38.5231 | 38.5999 | 38.5619 | 39.2413 |
| P_{G6}    | 37.336        | 36.7199  | 39.865   | 37.0628| 34.5273 | 38.4482 | 38.0833 | 38.2888 | 35.9774 |
| V_{1}     | 1.071         | 1.0782   | 1.0777   | 1.07666| 1.0715 | 1.0723 | 1.0702 | 1.0732 | 1.0731 |
| V_{2}     | 1.057         | 1.0645   | 1.0640   | 1.05715| 1.0583 | 1.0591 | 1.0569 | 1.0588 | 1.0589 |
| V_{3}     | 1.036         | 1.0432   | 1.0426   | 1.03604| 1.0364 | 1.0384 | 1.0357 | 1.0371 | 1.0378 |
| V_{4}     | 1.04          | 1.0473   | 1.0471   | 1.04038| 1.0399 | 1.0427 | 1.0403 | 1.0415 | 1.0414 |
| V_{5}     | 1.099         | 1.1000   | 1.1000   | 1.0983 | 1.0975 | 1.1000 | 1.0985 | 1.0983 | 1.0980 |
| V_{6}     | 1.056         | 1.0591   | 1.0602   | 1.05575| 1.0521 | 1.0627 | 1.0580 | 1.0573 | 1.0581 |
| Q_{G1}    | -2.678        | -1.1738  | -1.8489  | -2.6666 | -2.75418 | -0.0912 | -3.24025 | 2.9900 | 2.4424 |
| Q_{G2}    | 12.319        | 12.565   | 12.4664  | 12.3540 | 14.63630 | 18.527 | 12.5509 | 17.7547 | 17.9378 |
| Q_{G3}    | 35.27         | 22.889   | 22.9777  | 35.2538 | 22.6387 | 26.0632 | 22.83972 | 25.5261 | 25.9879 |
| Q_{G4}    | 22.964        | 35.847   | 35.6682  | 22.9900 | 34.70553 | 39.9714 | 34.9987 | 39.8429 | 39.5619 |
| Q_{G5}    | 30            | 28.500   | 28.5058  | 30.000 | 29.98716 | 30.000 | 30.000 | 29.9998 | 29.8480 |
| Q_{G6}    | 17.779        | 16.659   | 17.0942  | 17.7114 | 16.44832 | 19.737 | 18.50504 | 18.1606 | 18.5039 |
| F_{Cot} ($/h) | 810.346   | 811.422  | 810.7982 | 810.120 | 811.121 | 811.0344 | 810.4412 | 810.7258 | 810.3875 |
| Emission  | 0.891        | NA       | 0.8973   | 0.9114 | 0.8807 | 0.88361 | 0.8847 | 0.8986 | 0.8986 |
| VD (p.u.) | 0.469        | NA       | 0.4688   | 0.4592 | 0.5042 | 0.47525 | 0.4731 | 0.4760 | 0.4760 |

FIGURE 7. Convergence curves of different optimization techniques for case 1.

contribution of wind and solar generators reduced gradually, resulting in a shortage of scheduled power. So, an amount of spinning reserve is urgently needed in order to fill this shortage. This shortage in power automatically compensated by thermal generators which result in increasing the cost of thermal power generators due to the increase of the output power illustrated in Figure 7. In summary, total generation cost raises with the increase in the reserve-cost coefficient.

B. CASE 4 — OPTIMIZED COST AGAINST PENALTY-COST

Unlike to the past case, in the fourth case, all parameters of reserve cost are keeping as in first case excluding penalty cost-coefficients. Then coefficients of penalty-cost for all wind generators and photovoltaic power plant are raised from 4 to 6 by the following order, i.e., \( c_{4-a} = 5 \) (case 4-b), = 6 (case 4-a). The optimal power scheduled of six-generators is represented by bar-graph in Figure 9 and compared with those found for the case 1 at the same figure.

When penalty cost coefficient raises, scheduled amount of renewable energy generators increases too, leading to decrease the output of thermal generating units with a not uniform manner, Figure 9. This is judged on the basis of the economic dispatch between three thermal generators, and it is observed that considerable part of power is dispatched on the generator which having the lower production cost. On the other hand, the scheduled output for all renewable energy sources also seems not to uniform, which can be interpreted by the highly nonlinear relation between PDF and reserve / penalty cost of both solar and wind generators. It is also seen that the thermal generators cost \( Th_{Gx} \) is constant and a steady rise in total cost is observed.
To evaluate applicability of the proposed techniques on the large-scale and practical power system, the modified Algerian electricity grid DZA 114-bus[31] has been considered as test system. Algerian network topology is illustrated in Figure 13 (Annex). System consists of 175 transmission-lines, which sixteen branches are equipped with tap-changing transformers, and fifteen generators. The total-load demand is

\[(3727 + j 2070) \text{ p.u at } 100 \text{ MV A base.}\]

The slack-bus is Bus no 4. The modification is to insert two wind generators at buses #52 and #83 along with one solar generator at bus #109. All data of test system "MATPOWER format" are free only for referees. Therefore, there are a total of 46 variables to be optimized, including 15 active power of generators, 15 voltage magnitudes of generators, and sixteen tap-changer adjustment. Also, this power system exhibits undesirable voltage drops at some buses, making it harder to ensure the feasibility of solutions, especially reactive power generators. Minimum and maximum operating limits of the control variables are given in the table of results.

In this part, the adopted objective-function is the total generation cost minimization by means of the SMA, GTO, HGS, AEO and OPA algorithms. Fig. 10 shows the convergence.
curves of the considered optimizers and, as noticeably, the SMA converges to high quality solutions in the first quarter of iterations.

Based on the convergence plot presented in Fig. 10, it can be seen that SMA achieves the minimum value of generation cost compared with other optimization techniques.

Base case denotes the simulation without considering renewable energy sources, i.e., all power plants are the conventional power generators, and minimum values of active powers at buses #52, #83, and #109 are 34.5 MW, 30 MW, and 10 MW, respectively. In this case study, min-
Optimization of total generation cost is performed and the obtained results were listed in the first column of Table 7 below. Moreover, by observing the reactive power limits (Q) provided in Table 7, generators TG5, TG19, TG22, TG98,
TG98, WG52, and WG83 operate at their maximum limits of Q capacity for both cases. So, it is more necessary to regard the constraints on generators reactive power during implementation of any optimization method. Thus, from all results obtained so far, it is sufficient to highlight effectiveness of the proposed constraint handling-technique, that guarantee the feasibility of solutions, even with the real power system.

1) CASE 5 — OPTIMIZED COST AGAINST RESERVE-COST TO ALGERIAN POWER SYSTEM DZA114-BUS

In this case, scenario of case 3 is performed for DZA 114-power system. The coefficients of wind generators and solar photovoltaic unit are varied by a discrete-step of 1 starting from 6 to 8, i.e., = 6, (case 5-a), = 7, (case 5-b) = 8, (case 5-c). The penalty-cost-coefficients for all intermittent sources are remain the same as the first case. The optimal power scheduled of generators is provided in Table 8.

In this case study, increasing the coefficient of reserve cost results in a decreased contribution of wind and solar generators gradually, making in a shortage of scheduled power. So, an amount of spinning reserve is urgently needed to fill this shortage.

This shortage in power (MW) automatically compensated by thermal-generators which result in increasing the cost of thermal power generators due to the increase of the output power as observed in Table 8. Moreover, from Table 8, It can observe that active power output at slack bus for each three case 5-a, case 5-b and case 5-c increases to cover this shortage, meanwhile, output of renewable generators WG1 decrease from 350 mw to 200.86 MW and WG2 decrease from 300 MW to 174.66 MW for case 5-c. What equal to 270 MW should be compensate from thermal generators in an effort to maintaining power system stability. On the other hand, the output of solar generator is remains fix at 100 MW for three subcases, this is can be justify by technical aspect, i.e., for keeping each bus voltage magnitudes located near to the SG bus (#109) within the admissible limits [0.9-1.1] p.u. Fig. 12 presents generator reactive power scheduled for case 5 of DZA 114-bus

VI. CONCLUSION

In this article, an efficient and robust Slime Mould-inspired algorithm has been suggested for provide an optimal-solution of the stochastic OPF problem in the modified IEEE 30-bus test system and Algerian electrical network DZA 114-bus. Uncertainty nature of both solar and wind energy sources has been modelled based on the Weibull and lognormal PDFs distribution, respectively. To investigate the performance of SM algorithm, four optimization techniques: HGS, AEO, GTO, and orca predation algorithm-(OPA) are applied on different test systems. Numerical results of SMA are compared with the results found by aforementioned algorithms and other ones provided in literature. The results revealed that the SMA significantly gives a superior solution, while insuring the feasibility of solutions, where outperformed AEO, JS, HGS, MFO, GTO and BMO methods in the base case and other sub-cases whatever the constraints of test system. The results suggest that the proposed SMA can be successfully applied to solve highly nonlinear problems. The findings of this document are likely to be beneficial to researchers. Therefore, the proposed algorithm based SM technique with the superiority of feasible solutions method it is an excellent and highly recommended technique for the stochastic OPF problem, since it more efficient even in the case of practical electrical network.

ACKNOWLEDGMENT

The authors would like to acknowledge the financial support received from Taif University Researchers Supporting Project Number TURSP-2020/34, Taif University, Taif, Saudi Arabia, and in the Supporting Research Project PRFU, under Grant (A01L07UN100120210002) from the University of Bouira in Algeria.

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