Optimal reactive power dispatch solution by loss minimization using moth-flame optimization technique

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A B S T R A C T
In this paper, a newly surfaced nature-inspired optimization technique called moth-flame optimization algorithm (MFO) is utilized to address the optimal reactive power dispatch (ORPD) problem. MFO algorithm is inspired by the natural navigation technique of moths when they travel at night, where they use visible light sources as guidance. In this paper, MFO is realized in ORPD problem to investigate the best combination of control variables including generators voltage, transformers tap setting as well as reactive compensators sizing to achieve minimum total power loss and minimum voltage deviation. Furthermore, the effectiveness of MFO algorithm is compared with other identified optimization techniques on three case studies, namely IEEE 30-bus system, IEEE 57-bus system and IEEE 118-bus system. The statistical analysis of this research illustrated that MFO is able to produce competitive results by yielding lower power loss and lower voltage deviation than the selected techniques from literature.

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1. Introduction
Over the last few decades, electrical power system has become an increasingly important subject due to the modern economy that run by electricity. Electrical power system is a system of generating, transmitting and distributing electricity for industrial, housing and transportation uses. Moreover, electrical power system is also the heart of renewable energy systems. As the demands for electricity increased, the consumption of resources also will gradually increase. Undeniably, optimal reactive power dispatch (ORPD) plays an important role in operation and control of power system due to its remarkable influence on the reliability, security and economic operation issues. As a sub problem of optimal power flow (OPF), ORPD is defined as a renowned nonlinear optimization problem in power system which involving both discrete and continuous control variables while satisfying both equality and inequality constraints [1–5]. Thence, optimization process is utilized to obtain the best possible combinaisonal of control variables including generator bus voltages, transformers tap setting and reactive compensators sizing in order to minimize the objective functions.

There is variety of optimization techniques in overcoming ORPD problem as reported in literature. Referring to [6–11], conventional optimization methods such as linear programming [12,13], non-linear programming, quadratic programming [14], Newton method, gradient-based algorithm and interior point method [15] have been implemented in solving ORPD problem. Nevertheless, they are inefficient in dealing problems with nonlinear functions and discrete variables [1,16], thus, leading loss of accuracy. Furthermore, the so-called stochastic search optimization methods such as genetic algorithm (GA) [17,18], evolutionary programming (EP) [19], evolutionary strategy (ES) and tabu search (TS) were also applied to overcome the ORPD problem. The key success of stochastic search methods are their ability in obtaining global optimum and handling non-convex as well as discontinuous objective functions. However, they are inefficient in managing problems with discrete nature and integer [20].

Recently, development and exploitation in meta-heuristic methods have shown a better result in solving ORPD problem. Those methods include particle swarm optimization (PSO) [1,21], artificial bee colony (ABC) [20], harmony search algorithm (HSA) [3], improved HSA (IHSA) [22], modified HSA [23], gravitational search algorithm (GSA) [24,25], seeker optimization algorithm (SOA) [26] and gray wolf optimizer (GWO) [2]. Additionally, there are also researchers who used hybrid techniques to solve ORPD problem such as combined modified imperialist competitive algorithm and invasive weed optimization (MICA-IWO) [4], combined differential evolution and ant system [27] as well as hybrid particle swarm optimization and imperialist competitive algorithm (PSO-ICA) [28]. In [29], quasi-oppositional differential evolution (QODE) is proposed to solve ORPD problem by implementing quasi-oppositional based learning (QOBL). In [30], the researchers...
proposed a two-point estimate method (TPEM) to model the load uncertainty in a multi objective ORPD (MO-ORPD) problem. However, according to no free lunch (NFL) theorem [31], there is no specific technique that can solve all the optimization problem. Therefore, ORPD problem still can be solved by implementing new developed optimization algorithm.

This paper proposes the use of a novel nature-inspired heuristic technique known as moth-flame optimization (MFO) algorithm in solving ORPD problem. This technique serves as an alternative to other recent optimization techniques. The MFO algorithm has been developed by Seyedali Mirjalili [32], which inspired by the nature navigation method of moths at dark by travelling depending on a light source. In comparison with other methods, there are several contributions of this algorithm in solving optimization problem. First, MFO algorithm implements a population of moths to perform optimization and each moth is required to update their positions with respect to a flame. Thus, this helps to avoid the local optima entrapment and improve the exploration process in the search space. The moths will always update their positions according to the most promising flames obtained so far over the course of iteration. The flames will be remembered as the best optimum solutions. These serve as guidance for the moths, thence, this help them to retain the best results. Consequently, the convergence of MFO is ensured. Moreover, MFO algorithm is simple to implement as it does not required many control parameters while solving ORPD problem.

The rest of this paper is organized as follows: Section 2 discusses the mathematical formulation of ORPD problem followed by a concise introduction of MFO algorithm in Section 3. Section 4 presents the utility of MFO by implementing this algorithm in solving ORPD problem. The simulation results and discussions are provided in Section 5. Last but not least, Section 6 concludes the research of this paper.

2. ORPD mathematical formulation

2.1. Objective function

In this paper, the objective functions of ORPD problem are to minimize power losses and voltage deviation of the transmission system while fulfilling the equality constraint and inequality constraints. The ORPD problem can be formulated as the minimization of function \( f(x, u) \) as described as follows:

Minimize \( f(x, u) \)

Subjected to

\[
\begin{align*}
g(x, u) & = 0 \\
h(x, u) & \leq 0
\end{align*}
\]

where function \( g(x, u) \) is the objective function. Additionally, \( g(x, u) = 0 \) and \( h(x, u) \leq 0 \) are the equality and inequality constraints respectively. In ORPD, the equality constraint is the power balanced equation whereas the inequality constraints are generators voltage, transformers tap setting and reactive compensators sizing. \( x \) and \( u \) are the dependent variables vector and control variables vector respectively. As mentioned before, one of the objective functions of this paper is to minimize the total system transmission loss, which it is in fact an economic loss that neither provides any benefit nor profit. The other objective function, minimizing voltage deviation is important as well as it increase overall system stability. The total system transmission loss, \( F_1 \) and voltage deviation at load buses, \( F_2 \) can be formulated as follows [3]:

\[
F_1 = P_{\text{Loss}} (x, u) = \sum_{L=1}^{Nl} P_{\text{Loss}}
\]

\[
F_2 = VD(x, u) = \sum_{i=1}^{Nd} |V_i - V_i^{\text{SP}}|
\]

where \( Nl \) indicates the number of transmission lines and \( Nd \) is the number of load buses. \( V_i \) is the voltage at load bus-\( i \) and \( V_i^{\text{SP}} \) is the specified value (usually set as 1.0 p.u).

2.2. Equality constraint

The equality constraint which is the power equality of load flow stated that the difference between power generated and power demand is equal to power loss as declared in [3]. The equality constraint equations can be expressed as below:

\[
P_{\text{Gi}} - P_{\text{Di}} = V_i \sum_{j \in N_i} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij})
\]

\[
Q_{\text{Gi}} - Q_{\text{Di}} = V_i \sum_{j \in N_i} V_j (B_{ij} \cos \theta_{ij} - G_{ij} \sin \theta_{ij})
\]

where \( V_i \) and \( V_j \) are the voltage at load bus-\( i \) and bus-\( j \) respectively, \( B_{ij} \) and \( G_{ij} \) are the susceptance and conductance between bus-\( i \) and bus-\( j \) respectively. On the other hand, \( P_{\text{Gi}} \) and \( P_{\text{Di}} \) are the real power generation and real load demand respectively. Whereas, \( Q_{\text{Gi}} \) and \( Q_{\text{Di}} \) are the reactive power generation and reactive load demand respectively.

2.3. Inequality constraints

2.3.1. Generator constraints: bus voltages' generation as well as generation of real and reactive power must be restricted by their boundaries as below

\[
p_{\text{Gi}}^{\text{min}} \leq P_{\text{Gi}} \leq p_{\text{Gi}}^{\text{max}} \quad i = 1, ..., N_G
\]

\[
q_{\text{Gi}}^{\text{min}} \leq Q_{\text{Gi}} \leq q_{\text{Gi}}^{\text{max}} \quad i = 1, ..., N_G
\]

\[
V_{\text{Gi}}^{\text{min}} \leq V_{\text{Gi}} \leq V_{\text{Gi}}^{\text{max}} \quad i = 1, ..., N_G
\]

where \( N_G \) is the generators' number.

2.3.2. Transformer tap ratios must be within their minimum and maximum boundaries as below

\[
T_{\text{Ni}}^{\text{min}} \leq T_i \leq T_{\text{Ni}}^{\text{max}} \quad i = 1, ..., N_T
\]

where \( N_T \) is the transformers' number.

2.3.3. Reactive compensator sizes are limited by their ranges as below

\[
Q_{\text{Ci}}^{\text{min}} \leq Q_{\text{Ci}} \leq Q_{\text{Ci}}^{\text{max}} \quad i = 1, ..., N_C
\]

where \( N_C \) is the reactive compensators' number.

In this paper, it is worth noting that a special tool has been applied which is the MATPOWER software package [33] in order to achieve the objective functions. This package is utilized to ensure precise results can be attained by running the load flow program.

3. Moth-flame optimizer (MFO)

Moth-flame optimization (MFO) algorithm was initially developed by Seyedali Mirjalili [32] and being proven to be competitive with other well-known optimization techniques. In nature, moths are insects that are highly close to the butterflies’ family. During their lifetime, they basically undergo two main milestones which are larva stage before evolve to adult stage. The inspiration of this algorithm is the unique navigation technique of moths during night time. The moths used a mechanism known as transverse orientation when travel in dark which depending on the moonlight. They travelled by retaining their position at a fixed angle with
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