# Improved Multi-objective Lion Swarm Algorithm Based on Scheduling Model for Wind Power Systems

Qi Zhang, Mingyan Jiang*, Keqin Jiang
School of Information Science and Engineering, Shandong University, Qingdao, 266237, China

* Corresponding author. jiangmingyan@sdu.edu.cn (M.Y.J.)
Manuscript submitted May 25, 2023; revised July 19, 2023; accepted August 10, 2023; published October 9, 2023.
doi: 10.12720/sgce.12.4.118-123

**Abstract:** The multi-objective model is established to minimize the cost of power generation and optimize the energy and environmental benefits, and the improved lion swarm optimization algorithm is adopted in the solution method, i.e. the idea and mechanism of coati optimization is introduced into the lion swarm algorithm. The method enhances the high-dimensional search capability of the population and verifies the effectiveness, scientificity, and advancement of the improved algorithm. Experimental analysis is carried out with the micro-wind power grid-connected generation example to verify that the proposed model considers the cost of micro-grid from various aspects and helps to improve the reliability of the system. The objective of optimizing the cost of wind and solar energy penalties is to achieve the full utilization of wind and solar energy, which helps to solve the problem of "wind" and "solar" abandonment.

**Key words**: wind, water and fire power generation scheduling, multi-objective optimization, lion swarm algorithm

## 1. Introduction

The multi-objective optimization problem (MOP)[1] widely existing in practical production and life has multiple conflicting optimization objectives, such as logistics scheduling, product optimization design, production optimization control, vehicle path planning, etc. With the popularization and application of evolutionary optimization theory in practical problems, the multi-objective evolutionary optimization method has become a research hotspot of computational intelligence.

China's wind power is developing rapidly and the technology is becoming increasingly mature. In recent years, the country has seen a jump in growth, with new installations of wind power and photovoltaic power generation exceeding 120 million kilowatts by 2022, a record high for the third consecutive year. Wind-fire complementary models [2–4] are also widely used, but the random nature of wind power generation brings challenges to the full utilization of wind energy and the reliability of wind-fire power generation systems, especially as the problem of "abandoned wind" and "abandoned light" is becoming increasingly prominent in various regions. In this context, multi-objective generation scheduling, which takes into account environmental protection and economic efficiency, has received much attention.

In recent years, more attention has been paid to the study of multi-objective optimal scheduling of clean energy generation. Several new intelligent algorithms have emerged, such as the improved multi-objective wolfpack algorithm [5], bee colony algorithm [6], fish swarm [7], and other hybrid intelligent algorithms combined with traditional genetic algorithms. However, the vast majority of existing research has been on algorithm improvement and constraint optimization, and has yet to consider the cost of abandoned wind and abandoned light, by setting the optimal goal of reducing total operating costs and pollution emissions to research the reliability of power generation systems to promote the efficient use of new energy sources.

Based on this, this paper focuses on improving the multi-objective lion swarm algorithm to solve the optimization of wind power grid-connected system model considering the cost of wind and light abandonment, establishing a multi-objective optimization model for power generation system with the objective of minimizing total operating cost and total pollution emission, and conducting experimental analysis using microgrid calculations to demonstrate the feasibility of this model optimization.

## 2. Multi-objective Scheduling Model for Grid-connected Wind Power

### 2.1. Target function

Minimization of total running costs:

$$\min F=\sum_{t=1}^{T}\sum_{i=1}^{N_G}\left[U_{i,t}f\left(P_{Git}\right)+U_{i,t}\left(1-U_{i,t-1}\right)S_{i,t}\right]+\sum_{t=1}^{T}\tau_w\left(P_{f.wt}-P_{wt}\right)+\sum_{t=1}^{T}\tau_{pv}\left(P_{f,pvt}-P_{pvt}\right)+f_w+f_{pv} \tag{1}$$

$$f\left(P_{Git}\right)=a_iP_{Git}^2+b_iP_{Git}+c_i \tag{2}$$

Wind farm operating costs and Photovoltaic plant operating costs:

$$f_w=\sum_{t=1}^{T}\mu_wP_{wt},\ f_{pv}=\sum_{t=1}^{T}\mu_{pv}P_{pv} \tag{3}$$

where $F$ is the generation resource consumption function, $T$ is the duration of a dispatch cycle (24h), $N_G$ is total number of thermal power units, $U_{i,t}$ is cost of coal consumption in time period $t$ when thermal power unit $i$ is generating $f(P_{Git})$ is cost of coal consumption in time period $t$ when a thermal power unit is generating electricity, $P_{Git}$ is the magnitude of the output of thermal power unit $i$ in time period $t$, $S_{i,t}$ is thermal power unit start-up and shutdown costs, $P_{wt}$ is the magnitude of the output of the wind farm $w$ at moment $t$, $P_{pvt}$ is magnitude of the output of the $pv$ plant at moment $t$, $\tau_w$ is abandoned wind penalty cost factor for wind farm $w$, $\tau_{pv}$ is abandonment penalty cost factor for photovoltaic plant $pv$, $P_{f,wt}$ is predicted output of wind farm $w$ at time $t$, $P_{f,pvt}$ is predicted output of photovoltaic plant $pv$ at time $t$, $a_i$ 、 $b_i$ and $c_i$ are thermal power units a coefficient of the generation cost function, $\mu_w$ is wind farm operating cost factor, $\mu_{pv}$ is photovoltaic plant operating cost factor.

Second point Minimal total pollution emissions

$$\min E=\sum_{t=1}^{T}\sum_{i=1}^{N_G}\alpha_i+\beta_iP_{Git}+\gamma_iP_{Git}^2 \tag{4}$$

where $E$ is the energy and environmental efficiency function; $\alpha_i$, $\beta_i$ and $\gamma_i$ are the emission characteristic factors of the $i$ generator $F$.

### 2.2. Constraints

Power system load balancing constraints:

$$P_{Dt}=\sum_{i=1}^{N_G}U_{i,t}P_{Git}+\sum_{j=1}^{N_H}P_{Hjt}+P_{wt}+P_{pvt}+P_{pumpt} \tag{5}$$

where $P_{Dt}$ is the system load demand power magnitude at time $T$. Thermal power unit output constraints and hydroelectric power station output constraints:

$$P_{Gi.\min}\le P_{Git}\le P_{Gi.\max},P_{Hj.\min}\le P_{Hjt}\le P_{Hj.\max} \tag{6}$$

where $P_{Gi.\min}$ and $P_{Gi.\max}$ are the minimum and maximum output power, $P_{Hi.\min}$ and $P_{Hi.\max}$ are the minimum and maximum output power of the hydroelectric power station $j$ respectively. Wind farm capacity constraints, photovoltaic plant output constraints and Capacity constraints for pumped storage plants:

$$0 \le P_{wt} \le P_{f,wt}, 0 \le P_{pvt} \le P_{f,pvt}, 0 \le P_{pumpt} \le P_{pump.\max} \tag{7}$$

$P_{pump.\max}$ is the maximum power generation and pumping power of the pumped storage plant, the maximum power generation output of the pumped storage unit and the maximum pumping power are the same.

Climbing constraints for thermal power units:

$$P_{Git} - P_{Gi(t-1)} \le \delta_{Giup}, P_{Gi(t-1)} - P_{Git} \le \delta_{Gidown} \tag{8}$$

$\delta_{Giup}$ is the maximum rate of climb per unit time for unit $i$, $\delta_{Gidown}$ is the maximum rate of climb per unit time for unit $i$. Set equal ascent and descent climb rates for thermal power units: $\delta_{Giup} = \delta_{Gidown} = \delta_{Gi}$.

$$-\delta_{Gi} \le P_{Git} - P_{Gi(t-1)} \le \delta_{Gi} \tag{9}$$

$\delta_{Gi}$ is the upper and lower values of the climbing rate for thermal power unit $i$. Hydrodynamic balance constraints for hydropower plants:

$$V_{jt} = V_{j,t-1} + I_{jt} + (Q_{(j-1)t} - Q_{jt}) \tag{10}$$

$V_{jt}$ and $Q_{jt}$ are the reservoir capacity and flow rate and $I_{jt}$ is the incoming water. Utilities conversion relationship:

$$P_{Hjt} = \xi_{1j}(V_{jt})^2 + \xi_{2j}(Q_{jt})^2 + \xi_{3j}V_{jt}Q_{jt} + \xi_{4j}V_{jt} + \xi_{5j}Q_{jt} + \xi_{6j} \tag{11}$$

$\xi_{1j} \sim \xi_{6j}$ is the output parameter of the hydropower station $j$. Reservoir energy balance constraints for pumped storage power plants:

$$E_{t+1} = E_t + (\eta_p P_{cst} - \frac{P_{pumpt}}{\eta_g}) \tag{12}$$

$E_t$ is the energy stored in the pumped storage plant at time $t$, $E_{t+1}$ is the energy stored in the pumped storage plant at time $t+1$, $\eta_p$ is the pumping efficiency, $\eta_g$ is the turbine generation efficiency, $P_{cst}$ is the pumping power of the pumped storage plant at time $t$

Rotation standby constraint:

$$\sum_{i=1}^{N_G}\left(P_{Gi.\max} - P_{Git}\right) + \sum_{j=1}^{N_H}\left(P_{Hj.\max} - P_{Hjt}\right) + P_{pump.\max} - P_{pumpt} \ge K_d P_{Dt} + m_w P_{wt} + n_{pv} P_{pvt} \tag{13}$$

$$\sum_{i=1}^{N_G}\left(P_{Git} - P_{Gi.\min}\right) + \sum_{j=1}^{N_H}\left(P_{Hjt} - P_{Hj.\min}\right) + P_{pumpt} - P_{pump.\min} \ge K_d P_{Dt} + m_w P_{wt} + n_{pv} P_{pvt} \tag{14}$$

## 3. Improved Multi-objective Lion Swarm Algorithm

A large number of studies have shown that the improvement ideas of swarm intelligence optimization algorithms can be divided into four types: improving the internal structure of algorithms; designing adaptive operators; increasing the stagnation prevention mechanism and perturbation mechanism of algorithms; designing hybrid algorithms to combine two or more algorithms. In this paper, improvements are made in terms of perturbation mechanisms that update the position of the intelligence in the evolutionary phase of the lion swarm optimization (LSO) algorithm [8] and change the mechanism of getting caught in the local mechanism. The main improvements include combining the lionesses' update formula with the coati optimization algorithm(COA)[9] mechanism during the location update process, allowing the lionesses to collaborate with each other to update the formula after the location update, increasing the diversity of the initial population and helping to speed up the algorithm convergence.

$$x_i^{k+1}=\begin{cases}\frac{p_i^k+p_c^k}{2}\cdot\left(1+\alpha_f\gamma\right)+r\cdot\left(p_c^k-Ix_i^k\right)\\ \frac{p_i^k+p_c^k}{2}\cdot\left(1+\alpha_f\gamma\right)+r\cdot\left(x_i^k-p_c^k\right)\end{cases}\tag{15}$$

The performance of the algorithm in terms of local search as well as convergence accuracy is enhanced by modifying the formula for the lionesses to include a population of lionesses mainly for the local search function. This algorithm is called improved multi-objective lion swarm algorithm (IMOLSO).

## 4. Simulation of Wind Power Grid-connected Model Optimization

### 4.1. Simulation of the economic and environmental benefits of grid-connected wind power

To verify the effectiveness of the improved multi-objective lion swarm algorithm (IMOLSO) algorithm and the minimum optimized cost model and rationality of the wind power grid-connected power system proposed in this paper, a microgrid containing 10 thermal power units and 4 hydro power units is used as an example for simulation calculations. The scheduling period is taken as 24h, the total system load is 2.833pu (the system benchmark value is taken as 100MVA), and the wind farm is rated to handle Pw=0.9puA. Other parameters are set in the following Table 1.

Table 1. Microgrid parameters

| Heading Parameter Name | Parameter Setting |
|---|---|
| Cost of wind abandonment penalty | $1000\$/MW$ |
| Abandoned light penalty cost | $1000\$/MW$ |
| Wind Farm Operating Costs | $10\$/MW$ |
| Photovoltaic power plant operating costs | $12\$/MW$ |
| Power generation and pumping power limit | $200MW$ |
| Water pumping efficiency | 91% |
| Hydraulic turbine power generation efficiency | 90.5% |
| Load Rotation Standby Ratio | 2% |
| Standby capacity ratio of wind farms | 15% |
| Photovoltaic power backup capacity ratio | 5% |
| Positive rotational standby demand factor for wind farms *WU* | 30% |
| Positive rotational standby demand factor for wind farms *WD* | 30% |

The parameters of the IMOLSO algorithm are set as follows: the population size is 40; the maximum number of iterations is 1000; the other algorithm sizes and maximum number of iterations are equal to the IMOLSO algorithm. The optimization objective functions are, in order, the minimum energy and environmental efficiency function Function-1, and the minimum total operating cost Function-2.

### 4.2. Case simulation scenario results and analysis

As indicated by the calculation results in Table 2, in the multi-objective solution under the integrated microgrid environmental and economic indicators, the optimal Pareto front solution set gives each cost scenario under the integrated optimization objective function, with multi-objective particle swarm algorithm (MOPSO), LSO and IMOLSO obtaining 3, 7 and 9 solution sets corresponding to 3, 7 and 9 scenarios, respectively. Among them, the solution sets obtained by IMOLSO, both the objective function Function-1 and the objective function Function-2, are smaller than the other three optimization algorithms, making the optimal solution achieve the minimum operating cost, where the optimal cost is RMB 56.887 million under one dispatch cycle, i.e. the minimum total operating cost of the microgrid for one day is RMB 56.887 million.

Table 2. Optimization schemes under the integrated optimization objective function

| Algorithms | MOPSO | | LSO | | IMOLSO | |
|---|---|---|---|---|---|---|
| Objective function | Function-1 | Function-2 | Function-1 | Function-2 | Function-1 | Function-2 |
| Value of benefit optimisation ($ million) | 6.3620 | 4.9219 | 6.5629 | 4.9565 | 5.6875 | 4.6828 |
| | 6.3729 | 4.9211 | 6.5660 | 4.9556 | 5.6877 | 4.6826 |
| | 6.3746 | 4.9184 | 6.5679 | 4.9546 | 5.6877 | 4.6826 |
| | Null | Null | 6.5684 | 4.9540 | 5.6878 | 4.6824 |
| | Null | Null | 6.5694 | 4.9552 | 5.6878 | 4.6823 |
| | Null | Null | 6.5713 | 4.9521 | 5.6878 | 4.6823 |
| | Null | Null | 6.5725 | 4.9517 | 5.6878 | 4.6820 |
| | Null | Null | Null | Null | 5.6879 | 4.6819 |
| | Null | Null | Null | Null | 5.6887 | 4.6819 |
| | Null | Null | Null | Null | Null | Null |
| | Null | Null | Null | Null | Null | Null |
| | Null | Null | Null | Null | Null | Null |
| | Null | Null | Null | Null | Null | Null |
| | Null | Null | Null | Null | Null | Null |
| | Null | Null | Null | Null | Null | Null |

In summary, in the multi-objective optimization model, IMOLSO to obtain nine solutions, which are all optimal solutions, making the optimal solution to achieve the purpose of minimum operating costs and minimum pollution emissions, effectively alleviating the current severe "abandoned wind" and "abandoned light" phenomenon. It effectively alleviates the current serious phenomenon of "wind" and "light" abandonment. The solution reduces the pressure on the dispatch of the power generation system and ensures the sustainability of the system.

## 5. Conclusion

Considering the impact of the randomness and intermittency of wind and photovoltaic on the reliability of wind-fire-water generation systems, adding two penalty costs compared to other multi-objective optimal dispatch models further optimizes the efficiency model objectives for microgrids, further reduces the impact of the randomness of wind and photovoltaic, and increases the flexibility of the model.

An Improved Multi-Objective Lion Swarm Algorithm (IMOLSO) is proposed, which introduces the predation and attack mechanism of the coatis algorithm to enhance the computational performance of the algorithm, and the escape from predator property promotes the Pareto optimal frontier to approach the ideal Pareto frontier and maintains the diversity of solution sets.

The mathematical model of the wind power grid-connected power system problem is constructed by choosing two objectives: minimum total operating cost and minimum pollution emission. The results show that the model can provide a reasonable dispatch plan for decision makers by taking into account the economic and environmental benefits of electricity production, especially the increased cost of wind and light abandonment penalties. The results show that the model can provide a reasonable dispatch solution for decision makers. A microgrid with 10 thermal units and 4 hydropower units is compared with different Pareto frontiers.

## Conflict of Interest

The authors declare no conflict of interest.

## Author Contributions

Conceptualization, Q.Z. and M.J.; methodology, Q.Z.; sofware, Q.Z.; validation, M.J.; formal analysis, Q.Z.; investigation, M.J.; resources, M.J.; data curation, Q.Z.; writing-original draft preparation, Q.Z.; writing-review and editing, K.J.; visualization, K.J.; supervision, M.J.; project administration, M.J.; funding acquisition, M.J.. All authors had approved the final version.

## Acknowledgements

This study is supported by the Shandong Province Science Foundation of China (Grant No. ZR2020MF153) and Key Innovation Project of Shandong Province (Grant No.2019JZZY010111).

## References

[1] Nguyen, D. T., Doan, D. T. V., Tran, N. N. C. et al. (2023). A novel multiple objective whale optimization for time-cost-quality tradeoff in non-unit repetitive projects. *International Journal of Construction Management,* 23(5), 843-854.

[2] Yue, C., Xian, Y. J. (2023). Multi-objective reactive power co-optimization based on the MOPSO algorithm considering wind power integration. *Journal of Physics: Conference Series*, 2474(1), 012069.

[3] Wang, Y., Sun, Y., Li, Y., et al. (2023). Risk assessment of power imbalance for power systems with wind power integration considering governor ramp rate of conventional units. *Electric Power Systems Research*, 217, 109111.

[4] Li, Y., Zeng, Y., Zhang, W., et al. (2023). Coordinated optimization method for suppressing transient overvoltage caused by HVDC commutation failure considering large wind power integration. *Energy Reports*, 9, 1171-1182.

[5] Dou, M., Jia, R., Li, G. (2019). An optimization model of sewage discharge in an urban wetland based on the multi-objective wolf pack algorithm. *Environmental Monitoring and Assessment*, 191(12), 763.

[6] Jiang, M., and Yuan, D. (2014). *Artificial Bee Colony Algorithm and Its Applications*. Beijing: Science press.

[7] Jiang, M., and Yuan, D. (2012). *Artificial Fish Swarm Algorithm and Its Applications.* Beijing: Science press.

[8] Jiang, K., Jiang, M. (2021). Lion swarm optimization based on balanced local and global search with different distributions. *Proceedings of 2021 IEEE International Conference on Progress in Informatics and Computing (PIC)*. IEEE, 276-280.

[9] Dehghani, M., Montazeri, Z., TrojovskÁ, E., et al. (2023). Coati optimization algorithm: A new bio-inspired metaheuristic algorithm for solving optimization problems. *Knowledge-Based Systems*, 259, 110011.