Scholars Journal of Engineering and Technology

∂ OPEN ACCESS

Abbreviated Key Title: Sch J Eng Tech ISSN 2347-9523 (Print) | ISSN 2321-435X (Online) Journal homepage: <u>https://saspublishers.com</u>

Optimal Scheduling of DC Microgrids based on MOPSO Algorithm

Zhao Zi Hang^{1*}

¹School of Information Engineering, Shenyang University of Chemical Technology, Tiexi, Shenyang, China, 110142

DOI: <u>10.36347/sjet.2023.v11i03.005</u>

| Received: 19.02.2023 | Accepted: 21.03.2023 | Published: 25.03.2023

*Corresponding author: Zhao Zi Hang

School of Information Engineering, Shenyang University of Chemical Technology, Tiexi, Shenyang, China, 110142

Abstract

Review Article

The DC microgrid system contains a variety of distributed power sources, but the distributed power sources are uncertain and intermittent. In order to improve the economy of DC microgrid operation, mainly to reduce the microgrid operation cost and environmental management cost, and at the same time the largest proportion of scenery consumption, the optimization algorithm is effective for microgrid for optimal scheduling. A multi-objective optimal scheduling model for microgrids is established. A microgrid model with wind, photovoltaic, micro gas turbine and energy storage is constructed and solved using a multi-objective particle swarm algorithm. The multi-objective particle swarm algorithm is invoked for a typical 24h daily isolated micro-grid system in a certain region. The simulation results show that the optimal dispatching scheme can effectively improve the economy of the microgrid, reduce its operating costs as well as the ability to consume renewable energy scenery power.

Keywords: Microgrid; Optimal dispatch; MOPSO algorithm; Integrated operating costs; Absorptive capacity.

Copyright © 2023 The Author(s): This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CC BY-NC 4.0) which permits unrestricted use, distribution, and reproduction in any medium for non-commercial use provided the original author and source are credited.

0 INTRODUCTION

The economic operation of microgrids is currently a hot topic of research. In recent years, several scholars have done a lot of research work on the economic operation and optimal scheduling of microgrids [1]. The optimal scheduling of microgrids refers to the use of certain operating strategies, suitable software or analytical methods and intelligent optimization algorithms to optimize the power output of distributed power sources and determine the structure of the system, so that the economic cost, environmental benefits, power supply reliability and network losses of the system operation results in a multi-objective or a single objective The literature [2] has focused on the optimization of distributed power supply systems [2-4]. In [5], a bat algorithm was proposed to optimise the operation strategy of microgrids for the multi-objective optimisation of microgrid operation. In [6], the problem of poor global search ability of the swarm algorithm was addressed, and the Tenebrae whisker search algorithm was proposed to improve the update rules of individual swarm to enhance the individual global search ability. The results show that the improved swarm algorithm can effectively reduce the overall cost. In the literature [7], a multi-objective genetic algorithm was introduced to enhance the global and local search ability of the algorithm. The integrated objective cost was effectively reduced and good optimisation results were achieved. In [8], a multi-objective optimised

scheduling model for microgrids with minimum operating costs, minimum cost of customer outage losses and minimum environmental protection costs is established and solved using biogeographic algorithms. In summary, it can be seen that for the study of the amount of optimal dispatch of microgrids, intelligent algorithms have very good results for solving microgrid optimization problems.

This paper investigates the proposed DC microgrid optimisation problem with the objective function of optimising the operating cost of the microgrid and the cost of environmental management. A model containing wind power, photovoltaic, micro gas turbine, diesel generator and battery units is developed. The MOPSO algorithm is used to solve the developed model, and the feasibility of the model and algorithm is verified in an arithmetic example.

1. Microgrid systems

1.1 Photovoltaic mathematical model

The output characteristics of PV cells are influenced by external factors such as external temperature, light intensity, and the degree of tilt of the PV panels. With an irradiance of 1000 W/m^2 and an external temperature of 25° C as the test conditions [9], the output power and operating cost of the PV cell are as follows:

$$P_{PV} = P_{STC} \frac{G_C}{G_{STC}} [1 + K(T_C - T_{STC}) \dots (1)]$$

$$C_{PV} = \sum_{t=1}^{T} K_{PV,CB} P_{PV}(t) \dots (2)$$

Where T_{STC} , G_{STC} , P_{STC} are the rated ambient temperature, irradiance and power generated by the PV under standard test conditions respectively; K is the power temperature coefficient; $K_{PV,CB}$ is the PV unit operation and maintenance cost factor.

1.2 Wind power mathematical models

Wind power generation is mainly influenced by external wind speed, and the relationship between the output power of a wind turbine and the actual wind speed can be approximated as a segmented function [10]:

$$P_{WT} = \begin{cases} 0, v < V_{ci} \overrightarrow{\mathbb{R}} v \ge V_{co} \\ P_N \frac{v^3 - V_{ci}^3}{V_N^3 - V_{ci}^3}, V_{ci} \le v < V_N \dots \dots (3) \\ P_N, V_N \le v < V_{co} \end{cases}$$
$$C_{WT} = \sum_{t=1}^T K_{WT, CB} P_{WT}(t) \dots \dots (4)$$

Where P_N is the rated output power of the wind turbine, V_N is the rated wind speed; V_{ci} is the cut-in wind speed, V_{co} is the cut-out wind speed; C_{WT} is the operation and management cost, $K_{WT,CB}$ is the WT unit operation and maintenance cost factor.

1.3 Miniature gas turbine model

The use of micro-gas turbines (MT) in supplementary units to compensate for the unsatisfactory demand of the grid caused by the intermittent nature of wind and solar, and the cost of MT power generation still has certain economic advantages when electricity prices are higher [11]. In this article, the C65 gas turbine produced by Capston is used, the cost function of MT:

$$C_{MT} = C_{MT,FUEL} + C_{MT,CB} \dots (5)$$

$$\eta_{MT} = 0.0749 \left(\frac{P_{MT}}{65}\right)^3 - 0.3008 \left(\frac{P_{MT}}{65}\right)^2 + 0.40173 \left(\frac{P_{MT}}{65}\right) + 0.1069$$
.....(7)

$$C_{MT,CB} = \sum_{t=1}^{I} K_{MT,CB} P_{MT}(t) \dots (8)$$

Where C_{MT} is the total cost of MT power generation, $C_{MT,FUEL}$ is the fuel cost, $C_{MT,CB}$ is the MT

operation and management $cost; C_G$ is the unit price of MT fuel gas, take 2.5 yuan $\swarrow m^3; P_{MT}$ is the output of MT,LHV is the low calorific value of natural gas, take 9.68kw·h/ $m^3; K_{MT,CB}$ is the unit operation and maintenance cost coefficient.

1.4 Diesel generators

The fuel cost of DE is a function of its consumption characteristics, and the fuel cost of DE is expressed as a quadratic function:

$$F_{DE} = \alpha + \beta P_{DE} + \gamma P_{DE}^2 \dots (9)$$

Where F_{DE} is the fuel cost of DE; P_{DE} is the output power of DE; α , β , γ are the coefficients of DE fuel cost, and in this paper, α =6, β =0.12, γ =8.5×10⁻⁴.

1.5 Mathematical model of the battery

When the power supply of the distributed power supply is greater than the load demand, the remaining power is stored in the battery, and the energy storage discharge is supplied to the load when the microgrid is insufficient. The state of charge and battery capacity of the battery (BT) are important indicators for microgrid optimization ^[12].State-of-charge SOC describes the remaining charge of the battery. The SOC of the battery and the operation management cost C_{BT} can be expressed by the following formula:

$$SOC(t) = \begin{cases} SOC(t - \Delta t) - \frac{P_{ch}(t)\Delta t}{\eta_D} & \dots \dots \\ SOC(t - \Delta t) - P_{dis}(t)\Delta t\eta_c \end{cases}$$
(10)
$$C_{BT} = \sum_{t=1}^{T} K_{BT,CB} \left| P_{BT}(t) \right| \dots \dots \dots \dots \dots (11)$$

Where $P_{ch}(t)$, $P_{dis}(t)$ are charge and discharge power; η_D , η_c is the efficiency of charge and discharge; C_{BT} is the operation management cost, $K_{BT,CB}$ is the unit operation and maintenance cost coefficient, $P_{BT}(t)$ is the BT output.

2. Microgrid optimization dispatch model 2.1 Running costs

The power generation cost of the microgrid mainly considers the operating cost and the compensation cost of the interruptible load, so the power generation cost makes the operating cost of the microgrid minimize under the conditions of meeting the system equation constraints and inequality constraints, that is:

Where T is the number of time periods of the dispatching cycle of the microgrid;N is the number of micropower types; $CO_{i,t}$ is the cost of generating electricity at time t for the micropower supply; IR_t is the

interruptible fee of the microgrid at time $t;P_{i,t}$ is the power generated by the ith micropower supply at the time t.

(1) Cost of power generation. The operating cost of the microgrid mainly considers the fuel cost, depreciation cost, and maintenance cost of the unit, because PV and WT are clean energy and will not consume fossil fuels during operation, so PV and WT fuel costs are not considered, ie

Where $CF_{i,t}$ is the fuel cost of the micropower supply i at time t; $IV_{i,t}$ is the depreciation expense of the micropower supply i converted to a unit of time; $OM_{i,t}$ is the maintenance cost of the micropower supply at t time.

Depreciation Expense

Where $C_{INS,i}$ is the installation cost of the ith micropower supply; $P_{r,i}$ is the rated power of the ith micropower supply; $f_{c,i}$ is the capacity factor of the ith micropower supply; d is the interest rate or depreciation rate; m is the service life of the micropower supply.

Maintenance Costs

Where $K_{m,i}$ is the unit operation and maintenance cost of micropower supply i.

(2) Interruptible charges. When the microgrid island is running in an isolated area, there is insufficient power supply, and some non-important loads need to be interrupted to ensure the normal power supply of important loads. The strategy of interrupting the interruptible load in this paper is: only when the controllable power supply, uncontrollable power supply and energy storage device are in a full state, the interrupted partial load is used for the load with insufficient power supply, and the corresponding economic compensation for the interrupted load is required, The following equation is proposed:

Where A, B, C are the coefficients of the interruption cost, which are taken as 6.14, 1.2, 1.23×10^{-4} ; P_{IL} is the interruption power.

2.2 Environmental costs

The environmental cost mainly considers the emission treatment cost of CO_2 , SO_2 and NO_X of the unit [13]. Since PV and WT are clean energy sources

and do not produce polluting gases during operation, the environmental costs of PV and WT are not considered. With the smallest environmental cost as the objective function, its expression is

Where C_E is the cost of environmental treatment, C_{ij} is the cost of treatment of the jth polluting gas of the ith micropower supply.

2.2 Weighted processing

For the multi-objective optimization goal problem, multiple targets are weighted into a single target by normalization.

2.3 Constraints

(1) Power balancing

- (2) Micropower constraints

(3) Battery constraints

$$P_{ch\min} \le P_{ch} \le P_{ch\max}$$
(24)

Where P_{chmin} , P_{chmax} is the minimum and maximum value of charging power; P_{dismin} , P_{dismax} is the minimum and maximum values when the battery is discharged.

3. MODEL SOLVING ALGORITHMS

3.1 Introduction to the MOPSO algorithm

The PSO algorithm originated from the study of the behavior of predation by flocks. In PSO, the search for birds in the empty zone in the population pool is equivalent to the solution of an optimization problem, that is, "particles". Each particle has a fitness value, which is determined by the function being optimized. In addition, the direction and distance of each particle is determined by its speed. All particles follow the optimal particles in the population to search for the optimal solution in the interval. Its update process is:

 $V_{i+1} = \omega \times V_i + C_1 \times rand() \times (\text{pbest}_i - X_i) + c_2 \times rand() \times (\text{gbest}_i - X_i)$ $X_{i+1} = X_i + V_{i+1}$

© 2023 Scholars Journal of Engineering and Technology | Published by SAS Publishers, India 47

Where V_i is the velocity of the particle; X_i is the position of the particle; is the best location for each particle to be discovered so far; gbest is the best spot for all particles found in the entire population; rand() is a random number between (0, 1); X_i is the current position of the particle; c_1 and c_2 are learning factors. ω is the dynamic weight value of the particle swarm, and its value is

Where ω_{max} is the initial inertia weight; ω_{min} inertial weight when iterating to maximum

algebra; *inter_{max}* is the maximum number of iterations; inter is the current number of iterations.

Zhao Zi Hang., Sch J Eng Tech, Mar, 2023; 11(3): 45-52

3.2 MOPSO algorithm description and flow chart

Multi-target particle swarm operation (MOPSO) is based on PSO algorithm, mainly for the diversity of multi-target selection pbest and gbest problems, this paper uses MOPSO algorithm to solve the multi-objective scheduling model of microgrid. The algorithm selects individuals based on the Pareto hierarchical ranking principle, and can obtain excellent Pareto frontiers when solving multi-objective optimization problems. The flowchart of multiobjective microgrid optimal dispatch is shown in Figure 1



Fig 1: Flowchart of the multi-objective optimal dispatch

The specific operation process of multi-objective optimization scheduling is as follows:

1) Data initialization. Input microgrid system composition and structure parameters, model parameters, MOPSO algorithm parameters, etc. At the same time, initialize the particle population, and each particle individual in the population corresponds to the scheduling scheme within a scheduling cycle.

2) Individual particles are entered into the simulation

© 2023 Scholars Journal of Engineering and Technology | Published by SAS Publishers, India

48

model as system variables, variables that violate constraints are corrected, and operating costs, environmental costs, and penalties are calculated as individual fitness values.

- 3) Taking individual fitness as input to the optimization model, the offspring population is obtained by formula (26).
- 4) Determine the individual extreme value pBest. pBest as the initial individual extreme of the particle, and if the current particle dominates pBest, the current particle as the pBest individual extremum; If the two cannot be compared, the number of other particles dominated by the two in the group is calculated, and the more dominant is used as the individual extreme pBest.
- 5) The populations are sorted hierarchically, the optimal nondominated solution Pareto is stored in the external archive set, the non-Pareto solution is cleared, and whether the external archive set exceeds the specified capacity, if so, m particles are selected according to the congestion distance.
- 6) Global optimal value gBest. Using the Pareto optimal solution saved by the external archive set, this paper refers to the roulette method to select gBest from the external set according to the crowded distance of the optimal solution.
- 7) Small probability of variation. In order to prevent the MOPSO algorithm from prematurely convergence to the local optimal frontier instead of the global optimal frontier, this paper introduces a small probability random variation mechanism, which produces a small probability disturbance of \pm 30% on the position of the particle at the original position, which increases the optimization ability of the global optimal frontier of the particle.
- 8) Return to step 3) until the termination condition is

met. In this topic, the termination condition is set to the maximum number of iterations and the final optimization scheduling result is output.

4. SIMULATION

4.1 Study system

In order to verify the above model, this paper analyzes an actual microgrid system, takes 1d as a calculation cycle, selects the typical daily 24h load data provided by IEEE-RTS, and takes the peak load as 89kW. At the same time, in order to improve the utilization rate of renewable energy, PV and WT are operated in maximum power tracking mode, and their output is shown in Figure 3. The battery pack with a maximum charge and discharge power of 5 kW and a capacity of 20 kW·h for the ES energy storage device can interrupt 15% of the total load demand. The parameters of each distributed power source in the microgrid are shown in Table 1. The greenhouse gas emissions and treatment parameters of micropower are shown in Table 2. The relevant parameters of MOPSO are as follows: particle population size is 100, maximum iteration number is $100,c_1$ is $0.1,c_2$ is $0.2, \omega_{max}$ is $0.9, \omega_{min}$ is 0.4, external archive collection size is 100, and the mutation probability is 10% .

4.2 Simulation and analysis

The microgrid system in this paper includes a variety of distributed power sources, including PV, WT, DE, MT and energy storage, the operating parameters and costs of each DG in the microgrid are shown in Table 1, the emission coefficient and cost of each DG pollutant [14] are shown in Table 2, and the energy storage parameters are shown in Table 3. Real-time electricity price reference [15].

Туре	Power/kW		Overhead/ $(\mathbf{Y} \cdot k W^{-1})$	Longevity /a				
	Lower limit	Upper limit						
PV	0	20	0.0096	20				
WT	0	12	0.0296	10				
DE	0	30	0.0859	15				
MT	0	40	0.0401	10				

Table 2: Greenhouse gas emission and parameter processing

Туре	Emission factors / $(g \cdot kW^{-1})$				Handling factor / $(¥ \cdot kg^{-1})$
	MT	DE	PV	WT	
CO_2	1.600	1.400	0	0	0.092
SO_2	0.440	21.800	0	0	27.540
NOX	0.008	0.454	0	0	6.490

Table 3: Energy storage parameters

Туре	Parameters	Numerical	Parameters	Numerical
		values		values
	Maximum capacity / (kW·h)	150	Initial energy storage capacity / (kW·h)	50
Battery	Minimum capacity / (kW·h)	5	Maximum output power /kW	30
	Maximum input power /kW	30	Charge and discharge rate	0.9

© 2023 Scholars Journal of Engineering and Technology | Published by SAS Publishers, India



Fig 1: MOPSO algorithm simulation

Referring to the above parameter settings, the simulation optimization results were obtained by solving the model using MOPSO algorithm, as shown in Figure 2, from which it can be seen that as the cost of environmental management becomes smaller, the operation cost will When economic dispatch is carried out, the microgrid increases the DE units with low

generation costs and high pollutant emissions, leading to an increase in environmental cost costs. On the other hand, when environmental dispatch is used, the microgrid increases the number of MT units with high generation costs and low pollutant emissions, leading to a relative increase in the operating costs of the units.



Fig 2: Pareto optimal front using the proposed MOPSO algorithm

In terms of energy storage allocation, the MOPSO algorithm is very effective in charging and discharging energy storage, and reasonably regulates the microgrid power supply during peak and valley

hours, as shown in Figure 3. In terms of renewable energy consumption, it is clear from Figure 3 that the wind and PV power generation using the MOPSO algorithm basically follow the forecast curve.



Fig 3: Results of the economical optimal dispatch

The scenery consumption capacity of the microgrid is also an important indicator for the optimal scheduling of the microgrid. As can be seen from the following scenery consumption power diagram, the PV consumption power using the MOPSO algorithm

basically reaches about 80% of the predicted power, and the wind consumption power basically reaches about 70% of the predicted power, achieving a better effect of scenery consumption. As shown in Figure 4 and Figure 5.



Fig 4: MOPSO Photovoltaic Power Consumption



Fig 5: MOPSO Wind power consumption

5. CONCLUSION

This paper mainly studies the optimal dispatch problem of microgrid, and uses MOPSO algorithm to solve the dispatching model with the optimal operating cost and environmental governance cost of microgrid as the objective function, which shows that the MOPSO algorithm can achieve good results in reducing the operating cost of microgrid and the proportion of wind and solar consumption, and has better robustness, which can maximize the use of clean energy and cost saving to a certain extent. However, there is a problem of indepth comparison and optimization with other intelligent algorithms, and then the algorithm will be further optimized and explored to learn more optimized algorithms in microgrid scheduling.

REFERENCES

- Ouyang, T., & Zhang, H. (2020). Optimal dispatch of island microgrid based on MOPSO algorithm [J]. *Electronic Measurement Technology*, 43(20), 58-62.
- Wang, C., Wu, Z., & Li, P. (2014). Research on key technologies of microgrid. *Transactions of china electrotechnical society*, 29(2), 1-12.
- Zhu, J., Yang, W., & Xu, M. (2018). Microgrid Economic Scheduling Considering EV User Response [J]. *Journal of Yanshan University*, 42(1), 81-87 + 94.
- Nie, H., Yang, W. R., Ma, X. Y., & Wang, H. J. (2019). Optimal scheduling of off-grid microgrid based on improved bird swarm algorithm. *J. Yanshan Univ.*, 43(3), 228-237.
- Zhang, Y., Li, Y., Song, G., & Niu, J. (2022). Research on microgrid optimization based on bat algorithm [J]. *Northeast Electric Power*, 43(4), 4-10.
- Zhou, L., Dong, X., Zhu, J., & Sun, F. (2020). Optimal dispatching of microgrid based on improved bee colony algorithm [J]. *Electrical Automation*, 42(5), 45-47.

- Li, J. (2022). Research on optimal dispatch of multi-objective microgrid based on genetic algorithm [J]. *China Equipment Engineering*, (3), 137-139.
- Han, J., & Li, G. (2017). Multi-objective optimal dispatch of microgrid based on biogeographic algorithm [J]. *Journal of University of Jinan* (*Natural Science Edition*), 31(3), 220-228.
- Mao, M., Sun, S., & Su, J. (2011). Analysis of wind/solar/storage microgrid economics including electric vehicles [J]. *Automation of Power Systems*, 35(14), 30-35.
- He, Z. (2014). Economic operation optimization of microgrid considering energy storage and user-side response [D]. Guangzhou: South China University of Technology.
- Zhu, X., Ma, D., H., & Li, S. (2017). State of charge estimation of microgrid batteries based on BP neural network [J]. *Journal of Electronic Measurement and Instrumentation*, 31(12), 2042-2048.
- Wei, G., Zhi, W., & Rui, W. (2012). Multiobjective optimization of combined heat and power microgrid considering pollutant emission. Automation of Electric Power Systems, 36(14), 177-185.
- 13. Liu, G., Peng, C., & Xiang, L. (2011). Economicenvironmental dispatch using improved multiobjective particle swarm optimization. *Power System Technology*, *35*(7), 139-144.
- 14. Lu, X., Zhou, K., & Yang, S. (2017). Multiobjective optimal dispatch of microgrid containing electric vehicles. *Journal of cleaner production*, *165*, 1572-1581.
- Moghaddam, A. A., Seifi, A., Niknam, T., & Pahlavani, M. R. A. (2011). Multi-objective operation management of a renewable MG (microgrid) with back-up micro-turbine/fuel cell/battery hybrid power source. *energy*, 36(11), 6490-6507.

© 2023 Scholars Journal of Engineering and Technology | Published by SAS Publishers, India