Multi-objective optimization of solar thermal photovoltaic hybrid power generation system based on NSGA-II algorithm

Liang Meng[1,*], *Wen* Zhou[1], *Yang* Li[2], *Zhibin* Liu[3], and *Yajing* Liu[3]

[1]Power Grid Technology Center, State Grid Hebei Electric Power Research Institute, 050000 Shijiazhuang, China
[2]State Grid Xiong'an Digital Technology Co., Ltd, 071000 Baoding, China
[3]School of Electronic and Control Engineering, North China Institute of Aerospace Engineering 065000 Langfang, China

Abstract. In this paper, NSGA-Ⅱ is used to realize the dual-objective optimization and three-objective optimization of the solar-thermal photovoltaic hybrid power generation system; Compared with the optimal solution set of three-objective optimization, optimization based on technical and economic evaluation indicators belongs to the category of multi-objective optimization. It can be considered that NSGA-Ⅱ is very suitable for multi-objective optimization of solar-thermal photovoltaic hybrid power generation system and other similar multi-objective optimization problems.

1 Research background and its significance

Energy is one of the resources that mankind depends on for survival. With economic development and the increase of global population, global energy consumption has increased sharply, and the consumption of fossil energy such as coal, oil, and natural gas has increased rapidly. Fossil energy emits a lot of greenhouse gases while using it, which also exacerbates the energy crisis. Environmental pollution and energy crisis have urged countries in the world to transform their energy production and consumption methods to clean energy. For example, the EU has reached an agreement on the share of renewable energy in 2030, requiring that the share of renewable energy in EU energy production be increased to 32%, and this share will rise to 100% in 2050. Under this background, two emerging renewable energy utilization technologies, photovoltaic (PV, referred to as photovoltaic) and solar thermal technology (concentrating solar power, referred to as CSP), are about to usher in rapid development. P. Banda studied the deep learning method of photovoltaic cell defect classification [1]. Antonio Greco researched a photovoltaic power plant panel inspection method based on deep learning [2]. Afroza Nahar carried out mathematical modelling and numerical simulation of photovoltaic thermal system [3]. Adel Hamad Rafa studied a photovoltaic inverter control technology [4]. Changhui Yang studied

* Corresponding author: 15133128069@139.com

the economic benefit analysis of home distributed photovoltaics under different financing methods [5]. Piya Narkwatchara pointed out that the missing factors that were ignored when designing photovoltaic systems were air quality/working temperature and relative humidity [6]. However, the research on multi-objective optimization of solar thermal photovoltaic hybrid power generation system based on NSGA- Ⅱ algorithm is still insufficient.

2 Problem description and optimization goals

The purpose of mixing PV and CSP power plants is mainly to reduce costs (operating and installation costs) and achieve a higher capacity factor, thereby increasing the competitiveness of solar power generation [7].
Optimize the target:[8]

$$\text{Minimize:}\begin{cases} F_1(\overline{x}) = \mathrm{LCOE}(\overline{x}) \\ F_2(\overline{x}) = -\mathrm{CF}(\overline{x}) \\ F_3(\overline{x}) = C_t\mathrm{otal}(\overline{x}) \end{cases} \quad (1)$$

Restrictions:[9]

$$x_i^{min} \le x_i \le x_i^{max}, i = 1,2 \quad (2)$$

$$\overline{x} = (W_{i,pv} TES_h)^T \quad (3)$$

3 Result analysis

Export the optimization results from the work area, and draw the levelized electricity cost-negative capacity factor dual-objective optimization curve and the levelized electricity cost-negative capacity factor-unit capacity initial investment cost three-objective optimization curve as shown in the figure.

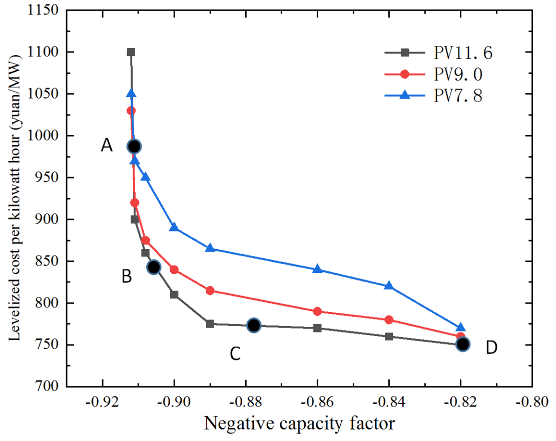

Fig. 1. Two-objective optimization levelized cost per kilowatt-hour-negative capacity factor.

It can be seen from Figure 1 that when the photovoltaic cost is 7.8 yuan/W DC, the maximum capacity factor is 91.5% at point A, and the LCOE is 942.7 yuan/MWh; the lowest LCOE appears at point D is 692.5 yuan/MWh, At this time, the capacity factor is approximately 81%. It is worth noting that when the capacity factor is the only objective function, design point A is the optimal solution, and design point D is the optimal solution for a single optimization of LCOE.

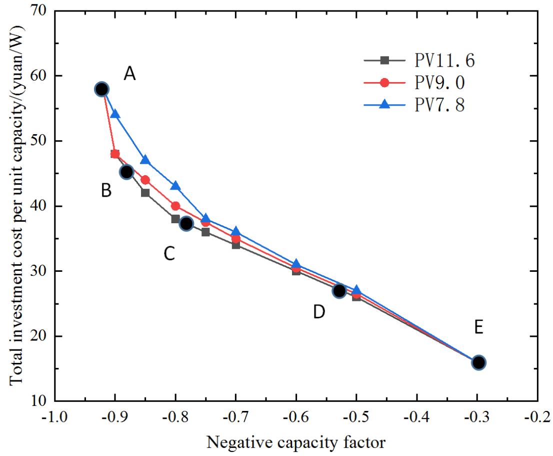

Fig. 2. Three-objective optimized initial investment cost per unit capacity-negative capacity factor.

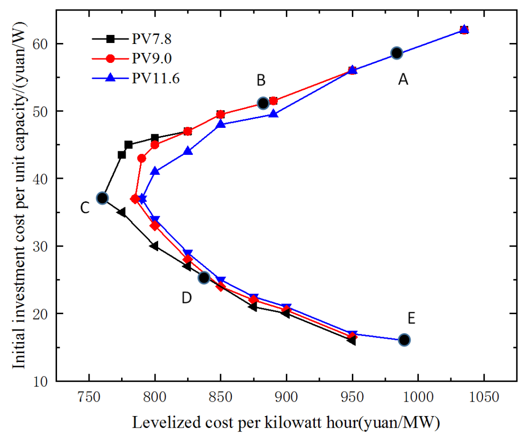

Fig. 3. Levelized cost per kilowatt hour (yuan/MW).

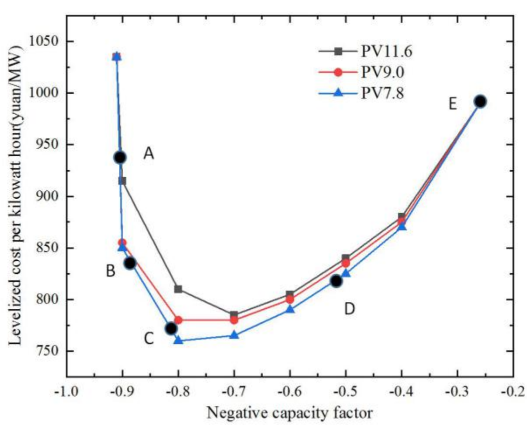

Fig. 4. Three-objective optimization of leveled electricity cost-negative capacity factor.

Figure 2~Figure 4 are the three-objective optimization curve obtained by using the NSGA-II algorithm, among which Figure 2~Figure 4. are the projections of the threedimensional Pareto front on the two-dimensional plane to achieve better visualization. When comparing the performance of these hybrid systems with independent trough solar thermal power generation systems, the advantages of hybrid power generation systems are fully demonstrated. The results show that the hybrid system can simultaneously reduce the LCOE, increase the capacity factor, and reduce the initial investment cost per unit capacity.

4 Conclusion

Optimization based on technical and economic evaluation indicators belongs to the category of multi-objective optimization. In this paper, NSGA-Ⅱ, one of the multi-objective genetic algorithms, is used as the optimization algorithm. The front of non-dominated solutions can be obtained in one run and the global optimal solution ratio is greater than 99.6%. It can be considered that NSGA-Ⅱ is very suitable for multi-objective optimization of solar-thermal photovoltaic hybrid power generation system and other similar multi-objective optimization problems.

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