Energy Informatics

RESEARCH

Construction of new energy consumption optimization model based on improved pathfinder algorithm

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Abstract

As traditional energy reserves continue to decline, the importance of new energy sources increases. However, the current traditional power system often fails to consider new energy sources, particularly in power supply systems that integrate multiple new energy sources. The cost, efficiency, and environmental factors seriously affect the energy system's efficiency. Therefore, this proposal presents a multi-objective optimization discrete assignment pathfinder algorithm. The algorithm can handle multi-objective optimization problems and adapt to various constraints, providing a more precise optimization scheme for new energy systems. The experimental results indicated that the proposed research method exhibits better performance compared to other algorithms of the same type. Compared with the multi-objective multivariate universe optimization algorithm and the multi-objective sparrow search algorithm, the research method was ahead in terms of fitness value by 9.54% and 14.67%, respectively. Meanwhile, in the grid simulation, the research method achieved an average efficiency of 96.16%, which is better than the comparative algorithms by 6.57–14.02%. The study not only improves the optimization efficiency of new energy consumption, but also provides a powerful decision support tool for the planning and operation of wind farms. It is of great significance for the improvement of power system efficiency and decarbonization, and helps to promote the large-scale integration and sustainable development of new energy.

Keywords: Multi-objective optimization, New energy consumption, Discrete assignment coding, Pathfinder algorithm

Introduction

In the tide of global energy transition, the efficient consumption of new energy has become a key link to promote sustainable development (Gong and Wang 2022). Specifically, the efficiency and economy of energy use are closely related to the effective acceptance and consumption of clean energy sources like solar, wind, and tidal energy in the power grid (Wu et al. 2023; Wang et al. 2023). Traditional energy consumption optimization models are often difficult to take into account the complexity of multi-objective decision-making, especially in the specific problem of wind farm layout, which needs to be solved to find a balance between maximizing energy output and minimizing environmental impact (Tian et al. 2021). The Pathfinder algorithm is a traditional optimization algorithm inspired by the migration behavior of organisms in nature. It aims to solve complex multi-objective optimization (MOO) problems. In this context, the pathfinder algorithm (PA) provides an excellent solution to this problem: the principle of PA is to simulate the migration behavior in nature, and it has a good global search capability for MOO problems (Tang et al. 2021a). But when it comes to discretized issues, like the optimization problem of wind farm layout, the typical PA proves to be inadequate. When dealing with this type of discrete data, there are several challenges to consider. These include limited adaptability, difficulty in adapting to dynamic environments, complex MOO, and limited model generalization ability. Therefore, in this study, MOO and discrete assignment coding (DAC) are applied to PA, and the model's ability to handle discrete problems is improved, while its search capability and solution diversity in the multivariate search space are optimized. The innovation of the research lies in the combination of PA and DAC techniques, which not only optimizes the performance of the original algorithm, but also expands its application scope in new energy consumption (NEC). By combining the PA with discrete complex coding technology, it enhances its ability to deal with discrete problems, improves the adaptability of dynamic environments, and the complexity of MOO. Additionally, it improves the generalization ability of the model and provides an effective solution for optimizing NEC. The discrete complex coding technique enables the algorithm to effectively search for the optimal solution in the discrete solution space, thereby improving search efficiency and accuracy. By introducing more complex weight allocation and priority determination mechanisms, the algorithm can achieve a more reasonable balance between maximizing energy output and minimizing environmental impact. Through this study, it is expected to provide more efficient guidance for solving optimization problems in NEC. The study is broken up into four sections. The first section provides a synopsis of the fields of research that are connected to PA and energy consumption optimization. The process of putting the study's suggested methodology into practice is covered in the second section. The third part is the validation and testing of the proposed methodology. The fourth part is a summary overview of the study as a whole.

Research background

PA, is a heuristic algorithm whose main idea is to solve optimization problems by mimicking the path-finding behavior of organisms in nature. This algorithm is commonly used to solve search and optimization problems, and is inspired by the behavior of animals to find a goal in complex environments by continuously trying and adjusting their directions. The core of PA is to simulate the process of explorers finding the optimal path in an unknown domain. The objective is to identify the best solution or path inside the specified search space. The path is chosen and modified based on environmental data or self-reported input. A hybrid approach combining quantum PA and Elman neural network was presented by Jia et al. for the identification of solid oxide fuel cell models. The approach can increase computing efficiency and recognition accuracy, according to experimental data (Jia and Taheri 2021). For the robot's movement path planning problem, Liu et al. proposed to optimize it using PA combined with triangular dissection. The experimental results demonstrated that the model possesses excellent performance, as well as significant advantages in path optimization and navigation efficiency (Liu et al. 2021). Zhou et al. proposed a convolutional sparse coding method using PA-optimized orthogonal matched tracking combined with an asymmetric Gaussian Chirplet model in the field of bearing fault detection. Experimental results indicated that the method was able to achieve excellent accuracy for fault detection of bearings while maintaining better performance (Zhou et al. 2021). Huang et al. faced with climate change and proposed the use of PA combined with representative concentration paths for hydropower generation prediction. The experimental results proved the future trend of increasing temperature and predicted the future energy demand which showed an increase year by year (Huang et al. 2021). Saudi et al. proposed a method using PA's combined with accelerated ultra-relaxation techniques to address the problem of excessive computational load in autonomous robot pathfinding. Experimental results indicated that this method effectively improves the efficiency of path generation as well as the quality of generation in the simulation of static indoor environments (Saudi 2022).

Energy consumption optimization refers to ensuring that the energy produced can be effectively utilized through efficient technology and management methods. In the realm of new energy utilization, one of the biggest challenges now facing us is how to manage the volatility and uncertainty of renewable energy sources like solar and wind while maintaining the steady operation of the power grid. Energy consumption optimization aims to enhance the capacity of renewable energy consumption in the power system through a series of measures and technologies. For the challenge of the best possible integration of dispersed generation and power distribution network reconfiguration, Shaheen et al. presented an enhanced equilibrium optimization technique that incorporates recovery strategies. According to experimental results, the technique can successfully lower the load on the electrical grid (Shaheen et al. 2021). A decision support approach for the elastic fluctuation problem in renewable power systems based on numerical simulation and optimization was put out by Tapia et al. The technique can successfully increase the system's robustness and stability, according to the experimental data (Tapia et al. 2021). Butt et al. addressed the current new energyization of the power grid and discussed the future development potential of smart technologies in the power grid. Their findings provided a reference for the future development of grid intelligence (Butt et al. 2021). Tang et al. proposed a power architecture foundation for converged computing as well as networking in response to the current 6G network requirements on the way to communication network development. Further findings revealed the role of this architecture in promoting and facilitating the development of future communication technologies (Tang et al. 2021b). To address the performance optimization of the base station network system, Li et al. proposed the use of an intelligent reflective surface framework combined with semidefinite relaxation, Gaussian randomization, and continuous convex approximation algorithms for optimization. Experimental results showed that the algorithm optimized at least 51.13% of the power (Li et al. 2021a).

In summary, PA solves optimization problems by simulating biological pathfinding behavior and has shown superiority in many fields, particularly in the optimization of NEC. However, the algorithm's adaptability and efficiency still need improvement in the face of the volatility and uncertainty of new energy sources such as wind and solar energy, as well as the complexity of the actual power grid system. Currently, the research focuses solely on the fundamental application of the algorithm, with inadequate integration and innovation with other intelligent technologies, and a lack of unified performance evaluation standards. To fully realize the potential of PA in optimizing NEC, a NEC optimization model based on the improved PA is proposed. MOO and DAC of PA can improve the consumption efficiency of renewable energy and the stable operation of the power grid.

Construction of improved pathfinder model for new energy consumption

Facing the challenge of the rapid popularization of new energy, the improved PA provides an efficient solution path for the construction of the NEC optimization model. The problem of new energy is first modeled, and then targeted optimization is performed for PA. The applicability of PA in MOO problems is extended, and the algorithm's ability in dealing with new energy optimization problems is enhanced by DAC processing.

New energy optimization problem model construction

The widespread availability and cost-effectiveness of wind resources make wind power generation the new energy component of choice. The primary idea behind the production of wind power is the transformation of wind energy into kinetic energy and then electrical energy. A wind turbine (WT)'s blades revolve as a result of the kinetic energy of the airflow passing over them, transforming mechanical energy into electrical energy. The rotor inside the generator rotates in a fixed coil, generating alternating current through electromagnetic induction, which is the conversion of kinetic energy into electrical energy. An environmentally friendly, renewable energy source that doesn't emit greenhouse gases or other pollutants is wind power. Since the layout of existing wind farms is closely related to their overall output power, the study starts by simulating the layout optimization problem for wind farms. It is assumed that a wind farm has a square layout and that the turbine blades are always facing and perpendicular to the direction of the wind. To properly increase the wind farm's output power, the WTs' locations must be carefully chosen in order to prevent the WTs' tail flows from interfering with one another. For the tail current problem of the WT, the Jensen tail current attenuation model is used for analysis, and its model is specifically shown in Fig. 1 (Keane 2021).

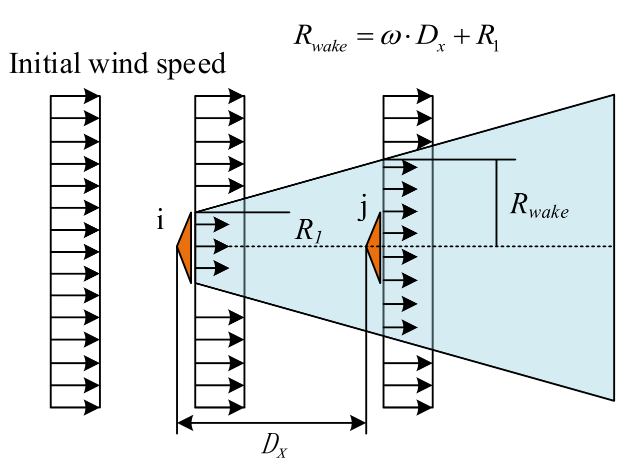

Fig. 1 Schematic diagram of wind farm wake effect model

Assuming that the radius of the wind blowing through the ith turbine is R_1, the wake with radius R from the region of linear expansion of the ith turbine can be expressed as shown in Eq. (1).

$$R_{wake} = \omega \cdot D_x + R_1 \tag{1}$$

The model can be represented as shown in Fig. 1. Where R_{wake} denotes the radius of the wake region, R_{wake} denotes the distance between turbines, and ω denotes a constant which can be calculated from the hub height of the wind farm, as shown in Eq. (2).

$$\omega = \frac{0.5}{\ln\left(\frac{h}{R_a}\right)} \tag{2}$$

In Eq. (2), h denotes the WT height and R_a denotes the WT surface roughness. For the wind speed of the downstream turbine, it can be derived using the law of conservation of momentum, as shown in Eq. (3).

$$1 - \frac{V_w}{V_0} = 2a \cdot \left(\frac{R_1^2}{R_{wake,ij}}\right) \tag{3}$$

In Eq. (3), V_w denotes the distance of turbine j from turbine i as the wind speed at D_{ij}. R_1 denotes the rotor radius of turbine i generator. $R_{wake,ij}$ denotes the radius of the wake area within turbine j generated by turbine i. Since the wake flow between the two turbines may be partially obscured in practical situations, it is shown in Fig. 2.

Then, in the case of partial shading, the calculation of the overlap area of its partial shading is specified as shown in Eq. (4).

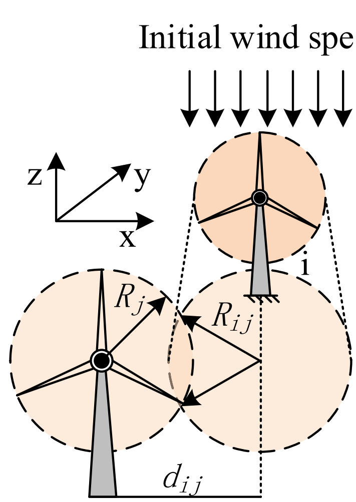

Fig. 2 Diagram of partial occlusion of wake flow

$$S_{overlap,ij} = R_{ij}^2 \cos^{-1}\left(\frac{d_{ij}^2 + R_{ij}^2 - R_j^2}{2d_{ij}R_{ij}}\right) + R_j^2 \cos^{-1}\left(\frac{d_{ij}^2 + R_j^2 - R_{ij}^2}{2d_{ij}R_j}\right) - \frac{\sqrt{\left(-d_{ij} + R_{ij} + R_j\right)\left(d_{ij} - R_{ij} + R_j\right)\left(-d_{ij} + R_{ij} - R_j\right)\left(d_{ij} + R_{ij} + R_j\right)}}{2} \tag{4}$$

The distance between the centers of turbines i and j is represented by the d_{ij} in Eq. (4). R_{ij} represents the wake's radius from turbine i at turbine j in the same plane. R_j stands for the turbine j's radius, and S_j for the downstream region of turbine j's swept area. A WT's wake loss is superimposed when it is within the wake loss area of many upstream WTs. At this time, the specific calculation of WT speed is shown in Eq. (5).

$$\left(1 - \frac{V_j}{V_0}\right)^2 = \sum_{i=1}^{N}\left(1 - \frac{V_{(i)}}{V_0}\right) \tag{5}$$

The speed to be computed for WT j in the lower wake region is indicated by V_j in Eq. (5). WT i's downstream wake impact speed is indicated by $V_{(i)}$, while the number of turbines is indicated by N. For turbine j, its output power is calculated as shown in Eq. (6).

$$P_j = \sum_{j=1}^{N} C_t \rho \pi R^2 V_j^3 \tag{6}$$

In Eq. (6), ρ denotes the air constant and R denotes the rotor radius. V_j denotes the wind speed it receives, and C_t denotes the rotor efficiency. Equation (7) demonstrates how the wind farm's building costs are determined.

$$\text{Cost} = N\left(\frac{2}{3} + \frac{1}{3}E^{-0.00174N^2}\right) \tag{7}$$

In Eq. (7), N denotes the WTs constructed. The goal of the study's optimization is to get both high efficiency and low cost. Equation (8) clearly illustrates this goal.

$$\text{Minimize:Objective} = \frac{\text{Cost}}{P_j} \tag{8}$$

Considering the universal availability and environmental friendliness of solar energy, solar power generation is chosen as an integral element. The main principle of solar power is the photovoltaic effect. When sunlight strikes a solar panel, the light energy is converted into electricity by the panel, which is usually made of semiconductor material. During the conversion process, photons from the sun interact with the semiconductor material, exciting the release of electrons and ultimately forming an electric current. The electrons flow through an electric field inside the panel and eventually generate direct current. Solar energy is a clean, sustainable energy source that does not consume resources or produce pollution, but its power generation efficiency is greatly affected by light intensity. For solar power generation equipment, its output power is usually related to the intensity of solar irradiation, and its calculation is specifically shown in Eq. (9) (Li et al. 2021b).

$$P_s(S) = \begin{cases} P_{sr}\left(\dfrac{S^2}{S_{std} \cdot R_c}\right), 0 < S < R_c \\ P_{sr}\left(\dfrac{S}{S_{std}}\right), S \geq R_c \end{cases} \tag{9}$$

In Eq. (9), S denotes solar irradiation intensity and P_s denotes solar panel output. P_{sr} denotes the rated output power of the solar panel unit, and S_{std} denotes the solar irradiation intensity under standard environment. R_c denotes the irradiance point value. Considering the stability and predictability of tidal energy sources, tidal power generation is chosen as a component. Tidal energy generation, on the other hand, utilizes the gravitational interactions between the Earth, the Moon, and the Sun, as well as the periodic rise and fall of ocean water levels caused by the rotation of the Earth, i.e., the phenomenon of tides, and converts the tidal kinetic energy contained therein into electrical energy. This process is usually achieved by constructing tidal power stations, which include tidal weirs and tidal turbines, in suitable coastal areas. As the tide rises or falls, water flows through the tidal turbine, driving it to rotate, similar to how a water turbine works. The turbine is connected to a generator, so the mechanical rotational energy of the turbine is converted into electrical energy. Although the method of generating power from tidal energy is sustainable and does not release greenhouse gases into the atmosphere, the amount of power produced varies depending on the tidal cycle (Chowdhury et al. 2021). As shown in Fig. 3, a schematic diagram of the principle of tidal energy generation is shown.

For the generating capacity of the tidal energy plant unit, the calculation is specifically shown in Eq. (10).

$$P_t(Q) = \rho g Q H \varepsilon \tag{10}$$

In Eq. (10), ρ is the density of water, g is the acceleration of gravity, and Q is the flow rate through the turbine unit. ε denotes the turbine efficiency, and H denotes the height difference between the reservoir and the sea surface. By modeling the three new types

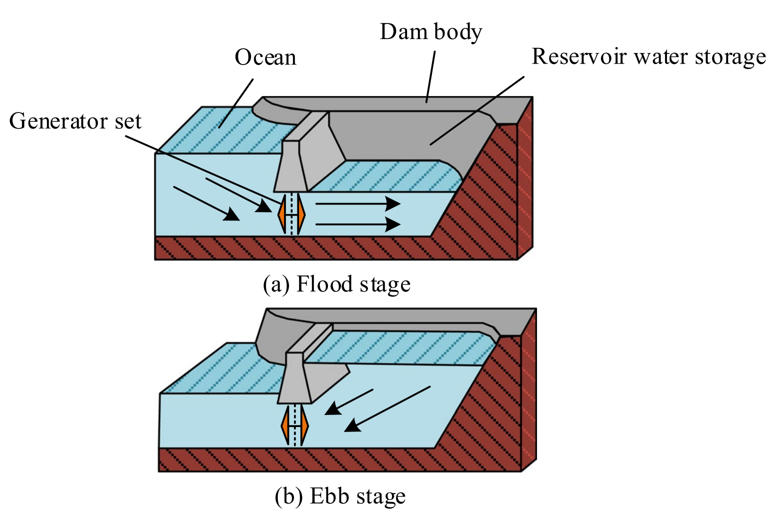

Fig. 3 Schematic diagram of tidal power generation principle

of energy generation systems, namely, wind, solar and tidal energy, the operation mechanism and influencing factors of the new energy sources can be understood in detail. Thus, the characteristics and constraints of various energy generation are clarified and provide the basis for the subsequent MOO problems. After clearly defining these optimization problems, the PA is then targeted to better adapt to the characteristics of these problems in order to solve the NEC problem more efficiently.

Discrete assignment coding and multi-objective optimization of models

PA is a heuristic search algorithm designed to find the optimal solution of a problem. The algorithm simulates the path-finding behavior of organisms in nature, and approaches the optimal solution of the problem by continuously adjusting the search direction and step size during the iteration process. It can be mainly divided into three steps, which are population initialization, pathfinding, and following phases. As shown in Fig. 4, it is the flow schematic of PA.

The algorithm begins by generating a set of random solutions to serve as a starting point for the search. It then calculates the fitness of each solution, which refers to its performance with respect to the objective function. During the iteration process, the algorithm selects the better-performing solutions based on their fitness and uses them to guide the remaining solutions in updating their positions, moving them closer to the better-performing solutions. The solution population eventually converges to the optimal or nearly optimal solution after this process, which is done repeatedly, drives it gradually toward the area with greater fitness (Priyadarshani et al. 2021). In the population initialization stage, the model is mainly initialized by optimizing the spatial randomization of the population individuals to complete the model. Its specific as shown in Eq. (11).

$$X_{n,d} = [x_{n,1}, x_{n,2}, \cdots, x_{n,D}];\ n = 1, 2, \cdots, N;\ d = 1, 2, \cdots, D \tag{11}$$

In Eq. (11), N denotes the individuals in the population, D is the dimension, and $X_{n,d}$ denotes the initialized population. For the initialization of individuals of its population, it is mainly generated by randomly distributing each dimension of the vector in the search space, which is shown in Eq. (12).

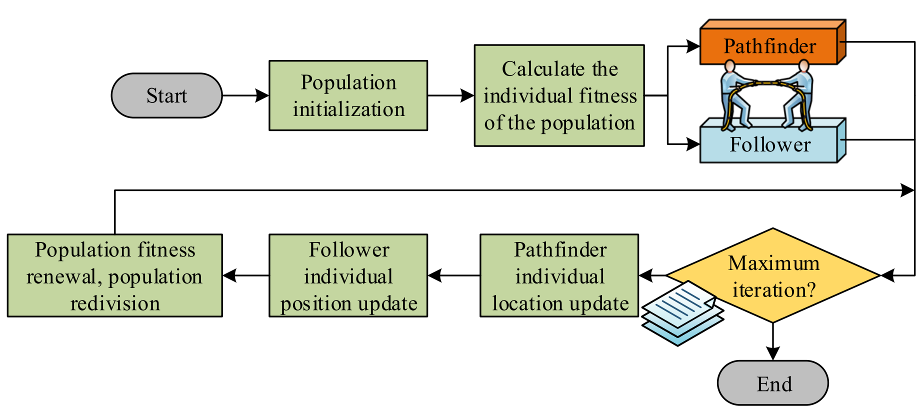

Fig. 4 Schematic diagram of the flow of the pathfinder algorithm

$$X_n = X_{\min} + rand(0,1) \times (X_{\max} - X_{\min}) \tag{12}$$

The bounds of the choice variables in the optimization space are represented by $X_{\max}$ and $X_{\min}$ in Eq. (12), while $rand(0,1)$ stands for a random number with a range of $[0,1]$. The optimization space is then updated to the optimal individual in each generation. Subsequently, it enters the pathfinder stage, in which the optimal individual in each generation of population individuals is selected as the pathfinder, and its update rule is shown in Eq. (13).

$$x_p^{i+1} = x_p^i + 2r_3 \times \left(x_p^i - x_p^{i-1}\right) + A \tag{13}$$

The pathfinder of the $i+1$th generation is indicated by the x_p^{i+1} in Eq. (13). The pathfinder belonging to the $i-1$th generation is indicated by x_p^{i-1}, while the pathfinder belonging to the ith generation is indicated by x_p^i. The variables i and r_3 represent the current number of iterations and a random number created with values in the range $[0,1]$, respectively, based on a uniform distribution. Where A denotes the random search perturbation added to an individual, the calculation of which is specifically shown in Eq. (14).

$$A = u_2 \cdot e^{\frac{-2i}{i_{\max}}} \tag{14}$$

In Eq. (14), $i_{\max}$ denotes the maximum iterations and u_2 denotes a random number uniformly distributed in the range of $[-1,1]$. By controlling A, local optimal solutions can be avoided. Finally, there is the follower phase. In this phase, all individuals except the pathfinder are selected as followers. Its update rule is specifically shown in Eq. (15).

$$x_n^{i+1} = x_n^i + W_1\left(x_{n-1}^i - x_n^i\right) + W_2\left(x_p^i - x_n^i\right) + \vartheta \tag{15}$$

In Eq. (15), x_n^{i+1} denotes the nth follower position in the $i+1$ generation after the ith iteration. x_n^i denotes the nth follower position at the i iteration. x_{n-1}^i denotes the position next to the nth follower in the i iteration. x_p^i denotes the position of the pathfinder at the i iteration. ϑ denotes the oscillation vector. W_1 and W_2 denote two random vectors whose values are specified as shown in Eq. (16).

$$\begin{cases} W_1 = \alpha \cdot r_1 \\ W_2 = \beta \cdot r_2 \end{cases} \tag{16}$$

In Eq. (16), r_1 and r_2 denote two random numbers respectively, whose values range from $[0,1]$. α denotes the communication coefficient of neighboring members in the population, and β denotes the attraction coefficient between each individual in the population and the pathfinder. For the oscillation vector ϑ, its calculation is specifically shown in Eq. (17).

$$\vartheta = \left(1 - \frac{i}{i_{\max}}\right) \cdot u_1 \cdot D, D = \|x_i - x_{i-1}\| \tag{17}$$

In Eq. (17), D denotes the distance between two individuals in the population and $i_{\max}$ denotes the maximum number of iterations. Given the limitations of PA for MOO problems, the introduction of a Pareto optimal solution set enables PA to solve MOO problems. This is based on the Pareto optimal concept, which provides a method for evaluating the relative advantages and disadvantages of solutions in multi-objective problems. In MOO, a solution is Pareto optimal if no other solution is better than it on all objectives, while being strictly better than it on at least one objective. This means that every solution in the Pareto optimal solution set cannot be dominated by other solutions on all targets simultaneously. The optimized multi-objective PA process is shown in Fig. 5.

The core idea of Pareto optimal solution is to find the optimal equilibrium in the MOO problem by setting up an algorithm that first determines the number of objectives, the population size, and the set of archives (Chen et al. 2021). Then iterations are performed to evaluate and update the current solution to obtain the optimal set of solutions, thus solving the complexity of the multi-objective problem. In each iteration, the termination is first checked to see if the termination condition is satisfied, and if not, the population update is performed. The population update should include fitness evaluation. Based on the fitness obtained from the evaluation, a global search strategy is used for further individual selection. The algorithm gradually approaches the Pareto frontier in this process and stops when the maximum iterations are reached, providing the optimal state solution. To deal with the WT layout optimization problem, DAC is introduced in PA. The purpose of introducing DAC to the PA is to adapt to discrete problems, such as WT layout optimization, and improve the accuracy and efficiency of the solution. This improvement allows the algorithm to handle discrete layout decisions of wind farms directly. It also increases the ability to consider geographical, environmental, and economic constraints. As a result, the algorithm is not only suitable for solving complex wind power layout problems, but also generates more practical and accurate optimization results

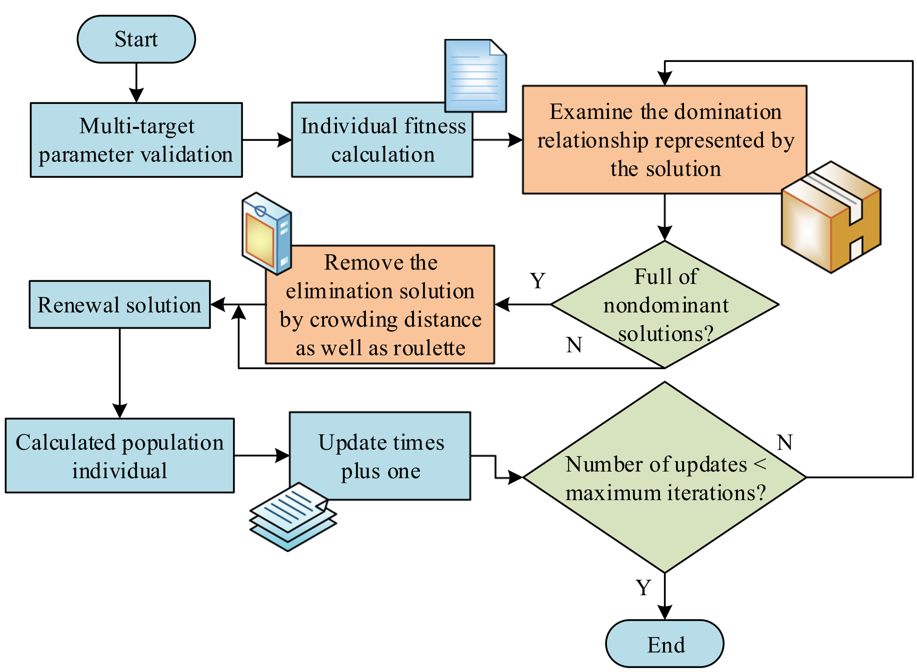

Fig. 5 Multi-objective pathfinder algorithm flow diagram

to effectively support complex decision-making. DAC needs to convert the continuous value representation to discrete values to match the problem characteristics. For each population individual, coded transformations are needed to compute fitness values. It is necessary to convert the complex solution's real and imaginary components to real values while working with real optimization problems. When dealing with discrete problems, it is necessary to convert the complex variables to integer variables and the real variables to binary variables. Such processing can better solve the WT layout optimization problem. the PA process after DAC is specifically shown in Fig. 6.

As shown in Fig. 6 for the PA where DAC has been performed. the solution of the algorithm is encoded as discrete complex values, where the real and imaginary parts of each solution represent different dimensions or aspects of the problem, respectively. This encoding provides the algorithm with the ability to handle discrete data and allows for more fine-grained exploration of the multidimensional search space. In each iteration of the algorithm, the quality of the current solution is first evaluated to determine the quality of the solution through an appropriate fitness function. The fitness function must be tailored to discrete data and accurately reflect the performance of each solution. Based on the fitness score, a percentage of good solutions are selected as 'pathfinders' in

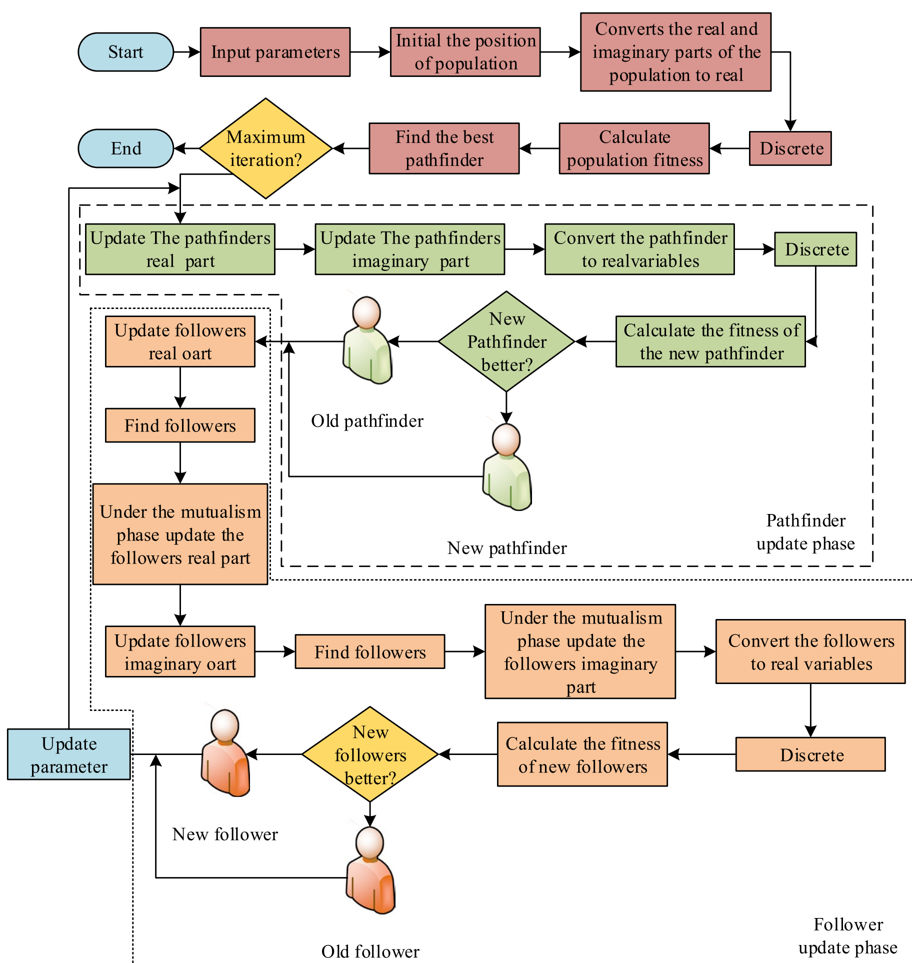

Fig. 6 Discrete complex coded pathfinder algorithm flow diagram

the population, while the remaining solutions are updated. Discrete mathematical operations are used to update the real part. Finally, after several iterations, the search range is gradually narrowed down to locate the optimal or near-optimal solution set in the multi-objective solution space. The PA of DAC can effectively solve those MOO problems that are difficult to be handled by traditional optimization algorithms. Through this improvement, not only the applicability of PA can be improved, but also the effectiveness and efficiency of this algorithm in NEC optimization problems can be strengthened.

Testing of MODASCPA algorithm for new energy consumption optimization

To ensure the accuracy of the test and avoid the error due to hardware limitation, considering the cost limitation as well as the cost-effectiveness, the researcher choose to rent the cloud server platform for the experiment. The IEEE 30 bus model is used to simulate the consumption of new energy grid power. In order to further demonstrate the performance of multi-objective discrete assignment coding pathfinder algorithm (MODASCPA) proposed by the study, the study selects the same type of multi-objective sparrow search algorithm (MOSSA) and multi-objective multi-verse optimizer (MOMVO) are compared with MODASCPA algorithm. The aim of this comparison is to assess the strengths and potential limitations of MODASCPA from multiple perspectives. MOSSA is selected for its efficiency and robustness in solving MOO problems, while MOMVO demonstrates excellence in MOO problems due to its unique cosmological heuristic mechanism. The details of hardware and software and model parameter settings used in the study are shown in Table 1.

The average convergence performance of the algorithm is evaluated with the target value of the average fitness value of the model in order to assess the training performance of the model. And Fig. 7 displays the test results. In Fig. 7, the MODASCPA model proposed by the Institute has a better convergence speed, while its average fitness value performs well, with the best average fitness value of 1.519×10^{-3}, which is 8.41% and 14.62% ahead compared to MOSSA as well as MOMVO, respectively.

Table 1 Details about software and hardware configuration and parameter settings

Hardware		Software		
Name	**Details**	**Category**	**Name**	**Version**
Supplier	Amazon	Programming languages	Python	3.8.10
Instance type	c5.9xlarge	Mathematical library	Intel Math Kernel Library	2020.0.4
CPU	Intel Xeon Platinum 8000	Parallel computing	OpenMPI	4.0.3
RAM	144 GiB	Data storage	MySQL	8.0.20
Operating system	Ubuntu Server 20.04 LTS	Version control	Git	2.25.1

Parameter setting			
Parameter	**Details**	**Parameter**	**Details**
Population size	100	Max velocity	15%
Max iterations	175	Topology structure	Global
Cognitive coefficient	2	Termination condition	Maximum iteration
Social coefficient	2	Population initialization	Random
Inertia weight	0.7	Velocity initialization	[− 10, 10]

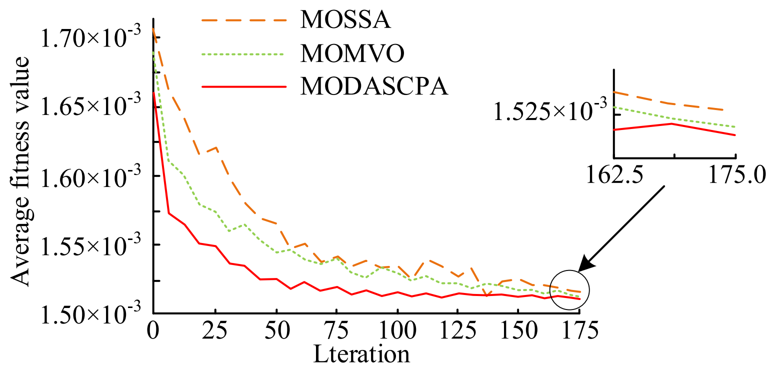

Fig. 7 Average convergence performance test results of three models

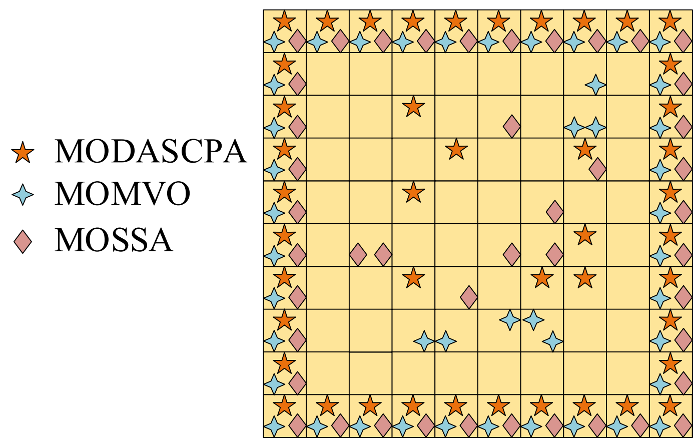

Fig. 8 Visual output results of wind farm layout optimization for three models

A wind farm with dimensions of 2000 m in length and width and a 10×10 WT layout is used to examine the model's optimization performance for wind farm layout. The model's optimization results are produced and visualized, and the output results are displayed in Fig. 8. In Fig. 8, the MODASCPA proposed by the Institute can accurately output effective wind farm optimization layout scheme, while the layout scheme output by MOMVO and MOSSA is congested and overlapped, and cannot be applied to the actual wind farm layout optimization.

To evaluate the practical application efficiency of the model, the fitness and error rate of the model are tested, and the test results are shown in Fig. 9. Figure 9a shows the fitness value test of the three models. The fitness value of the MODASCPA model proposed by the research has the best performance, and its fluctuation range is smaller. Figure 9b shows the error rate test of the three models, from which it can be seen that the MODASCPA model proposed in this study has a lower error rate performance than the comparison model.

The model's MOO performance is evaluated, and Fig. 10 displays the findings. In Fig. 10, the proposed method of the study has the best performance in terms of solution set, which has higher diversity and more solutions at the same time. It shows that MODASCPA possesses better performance in MOO problem and can better

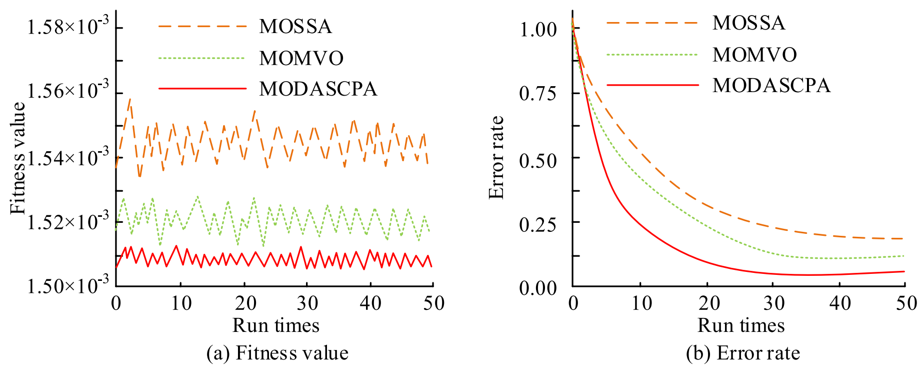

Fig. 9 The running test results of three models

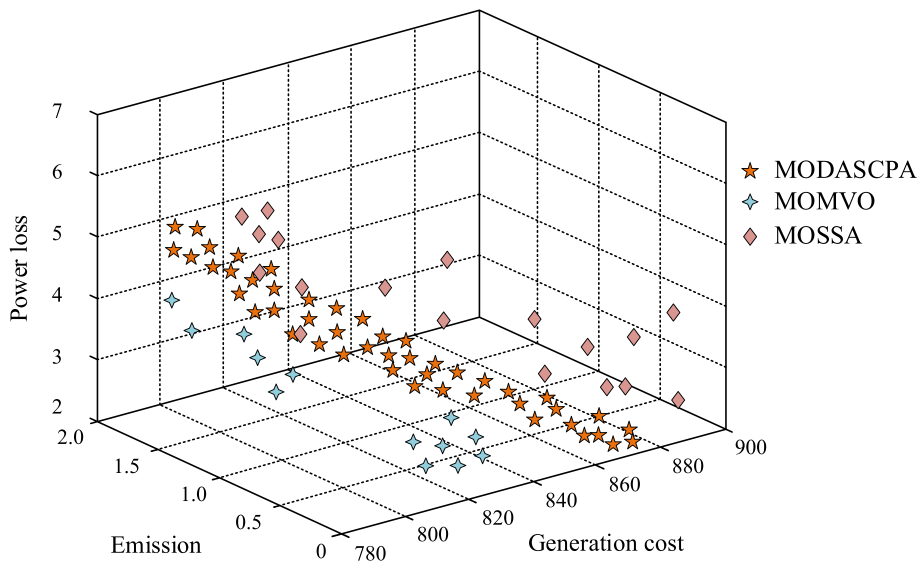

Fig. 10 Multi-objective optimization performance test of three models

optimize the NEC problem to improve the energy output efficiency as well as utilization efficiency.

The real output power of the optimized grid is used to test the model's actual optimization effect. And Table 2 displays the test results. In Table 2, the proposed MODASCPA has the best average efficiency performance with 96.16%, which is 6.57% and 14.02% ahead compared to MOMVO and MOSSA, respectively. In summary, the proposed MODASCPA has the best performance in NEC optimization problems, the model has better convergence performance as well as training performance, and also has better performance in practical applications. In addition to producing a wind farm optimization layout scheme that is actually workable, MODASCPA also exhibits superior efficiency performance in simulation, which can effectively increase the rate of energy utilization and encourage the reform and innovation of new energy optimization.

Test the adaptability and robustness of the model by comparing the particle swarm multi-objective optimization algorithm (PSMOOA). The genetic multi-objective optimization algorithm (GMOOA). PSMOOA is chosen due to its extensive application and

Table 2 Test results of actual output efficiency of three models

Models	Experiment No	Output power (kW)	Efficiency (%)	Average efficiency (%)	Objective function (Cost/kW)
MODASCPA	1	15,678	95.89	96.16	0.0014678
	2	16,261	96.78		0.0015004
	3	16,189	95.82		0.0014972
MOMVO	1	10,117	89.43	89.59	0.0015892
	2	10,045	90.61		0.0015534
	3	9987	88.72		0.0015484
MOSSA	1	9146	81.42	82.14	0.0016231
	2	9251	82.13		0.0016062
	3	9274	82.89		0.0016525

Table 3 The adaptability and robustness test results of the five-part model

Models	Test index	Dateset			Average
		ZDT	PFR	REGLD	
MODASCPA	Accuracy (%)	95.2	96.7	95.4	95.8
	Relative robustness (%)	96.2	96.4	95.7	96.1
MOMVO	Accuracy (%)	90.2	90.7	89.7	90.2
	Relative robustness (%)	85.4	86.2	87.4	86.3
MOSSA	Accuracy (%)	88.2	81.7	86.4	85.4
	Relative robustness (%)	79.4	77.2	76.4	77.6
PSMOOA	Accuracy (%)	82.1	83.4	86.1	83.8
	Relative robustness (%)	75.2	71.7	76.4	74.4
GMOOA	Accuracy (%)	77.2	71.4	68.2	72.2
	Relative robustness (%)	62.7	68.0	65.9	65.5

validation in the field of MOO. PSMOOA represents population-based search strategies, while GMOOA represents evolution-based search strategies. This provides a rich perspective for comparing the efficiency and effectiveness of different algorithms in finding and maintaining Pareto optimal solution sets. The proposed algorithm's applicability is tested using the Zitzler-Deb-Thiele (ZDT) dataset, Pareto front repository (PFR) dataset, and renewable energy generation and load demand dataset (REGLD). Test results are presented in Table 3, which shows that the algorithm maintains better accuracy across various datasets, demonstrating its superior adaptability. At the same time, the research method remains robust, indicating its superior stability.

Discussion

The intensifying energy crisis presents a key challenge to ensuring energy security, particularly in terms of effective access to new energy. To address this challenge, the proposed multi-objective optimization discrete assignment coding pathfinder algorithm (MODASCPA) improves the absorption efficiency of new energy systems, optimizes power grid stability, enhances wind power distribution efficiency, and provides technical support for large-scale grid-connection of new energy. This algorithm assists grid operators in developing more accurate and efficient energy distribution strategies by providing optimal solutions in multiple dimensions. It also promotes the transition from traditional energy systems to cleaner and more sustainable energy sources. However, while MODASCPA has shown excellent performance in experiments, further verification is needed to assess its versatility and scalability in practical applications. The algorithm's performance may be impacted by larger problem sizes, and real-world applications on a large scale may expose limitations in response time and resource utilization. Additionally, it is important to note that the complexity of the energy system in the real world often surpasses the assumptions made in the model. Therefore, the algorithm must be able to handle uncertainty and dynamic changes in order to adapt to the constant changes of the actual grid. To address these limitations and improve the practical application of the algorithm, future research should focus on exploring its universality and validating and optimizing its performance through larger scale experiments and real grid data. Additionally, research should prioritize improving the algorithm's real-time response and resource efficiency to ensure quick response times and efficient use of computing resources during practical operation. MODASCPA and its derived algorithms are expected to provide technical support for achieving sustainable and efficient energy systems with further improvements and adjustments.

Conclusion

With the worsening of the energy crisis, the transformation of the traditional energy system has become an inevitable trend, and the efficient access of new energy sources to the power grid is the key to realize a sustainable energy system. In this study, in order to effectively improve the efficiency of new energy system consumption and optimize the stability of the grid system, the study proposes the DACPA of MOO to obtain the best optimization scheme of new energy system consumption. The experimental results indicated that MODASCPA has a significant advantage over MOMVO and MOSSA in terms of fitness value performance, with an improvement of 9.54% and 14.67%, respectively, which suggests that it has higher efficiency and better global search capability in solving complex optimization problems. Meanwhile, MODASCPA performed the best in terms of diversity of solution sets and was able to provide a wider range of optimization solutions, with an average efficiency as high as 96.16%, which is significantly better than MOMVO's 89.59% and MOSSA's 82.14%. At the same time, the research method is highly adaptable and robust. Compared to the traditional method, this approach considers multiple optimization objectives comprehensively. It uses DAC technology to meet the actual operation requirements of the power grid. It avoids falling into local optima through efficient global search capability and optimizes the diversity of solution sets. Therefore, it provides a more comprehensive and flexible solution strategy for new energy grid-connection problems than the traditional method. The proposed research is of great significance to both the algorithm optimization and NEC fields, which not only improves the efficiency of the optimized layout of wind power, but also provides effective technical support for the large-scale grid connection of new energy sources, and can effectively promote the optimization of the traditional energy system for the new era of reform. However, further exploration is needed to determine the scalability and universality of this technology in practical applications, particularly in large-scale complex power grid systems. Additionally, the algorithm may encounter issues with long response times and low resource utilization during actual operation. In the future research, the applicability of the algorithm should be further verified and optimized, and its response time and resource consumption should be further explored and improved.

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References

Butt OM, Zulqarnain M, Butt TM (2021) Recent advancement in smart grid technology: future prospects in the electrical power network. Ain Shams Eng J 12(1):687–695

Chen L, Liu F, Wang W, Masouros C (2021) Joint radar-communication transmission: a generalized Pareto optimization framework. IEEE Trans Signal Process 69(1):2752–2765

Chowdhury MS, Rahman KS, Selvanathan V, Nuthammachot N, Suklueng M, Mostafaeipour A, Techato K (2021) Current trends and prospects of tidal energy technology. Environ Dev Sustain 23:8179–8194

Gong F, Wang Y (2022) A new rock brittleness index based on the peak elastic strain energy consumption ratio. Rock Mech Rock Eng 55(3):1571–1582

Huang J, Cang J, Zhou Z, Gholinia F (2021) Evaluation effect climate parameters change on hydropower production and energy demand by RCPs scenarios and the Developed Pathfinder (DPA) algorithm. Energy Rep 7(1):5455–5466

Jia H, Taheri B (2021) Model identification of solid oxide fuel cell using hybrid Elman neural network/quantum pathfinder algorithm. Energy Rep 7(1):3328–3337

Keane A (2021) Advancement of an analytical double-Gaussian full wind turbine wake model. Renewable Energy 171(1):687–708

Li Z, Chen W, Wu Q, Wang K, Li J (2021a) Joint beamforming design and power splitting optimization in IRS-assisted SWIPT NOMA networks. IEEE Trans Wireless Commun 21(3):2019–2033

Li Z, Xu X, Sheng X, Lin P, Tang J, Pan L, Yamauchi Y (2021b) Solar-powered sustainable water production: state-of-the-art technologies for sunlight–energy–water nexus. ACS Nano 15(8):12535–12566

Liu Z, Liu H, Lu Z, Zeng Q (2021) A dynamic fusion pathfinding algorithm using delaunay triangulation and improved a-star for mobile robots. IEEE Access 9:20602–20621

Priyadarshani S, Subhashini KR, Satapathy JK (2021) Pathfinder algorithm optimized fractional order tilt-integral-derivative (FOTID) controller for automatic generation control of multi-source power system. Microsyst Technol 27:23–35

Saudi A (2022) Pathfinding algorithm based on rotated block AOR technique in structured environment. AIMS Math 7(7):11529–11550

Shaheen MAM, Hasanien HM, Alkuhayli A (2021) A novel hybrid GWO-PSO optimization technique for optimal reactive power dispatch problem solution. Ain Shams Eng J 12(1):621–630

Tang C, Zhou Y, Tang Z, Luo Q (2021a) Teaching-learning-based pathfinder algorithm for function and engineering optimization problems. Appl Intell 51(1):5040–5066

Tang X, Cao C, Wang Y, Zhang S, Liu Y, Li M, He T (2021b) Computing power network: the architecture of convergence of computing and networking towards 6G requirement. China Commun 18(2):175–185

Tapia T, Lorca A, Olivares D, Negrete-Pincetic M (2021) A robust decision-support method based on optimization and simulation for wildfire resilience in highly renewable power systems. Eur J Oper Res 294(2):723–733

Tian L, Huang Y, Liu S et al (2021) Application of photovoltaic power generation in rail transit power supply system under the background of energy low carbon transformation. Alex Eng J 60(6):5167–5174

Wang Y, Liu Y, Feng W et al (2023) Waste haven transfer and poverty-environment trap: evidence from EU. Green Low-Carbon Econ 1(1):41–49
Wu Z, Zhao Y, Zhang N (2023) A literature survey of green and low-carbon economics using natural experiment approaches in top field journal. Green Low-Carbon Econ 1(1):2–14
Zhou Q, Zhang Y, Yi C, Jin J, He L, Hu Q (2021) Convolutional sparse coding using pathfinder algorithm-optimized orthogonal matching pursuit with asymmetric Gaussian chirplet model in bearing fault detection. IEEE Sens J 21(16):18132–18145

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