Improved Symbiotic Organisms Search Algorithm for Optimal Operation of Active Distribution Systems Incorporating Renewables and Emerging Data-Center Resources

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Abstract
The optimal operation analysis plays an important role in estimating the expected return of investment for power systems. However, this work could be highly challenging under the context of active distribution network, where a variety of renewable energy sources and emerging active loads (such as Internet data centers) could be penetrated that introduce a high level of nonlinearity and nonconvexity characteristics into the system modeling. To overcome such challenge, this paper presents a new methodological framework based on the improvements of symbiotic organisms search (SOS) algorithm to address the optimal operation problem of active distribution systems containing renewable energy sources and datacenter resources, aiming to provide a practical tool for system analysis, particularly subject to nonconvexity nature of system components. For this purpose, a generic model for the distribution system including wind power, PV, and datacenter resources is first developed, which not only captures the uncertain nature of system components but also accounts for their spatiotemporal flexibility during operation. On this basis, in order to improve the computation efficiency of the problem, the SOS algorithm is improved by designing the selection strategy of random parameters. By using the penalty function method, the concerned problem is expressed as a nonlinear unconstrained optimization problem. The performance of the proposed model and algorithm is examined through comparative studies. It is shown that the proposed method is able to schedule the renewable energy resources and flexible demand of datacenters coordinately to reduce the operation cost of the system significantly in the case study. In addition, the proposed algorithm demonstrates a higher level of accuracy as well as better convergence efficiency compared to other conventional techniques.

KEYWORDS
Active distribution system, datacenter resources, distributed generation, flexibility, operation
1 | INTRODUCTION

With the electrification progress in human societies, there is a much stronger interdependency between power consumption and human activities. In this regard, the efficient exploitation of renewable energy sources (RESs) has become a "must-do" way to alleviate the energy demands and promote the sustainable development of human race.1 Active distribution system (ADS) is widely believed to be a feasible technical solution for efficient accommodation and usage of geographically-dispersed RESs, particularly those with stochastic and intermittent nature, such as wind power, photovoltaic (PV). However, introducing a high proportion of RESs into distribution power systems could bring about significant challenges for power balancing; and this also necessitates a transformation of power system operation paradigms. As a result of this situation, the optimal operation simulation tool is considered an essential tool for power system analysis.2-7

In fact, a large number of scholars have been absorbed in the above-mentioned problem with the consideration of various kinds types of RESs and distributed energy resources. In,8 a novel multi-time scale coordinated scheduling method including day ahead, hour ahead, and real time was proposed in a combined system including wind power, photovoltaic power, thermal power, and storage. It can be observed from the simulation results that the research strategy used in this article could ensure the optimal economy of the system, while fully tapping the potential adjustment of each power supply of the system. To solve the intermittency and uncertainty of RESs in the distribution network, a robust optimization strategy on the basis of minimum confidence interval is conducted to solve the problem of optimal operation of active distribution network.9.10 Zeng et al10 established a dynamic two-stage optimization model for active distribution network with the consideration of economy and environment, which was solved by discrete genetic algorithm. Reference11 established a two-stage robust optimization model considering economy and robustness, which was solved by benders’ dual decomposition algorithm. The results showed that this method could maximize the coordination and optimization of economy and robustness of the microgrid. The above researches focus on the intermittency and uncertainty of RESs generation in the optimization of power system. Most of them are coordinated dispatching of various supply-side resources to achieve the optimal system economy. But neither considers the importance of flexible resources such as load-side data centers in the active distribution network operation.

In the wake of the continuous and vigorous expansion of 5G technology and big data, the introduction of the concept of "new infrastructure", more special loads such as datacenters with colossal energy consumption are connected to the distribution network. Thus, more demand for electric energy is needed in data process at computing nodes and heat dissipation from air conditioners, and its power consumption usually has great volatility and importance for the operation of distribution network.12 For such batch processing loads as scientific computing, data processing, data storage, etc.,13,14 as long as they are completed within the specified time, the loads can be delayed, and such load-adjustable feature makes the datacenter an important demand response resource in the operation of the distribution network. Regarding the datacenter’s participation in the operation of the distribution network, Reference15 has studied the scheduling problem with multi-state servers. By optimizing the sleeping and working frequency of the server, the results showed that real-time adjustment of the server work state could significantly reduce the power consumption level of the datacenter. In addition to reducing the power consumption of the datacenter by adjusting the working characteristics of the server, energy storage equipment can also be integrated with the datacenter to participate in its optimized operation. For example, a datacenter power controlling strategy was proposed in,16 and through comprehensive optimization of load delay processing and internal energy storage charging and discharging plans, the peak power of the datacenter can be effectively reduced. The above research shows that by adjusting the datacenter’s operating characteristics, the operating power consumption can be significantly reduced. Therefore, it can be further considered that the datacenter can participate in managing the power grid. Considering multiple goals such as economic benefits, renewable energy consumption, load tracking, the above studies mostly consider the adjustment of the energy consumption characteristics of the datacenter and its participation in optimizing the active power of the power grid. However, they did not involve the data center’s participation in operation adjustment and active-reactive joint optimization in the source-load coordination interaction.

As such, different methods are conducted to address the optimal operation problem of ADSs. Attia et al17 made corresponding improvements to sine-cosine algorithm (MSCA) to address the optimal operation problem of ADSs. Based on simulation results, it could be observed that in contrast with SCA and other optimization algorithms, MSCA has a strong superiority. The authors in [19] applied the group search optimization (GSO) to deal with the same problems in medium and high voltage power distribution system.18 Biswas et al., studied the optimal operation problem of ADSs by using the pigeon-inspired algorithm (PIO)19 Zeng et al in Reference20 established a co-optimization model for electric vehicle charging station location and incentive mechanism design, and applied genetic algorithm (GA) to solve it. Researcher in [22] introduced the evolutionary
particle swarm optimization (EPSO) algorithm to handle the power system operation objects on an IEEE 30-bus test system which contains WG.\textsuperscript{21} Besides, many researches have been used self-adaptive evolutionary programming (SAEP) optimization algorithm,\textsuperscript{22} GAABC algorithm,\textsuperscript{23} and bacteria foraging-based algorithm\textsuperscript{24} to handle the OPF problem and scheduling optimization in power systems. Beyond above all, these algorithms will converge prematurely when solving some problems and there is a high probability of falling into local optimum, especially when the problem's dimensionality is enormous. The SOS algorithm\textsuperscript{25,26} was proposed by Cheng and Prayogo. The method mentioned above simulates the three main interaction modes of mutualism phase, commensalism phase, and parasitism phase among various organisms in nature to improve their ability to adjust themselves to the environment to survive. Compared with other algorithms, it has only two commonly used parameters: biological population size and maximum iteration algebra. It is commonly used in functional optimization, engineering optimization design, and combinatorial optimization and has good accuracy and stability.\textsuperscript{27-29} For example, the SOS algorithm has application in making optimization to the controller parameter setting process.\textsuperscript{30} By mapping the SOS algorithm from continuous space to discrete space, the optimal solution can be searched for in the specified solution set range.\textsuperscript{31} The principle of complex coding diploid is introduced into SOS algorithm. The search range is extended from one dimension to flat, which improves the ability to find the global optimal value.\textsuperscript{32} In addition, the SOS algorithm is also commonly used in route planning to find the optimal route.\textsuperscript{33} In the optimization of power systems, a symbiosis search algorithm was used in\textsuperscript{34} to solve economic scheduling problems that consider valve-point effects, restricted areas, transmission line penalty, various bunkers, and other operating restrictions of distribution power systems. The same algorithms are introduced to deal with the dynamic scheduling problem with the consideration of valve-point effects of generators.\textsuperscript{35} But the above algorithm cannot solve problems effectively.

In this study, we introduce a new framework on the basis of improved SOS for investigating the optimal operation problem of ADSs with renewables and emerging datacenter resources. Datacenter is considered as a new type of flexibility resources to promote the utilization efficiency of RESs and incorporated into the operation decision-making of ADSs. To address the disadvantages of SOS algorithm including poor stability, a greater possibility of sinking into a local optimum, and slow convergence, this research is aimed at improving the parameter settings of the SOS algorithm in the two phases of mutualism and commensalism phase, and then uses the improved SOS algorithm to deal with the proposed problem.

The main contributions of this paper can be listed as below:

1. An optimal power flow analysis framework for distribution systems with the inclusion of both distributed renewable energy sources and datacenter resources is developed. Unlike existing literatures, this paper introduced the flexible characteristics of datacenter resources as well as their associated uncertainties into the proposed optimal model.

2. In this paper, the control parameters and random parameters in the mutualism and the commensalism phase of the SOS algorithm are improved accordingly. By changing the benefit factor, each organism can obtain equal benefits in the search phase; by narrowing the search interval of random factors, the speed of the algorithm is further accelerated and the accuracy of the solution is increased.

3. Different case settings are introduced to verify the effectiveness of the proposed optimal model for distribution network with RESs and data center resources.

The organization of the paper is summarized as follows. Section 2 presents modeling of datacenter resources. Formulation of optimal operation problem is presented in Section 3. Solving algorithm is described in Section 4. Section 5 explains Numerical analysis. Finally, section 6 presents the conclusions.

## 2 | MODELING OF DATACENTER RESOURCES

In practice, people's data requirements usually include web browsing, video watching, online learning, game entertainment, data processing, video calls, etc. The data center operator can change its service quality according to different task types with the user's permission, thus reducing the communication capacity, which indirectly regulates the operating power of the data center. The datacenter is connected to the grid node 13 to meet the data load of all nodes in the entire system, the task volume is predicted to be 9,500,000, and the task demand is randomly distributed between 10 Mbps and 1.5 Gbps. For the convenience of calculation, this paper assumes that the size of each task is 0.15 Gbps. To reduce the complexity of handling the model, the datacenter considered in this paper only installs one kind of server, and then when the task arrives, it is evenly distributed to the servers that are power on.

The datacenter's energy consumption is mainly composed of IT equipment (mainly servers), cooling equipment, and other auxiliary equipment. The power consumption model of a single server is shown in (1)
\[ P_{\text{ser}} = P_{\text{idle}} + \mu_{\text{DC}} (P_{\text{peak}} - P_{\text{idle}}) \]  

where \( P_{\text{ser}} \) is the power demand of per sever, \( P_{\text{peak}}, P_{\text{idle}} \) is the silent power and rated power of the server, respectively, \( \mu_{\text{DC}} \) is the utilization rate of the present DC servers, which can be calculated by (2).

\[ \mu_{\text{DC}} = \frac{L_{\text{data}}}{n_{\text{ser}} v_{\text{ser}}} \]  

where \( L_{\text{data}} \) is the amount of tasks arrived, \( n_{\text{ser}} \) is the number of current severs that need to be powered on, \( v_{\text{ser}} \) are the serve rate of severs which show the solving ability of severs.

According to,\(^{40}\) the energy consumption of cooling equipment in the datacenter can be expressed by the typical power utilization factor (PUE) and the power consumption of IT equipment, which is shown in (3).

\[ P_{\text{DC}} = P_{\text{U}} \cdot n_{\text{ser}} P_{\text{ser}} \]  

where PUE can be calculated by dividing the energy expenditure of the DC by the IT equipment, which is 1.5 in this paper.

Aiming to meet the delay restriction of data users, the DC operator must meet certain delay requirements and cannot exceed the contract limit

\[ \frac{1}{v_{\text{ser}}} - \frac{L_{\text{data}}}{n_{\text{ser}}} + \frac{1}{v_{\text{ser}}} \leq T_{\text{sign}} \]  

where \( T_{\text{sign}} \) is the maximum time delay on contract

The number of servers in the power-on state cannot exceed the number of servers allocated.

\[ n_{\text{ser}} \leq N_{\text{ser}} \]  

where \( N_{\text{ser}} \) is the number of severs allocated.

The server’s service rate cannot exceed the maximum limit.

\[ \mu_{\text{DC}} \leq \mu_{\text{max}} \]  

where \( \mu_{\text{max}} \) is the permitted maximum utilization rate of servers, which is 0.9 in this paper.

In this paper, the datacenter changes the operating power consumption by adjusting its operating characteristics. The datacenter will reduce the user’s service quality in the process of power adjustment. Hence, the system operator needs to give the datacenter corresponding price compensation, according to the energy consumption change of the datacenter. We only consider the compensation of load reduction for datacenter, which is expressed by (7) as follows

\[
\begin{align*}
CF_{\text{dc–DR},i}(P_{\text{DCS,i}}) &= dc_i \times \Delta P_{\text{DCS,i}} \\
\Delta P_{\text{DCS,i}} &= \max (P_{\text{DCS0,i}} - P_{\text{DCS,i}}, 0)
\end{align*}
\]

where \( CF_{\text{dc–DR},i}(P_{\text{DCS,i}}) \) represents the demand response expense that the system operator has to pay for the datacenters. \( dc_i \) is the demand response cost of per unit in the \( i \)th datacenter, \( \Delta P_{\text{DCS,i}} \) is the power adjustment in the \( i \)th datacenter to participate in demand response, \( P_{\text{DCS0,i}}, P_{\text{DCS,i}} \) is the power demand (without demand response), and demand response case, respectively, represents the compensation for the load reduction only.

In order to ensure a certain quality of service, the communication capacity that can be reduced should be kept within a reasonable range, as shown in (8)

\[ 0 \leq L_{\text{cut data}} \leq L_{\text{cut max data}} \]  

where \( L_{\text{cut data}} \) represents the communication amount that can be reduced, and \( L_{\text{cut max data}} \) is the allowed maximum reduction amount of communication.

## 3 | FORMULATION OF OPTIMAL OPERATION PROBLEM

In this paper, the supply side and the demand side are both optimized. The effect of RESs and datacenter resources have been fully considered to deal with the optimal operation problem considering the security constraints. The main goal of the proposed problem aiming at source-load synergy was to minimize an identified objective function by finding the optimum values of independent variables under satisfying various the system constraints.

### 3.1 | Description of variables

The dependent variables mainly include the active power of generator of balanced node, voltage value of load node, reactive power output of THG units, renewable energy units and consortium of data center and photovoltaic system. The independent variables mainly include active power output of THG sets except for balance node, active power output of renewable energy generating sets and active power output of consortium of data center and photovoltaic system, and voltage value of all generator nodes.

### 3.2 | Fuel cost and carbon tax of THG

The classical cost function of THG units is in the form such as (9), where \( x_i, y_i, z_i \) are parameters related to generation cost of the \( i \)th THG.

\[ CF_1(P_{\text{THG}}) = \sum_{i=1}^{N_{\text{THG}}} x_i + y_i P_{\text{THG}} + z_i P_{\text{THG}} \]
The total emission from a traditional generating unit with fossil fuel and the carbon tax model can be mathematically described as in (10) and (11), where \( \sigma_i, \beta_i, \tau_i, \omega_i \) and \( \mu_i \) are emission coefficients of the \( i \)th thermal generating unit. \( C_E \) and \( C_{tax} \) can be identified as emission cost and tax, respectively.

\[
F_E = \sum_{i=1}^{NHG} \left[ \sigma_i + \beta_i P_{THG}^i + \tau_i P_{THG}^2 \right] \times 0.01 + \omega_i \exp(\mu_i P_{THG}) \tag{10}
\]

\[
C_E = C_{tax} \times F_E \tag{11}
\]

### 3.3 | Cost models of RESs

Mathematical expression of cost calculation of wind turbine and a PV power source can be defined as formulas (12) and (13), where \( \omega_i \), and \( P_{WS,i} \), are the unit price and active power of the wind power cluster installed at \( i \)th bus, \( P_{PV,i} \), and \( P_{PV,i} \), are the unit price and active power of the PV power station connected at \( i \)th bus.

\[
CF_{w,i}(P_{WS,i}) = w_i \times P_{WS,i} \tag{12}
\]

\[
CF_{pv,i}(P_{PV,i}) = P_{PV,i} \times P_{PV,i} \tag{13}
\]

In this paper, the cost calculation models of overestimation and underestimation due to the uncertainty of renewable energy are described as formula (14)-(17). installed at \( i \)th nodes, \( C_{Ow,j} \) and \( C_{Uw,j} \) are the uncertainty cost coefficients in the case of overvaluation and undervaluation, \( P_{w,i} \) and \( P_{w,i} \) are, respectively, the actual power and maximum available power of the wind power cluster installed at \( i \)th nodes. \( f_w(p_{w,i}) \) is the probability distributions function of wind power output \( p_{w,i} \). \( CF_{Ow,j} \) and \( CF_{Uw,j} \) are the uncertainty cost coefficients in the case of overvaluation and undervaluation, and \( f_w(P_{PV,i} < P_{PV,i}) \) represents the probability that the actual output power of the photovoltaic is lower than the dispatched power. \( E(P_{PV,i} < P_{PV,i}) \) gives the expectation that the actual output power is lower than the scheduled power.

### 3.4 | Objective functions

The objective function of the proposed optimal operation problem with wind and PV under various kinds of condition could be expressed as follows:

### 3.4.1 | Overall cost calculation model

The overall cost calculation model of the above mentioned problem considered in this paper is determined as the objective function shown in formula (18).

\[
f_{obj}(A, B) = F_{obj,1} = CF_1(P_{THG}) + \sum_{i=1}^{NW} (CF_{w,i}(P_{WS,i}) + CF_{Ow,i}(P_{WS,i} - P_{w,i}) + CF_{Uw,i}(P_{w,i} - P_{WS,i})) + \sum_{i=1}^{NPV} (CF_{pv,i}(P_{PV,i}) + CF_{Opv,i}(P_{PV,i} - P_{PV,i}) + CF_{Upv,i}(P_{PV,i} - P_{PV,i})) + \sum_{i=1}^{NDC} CF_{dc-DRC,i}(P_{DCS,i}) \tag{18}
\]
3.4.2 Overall cost model considering emission and tax

The objective function of the proposed OPF problem is given as in (19).

\[ f_{obj} = F_{obj2} = F_{obj1} + C_E \]  

(19)

3.4.3 Voltage deviation

The voltage deviation of the nodes in the any power distribution network can be solved according to formula (20).

\[ f_{obj} = F_{obj3} = VD = \left( \sum_{i=1}^{NPQ} |V_i - 1| \right) \]  

(20)

3.5 Equality constraints

Equality constraints considered for optimal operation problem contain balance constraints of active power and reactive power in ADS. These equations are expressed as formula (21)-(22).

\[ P_{Gk} - P_{Lk} - P_{DCk} = V_i \sum_{m=1}^{Nk} V_m \left[ G_{km} \cos(\delta_{km}) + B_{km} \sin(\delta_{km}) \right] = 0 \quad \forall k \in N_{bus} \]  

(21)

\[ Q_{Gk} + Q_{Lk} - Q_{DCk} = V_i \sum_{m=1}^{Nk} V_m \left[ G_{km} \sin(\delta_{km}) - B_{km} \cos(\delta_{km}) \right] = 0 \quad \forall k \in N_{bus} \]  

(22)

where \( P_{Gk}, P_{Lk}, P_{DCk} \) respectively indicate active powers of the generator sets installed at ith bus (including THG, WG, PV, and prosumer units), the conventional power load bus, and the datacenter node. The \( Q_{Gk}, Q_{Lk}, Q_{DCk} \), respectively indicate reactive powers of the ith generator sets (such as THG, WG, PV), the shunt VAR compensator, the conventional power load bus in the distribution power network. The \( N_{bus} \) indicates the total number of buses, \( V_i \) and \( V_m \) are respectively indicate the voltage values at buses k and m, \( \delta_{km} \) is used to indicate the difference values of voltage phasor angle at buses k and m, and \( G_{km} \) and \( B_{km} \) are respectively used to indicate the conductance value and susceptance value of the power line with node k and node m as endpoints.

3.6 Inequality constraints

3.6.1 Generator constraints

The active and reactive power outputs of THG, WG and PV must meet the maximum and minimum restriction, likewise the constraint of voltage values of generator sets (containing THG, WG, PV). These constraints are shown in formula (23).

\[
\begin{align*}
P_{THG, min} &\leq P_{THG} \leq P_{THG, max} \quad \forall i \in N_{THG} \\
P_{WS, min} &\leq P_{WS} \leq P_{WS, max} \quad \forall i \in NW \\
P_{PV, min} &\leq P_{PV} \leq P_{PV, max} \quad \forall i \in NPV \\
Q_{THG, min} &\leq Q_{THG} \leq Q_{THG, max} \quad \forall i \in N_{THG} \\
Q_{WS, min} &\leq Q_{WS} \leq Q_{WS, max} \quad \forall i \in NW \\
Q_{PV, min} &\leq Q_{PV} \leq Q_{PV, max} \quad \forall i \in NPV \\
V_{G, min} &\leq V_G \leq V_{G, max} \quad \forall i \in NG
\end{align*}
\]

(23)

3.6.2 Transformer tapping ratio constraint

The change in the tap ratio of the transformer must meet the requirements of the largest and smallest value limits, which can be expressed as formula (24).

\[ T_{i, min} \leq T_i \leq T_{i, max} \quad \forall i \in NT \]  

(24)

where \( T_{i, min} \) and \( T_{i, max} \) respectively indicate lower and upper tap ratio values of the transformers installed at ith bus.

3.6.3 Constraints of shunt VAR compensator

Shunt VAR compensators must operate in the range of the allowable minimum and maximum values limits, which can be expressed as formula (25). where \( Q_{SV, min} \) and \( Q_{SV, max} \) respectively indicate smallest and largest reactive power outputs of the shunt VAR compensators installed at ith bus.

\[ Q_{SV, min} \leq Q_S \leq Q_{SV, max} \quad \forall i \in NC \]  

(25)

3.6.4 Security constraints

The voltage amplitude of each conventional load node can not exceed the maximum and minimum restrictions, and apparent power flow of each transmission line in the grid cannot exceed the maximum allowable capacity. These two constraints are all shown in (26).

\[
\begin{align*}
V_{L, min} &\leq V_L \leq V_{L, max} \quad \forall i \in NPQ \\
S_{li} &\leq S_{li, max} \quad \forall i \in NTL
\end{align*}
\]

(26)

where \( V_{L, min} \) and \( V_{L, max} \) are the smallest and largest voltage values of the ith PQ bus. \( S_{li} \) and \( S_{li, max} \) are the apparent power flow of the ith line and its maximum technically allowed apparent power flow capacity.

The objective function of the optimal operation problem in this paper including RESs and data center demand response can be identified as in (27).
where $f_{obj}(A, B)$ or $f_{obj}(A_0, B_0)$ is defined as objective functions under normal and emergency conditions. Also, $\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5,$ and $\lambda_6$ denote the penalty coefficients, which are set on the basis of preference of consumer. Each of the penalty cost is set as $\lambda_1 = 100, \lambda_2 = 100, \lambda_3 = 250, \lambda_4 = 250, \lambda_5 = 250$ and $\lambda_6 = 300.$

4 | SOLVING ALGORITHM

4.1 | Standard SOS algorithm

As a new heuristic algorithm, SOS optimization method was born inspired by the symbiosis and interaction behavior of ecosystems. In the initial stage, the algorithm will randomly generate a certain number of initial populations within a certain range, and these populations will be used as the initial solution of the current optimization problem. First, create organisms for candidate solutions, and generate candidate solution vectors based on the maximum and minimum restrictions of the variables. The production of the ecosystem and organisms can be represented in Figure 1. The three stages of mutualism, commensalism and parasitism will be explained separately below.

4.1.1 | Mutualism phase

According to the mutually beneficial behaviors between the two organisms in the ecosystem, the mutualism phase in the SOS algorithm can be deduced. $X_m$ and $X_n$ respectively represent the randomly selected organisms in the biome, and $X_n$ is discretionarily selected from the ecosystem to exert an influence with organism $X_m.$ Two randomly selected organisms $X_m$ and $X_n$ interact with each other to produce more adaptable organisms $X_{m\text{new}}$ and $X_{n\text{new}}.$ This interactive process can be mathematically expressed by formula (28).

$$X_{m\text{new}} = X_m + \text{rand}(0, 1) \times (X_{\text{best}} - \text{Mut Vect} \times BF_1)$$

$$X_{n\text{new}} = X_n + \text{rand}(0, 1) \times (X_{\text{best}} - \text{Mut Vect} \times BF_2)$$

$$\text{Mut Vect} = \frac{X_m + X_n}{2}$$

where $\text{rand}(0, 1)$ denotes a random number greater than or equal to 0 and less than or equal to 1, $BF_1$ and $BF_2$ are both beneficial factors that indicate the beneficial connection among organisms in the biome to generate new organisms, and the beneficial factors are both discretionarily chosen as 1 or 2. The $\text{Mut Vect}$ is expressed as the relationship between $X_m$ and $X_n$ organisms, and is the optimal solution in the ecosystem. The organisms update with the new optimization result by comparing the fitness values of the old organism and the new organism, and the organisms will not update in search space or ecosystem when the fitness value of the new organism is the worse one.

4.1.2 | Commensalism phase

The interaction of two organisms is beneficial to one organism but has no effect on the other during the phase, both $X_m$ and $X_n.$ During the interaction process, the organism $X_m$ gains benefits from the interaction, whereas the other organism does not undergo any changes. This interactive process can be mathematically expressed by formula (29).

$$X_{m\text{new}} = X_m + \text{rand}(-1, 1) \times (X_{\text{best}} - X_n)$$

---

*FIGURE 1* The relationship model of organisms and ecosystem
After generating a new organism, determine whether the current optimal solution needs to be updated by comparing the fitness values of the old organism and the new organism.

4.1.3 Parasitism phase

However, during this phase, the interaction of two organisms is beneficial to one organism but has bad effect on the other. In a parasitism phase, the organism \( X_n \) is randomly chosen from the ecosystem in a parasitism phase. A parasite vector \( \text{parasite}_V \) is constituted form the organism \( X_n \). The pros and cons of fitness value are compared between the parasitic vector and the organism \( X_n \), and the one with better fitness value is chosen to keep.

4.2 Improvements to the SOS algorithm

According to the above analysis of the standard SOS algorithm, it can be seen that the control parameters that affect the performance of the algorithm’s capability are few in contrast with other algorithms. In the mutualism phase, the benefit factor is randomly selected as 1 or 2. This selection method may lead to a new solution in the infeasible region, thus increasing the deviation of the objective function between the optimal organism and the entire ecosystem, reducing the stability and reliability of the algorithm. On the other hand, the interval of random factors in the commensalism phase is too large, which leads to that the search range in the optimization process is too large, thereby reducing the convergence effect and convergence speed of the algorithm. It is manifest that when the standard SOS algorithm is used to handle the optimal value, it has greater possibility to sink into the local optimal solution, which reduces the solution speed of the problem. Based on the above analysis, aiming at overcoming the limitations of the original algorithm, our research improves some of the parameters in the algorithm to obtain a better solving effect. The following content explains the improvement measures.

4.2.1 Improvement of benefit factor

In the mutualism phase, two biological individuals in nature obtain corresponding benefits from each other through mutual interaction. The amount of the benefits depends on the random value of the benefit factor. When the value of the benefit factor is 1, the individual gains part of the benefit from the other. When the benefit factor is all 2, they get all the benefits from each other during the interaction, which leads to more significant differences between individuals, which will cause some individuals exceed the limit. Based on this, this paper proposes an adaptive benefit factor improvement method. The benefit factor is set to be \( BF_1 = BF_2 = 2 \) in the early stage of the search, which means that each individual can obtain the greatest benefit from the other in the early stage of survival, so that the algorithm generates more differentiated individuals in the early stage of the search, thus expanding the search range of biological individuals. In the later phase of the search, the benefit factor is set to be \( BF_1 = BF_2 = 1 \) so that the individual obtains an equal part of the benefit during the interaction process. While reducing the differences between individuals, the search range of the solution is reduced as much as possible, and the overall convergence effect of the algorithm is improved. The mathematical expression of specific improvement is shown as (30)

\[
\begin{cases} 
BF_1 = BF_2 = 2 & \forall N_{\text{iter}} \leq N_{\text{iter}}^{\text{max}} / 2 \\
BF_1 = BF_2 = 1 & \forall N_{\text{iter}} > N_{\text{iter}}^{\text{max}} / 2
\end{cases}
\]  

where \( N_{\text{iter}}^{\text{max}} \) is the maximum number of iterations in the ISOS algorithm, \( N_{\text{iter}} \) is the current iteration number of the algorithm, \( \forall N_{\text{iter}} \leq N_{\text{iter}}^{\text{max}} / 2 \) represents the early stage of the algorithm iterative optimization, \( \forall N_{\text{iter}} > N_{\text{iter}}^{\text{max}} / 2 \) indicates the late stage of algorithm iterative optimization.

4.2.2 Selection of random numbers in commensalism phase

From the above analysis of the commensalism phase, it can be seen that rand \((−1, 1)\) in the formula is randomly selected in \([-1,1]\), which may result in maintaining a larger search range in the later stage of optimization. It will affect the individual’s optimization in the process of algorithm solving and affect the solution speed and convergence characteristics of the algorithm. Based on this, in this paper, the fixed range of random numbers is changed to a shrinking range that can be modified according to the number of iterations; that is, the boundary value of the search range is gradually reduced as the number of iterations gradually gets bigger, thereby speeding up the convergence speed of the algorithm. From the mathematical representation point of view, to define the boundary of the search range \( \alpha \), the random number selection rule is improved from the determined \(\text{rand}(-1,1)\) to \(\text{rand}(-\alpha, \alpha)\), and the change of \( \alpha \) is shown as in (31). In order not to cause the later search range to be too small causing inferior solutions, the smallest random number range is half of the initial range. In this way, it can ensure the accuracy of the algorithm’s optimization and the acceleration of the algorithm’s convergence speed.

\[
\alpha = 1 - 0.5 \frac{N_{\text{iter}} - 1}{N_{\text{iter}}^{\text{max}}}
\]  

(31)
Formula (31) uses a linear decreasing method, and the search range boundary is gradually reduced from 1 to 0.5 as the number of iterations increases. Therefore, the improved mathematical model for the generation of new individuals in the commensalism phase can be expressed as (32)

\[ X_{\text{new}} = X_m + \text{rand}(\alpha, \alpha) \times (X_{\text{best}} - X_n) \]  

According to the characteristics of the SOS algorithm parameters, this paper changes the uncontrollable random parameter into a controllable random parameter, so that the selection and change of the random parameter can be adapted to the development of the individual. This paper has made corresponding adjustments to some defects of the algorithm, and it is still the same as the original algorithm. The parameter setting is simple, without complicating the implementation process, and it is easy to master and study.

The flowchart of the above-mentioned improved improved SOS algorithm is shown in Figure 2.

5 | NUMERICAL ANALYSIS

5.1 | Parameter settings

In this study, we use various kinds of algorithms (ISOS, SOS, ABC, SFLA, GA, and PSO) to handle the optimal operation of an IEEE 30-bus test system, as well as the uncertainties of wind, PV, and data center DR are all considered. The parameter settings of test system can be obtained from Refs. 36, 38, 40. The data center connected to the 13 nodes of the ADS is equipped with 24,000 servers. The server service rate is 500 servers/s, the peak power is 300 W, the silent power is 150 W, and the proportion of data load can be adjusted is 20%. Three wind turbines are installed at 8 nodes in the system, each with a rated power of 8 MW. 50MW and 26.4MW of PVs are installed at 11 nodes and 13 nodes respectively. Wind speed and solar irradiation distribution are defined via the Weibull distribution function and the light intensity PDF respectively according to Refs. [24,37]. Power generation cost parameters and carbon emission parameters of the THG can be seen in Table 1. The schematic diagram of the modified IEEE 30 bus test system can be seen in Figure 3.

The parameters of test system could be obtained in Table 2, and Table 3 and Table 4 separately provide the maximum and minimum restrictions of dependent and independent variables. These parameters can be obtained from Refs. [23,39,41,42].

The optimal operation analysis of distribution systems with RESs and data-center-based DR are implemented via MATPOWER 6.0. After the preliminary calculation results, the population size of the ISOS algorithm is set to 30, and the maximum number of iterations is 200. In this study, to ensure the validity of the results, all algorithms in various cases are solved 30 times.
The modified IEEE 30-bus test system with RESs and data center DR was tested via the multiple study cases described below. The details of each case can be obtained from Table 5.

### Simulation results

Table 6 displays the obtained results of optimization from the improved SOS algorithm for all cases. Figures 4 and 5, respectively, display the voltage distribution of the power supply node.

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**TABLE 1** Fuel and emission parameters of THG

| Parameter | Units | \(P_{THG1}\) | \(P_{THG2}\) | \(P_{THG3}\) | Parameter | Units | \(P_{THG1}\) | \(P_{THG2}\) | \(P_{THG3}\) |
|-----------|-------|-------------|-------------|-------------|-----------|-------|-------------|-------------|-------------|
| \(x\) (S/h) | 0 | 0 | 0 | \(P_{THG}\) | \(0\) | \(0\) | \(0\) |
| \(y\) ($/MW) | 2.00 | 1.75 | 1.00 | \(\beta\) (ton/MWh) | \(-0.05554\) | \(-0.06047\) | \(-0.05094\) |
| \(z\) ($/MW²h) | 0.00375 | 0.01750 | 0.06250 | \(\tau\) (ton/MW²) | 0.06490 | 0.05638 | 0.04586 |
| \(\sigma\) (ton/h) | 0.04091 | 0.02543 | 0.04258 | \(\omega\) (ton/h) | 0.000200 | 0.000500 | 0.000001 |

**TABLE 2** Parameters of the test system

| Characteristics | IEEE 30-bus system |
|-----------------|---------------------|
| Number | Details |
| Bus | 30 | 38 |
| Branch | 41 | 38 |
| Thermal generators | 3 | Buses: 1, 2 and 5 |
| Slack generator | 1 | Buses: 1 |
| Wind farm | 1 | Buses: 8 |
| PV system | 1 | Buses: 11 and 13 |
| DC system | 1 | Buses: 13 |
| Transformer | 4 | Branches: 11, 12, 15 and 36 |
| Capacitor bank | 2 | Buses: 10, 24 |
| Control variable | 17 | — |
| Load bus voltage limit | 24 | [0.95-1.05] p.u. |

**TABLE 3** Maximum and minimum limits of dependent variables

| Variables (A) | \(A_{min}\) | \(A_{max}\) | Variables (A) | \(A_{min}\) | \(A_{max}\) |
|---------------|-------------|-------------|---------------|-------------|-------------|
| \(P_{THG1}\) (MW) | 50 | 200 | \(Q_{THG3}\) (MVAr) | -15 | 62.5 |
| \(V_{L,18}\) | 95 | 1.05 | \(Q_{BS3}\) (MVAr) | -24 | 30 |
| \(Q_{THG1}\) (MVAr) | -20 | 150 | \(Q_{PS3}\) (MVAr) | -20 | 25 |
| \(Q_{THG2}\) (MVAr) | -20 | 60 | |

**TABLE 4** Maximum and minimum restrictions of independent variables

| Variables (B) | \(B_{min}\) | \(B_{max}\) | Variables (B) | \(B_{min}\) | \(B_{max}\) |
|---------------|-------------|-------------|---------------|-------------|-------------|
| \(P_{THG2}\) (MW) | 20 | 80 | \(V_{G1}\) (p. u.) | 0.95 | 1.10 |
| \(P_{THG3}\) (MW) | 15 | 50 | \(V_{G12}\) (p. u.) | 0.95 | 1.10 |
| \(P_{WS1}\) (MW) | 0 | 60 | \(T_{11}\) (p. u.) | 0.90 | 1.10 |
| \(P_{PS5}\) (MW) | 0 | 50 | \(T_{12}\) (p. u.) | 0.90 | 1.10 |
| \(V_{G1}\) (p. u.) | 0.95 | 1.10 | \(T_{15}\) (p. u.) | 0.90 | 1.10 |
| \(V_{G2}\) (p. u.) | 0.95 | 1.10 | \(T_{36}\) (p. u.) | 0.90 | 1.10 |
| \(V_{G5}\) (p. u.) | 0.95 | 1.10 | \(Q_{C10}\) (MVAr) | 0 | 30 |
| \(V_{G6}\) (p. u.) | 0.95 | 1.10 | \(Q_{C24}\) (MVAr) | 0 | 30 |

The modified IEEE 30-bus test system with RESs and data center DR was tested via the multiple study cases described below. The details of each case can be obtained from Table 5.

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**FIGURE 3** Modified IEEE 30-bus test system with RESs and DC systems.
and the load node in the system. Figure 6 shows the output of each device in different case. Comparing the cost of case 2 with the cost of case 1 in Table 6, although case 2 has a corresponding demand response cost, under the influence of the demand response of the type of special load of the data center on the demand side, it reduces the cost of thermal power fuel and carbon tax. As a result, the total cost is reduced. Compared with case 1, the reduced carbon tax cost shows that the output of thermal power has decreased, and the increase in total cost is mainly related to the increase in output of renewable energy such as wind power and photovoltaics. For case 3, the optimization of the overall cost with non-linear cost function and emission tax, as well as the cost calculation models of the RESs, used the objective function given in (18). It is manifest from the obtained results that the carbon emission cost and carbon emission amount in this case are both lower than case 1. For case 4, because the voltage deviation is mainly considered as the objective function, the voltage deviation is the smallest, but it has the highest operating cost.

In the continuous operation of the active power system, the reliability may be insufficient due to failures such as the power failure of the line or the generator. Thus, the power
systems must be able to guarantee strong voltage stability under fault these conditions. In this paper, we considered multiple transmission lines to fail separately, and these lines are represented by nodes (15-23, 12-15, and 6-28) (15-23, 12-15, and 6-28), respectively, denoted as case5.1, case5.2, and case5.3. Compared with the steady state, the total cost under the three fault conditions has been improved, and the voltage deviation of case5.1 is significantly increased. This shows that we need to invest more costs in the event of a failure to ensure that the system has high reliability.

5.3 Evaluation of algorithm effectiveness

Aiming at testing and proofing the validity and advantages of the algorithm in solving the optimal operation problem including wind power-photovoltaic uncertainty and demand-side data center demand response that takes into account security constraints, this paper considers the use of optimization algorithms such as ISOS, SOS, ABC, GA, and PSO to solve scenarios 1-5 in turn. To ensure the accuracy of the results, each algorithm is run 30 times. In this calculation example, the number of populations of each algorithm is set to 30, the maximum number of iterations is 200, and other parameters adopt default values. As shown in Figure 7, the algorithms 1-5 in Figure 7 represent the ISOS, SOS, ABC, GA, and PSO, respectively.

It could be obviously observed the optimization results of the other four algorithms are worse than the improved SOS algorithm. Taking case1 as an example, the ISOS algorithm corresponds to the objective value of 769.63 $/h, 10.80 $/h, 4.98 $/h, 2.064 $/h, 41.32 $/h, and the value is 1.73 $/h lower compared with the optimization results from SOS, ABC,
GA, and PSO algorithms, respectively. It fully illustrates the superiority of ISOS in solving the discussed problem.

The standard deviation of the objective function value for different cases under different algorithm applications can be seen in Figure 8. It is manifest from the figure that the improved ISOS algorithm in each case has the smallest standard deviation during optimization. This result fully reflects the stability of the algorithm in the optimization process and effectively avoids the randomness of the algorithm in the solution. In addition, aiming at proving the speed advantage of the proposed improved SOS algorithm in the optimization solution, the Fitness function of case 5.1 under different algorithm applications is saved, which can be noticed in Table 7. It can be obviously observed from Table 7 that the ISOS algorithm can converge to the optimal value in a relatively shorter time during the iteration process. Although the other four algorithms can also converge to the optimal value, ISOS obviously has better solving performance in convergence accuracy and faster convergence speed. Through comparison with other algorithms, we can see that the improvements made to the standard SOS algorithm are effective.

6 | CONCLUSION

This paper proposes an efficient algorithmic framework to address the optimal operation decision-making problem of ADSs including RESs and emerging datacenter resources, by
leverage a version of SOS heuristic algorithm. Datacenter loads are considered as a new type of flexibility resources and utilized to make better optimization of RES exploitation and utilization. Besides, this article first improves the parameter value rule based on the parameter characteristics of SOS. The mentioned improved method is tested on the IEEE30-bus case and a collection of comparative analysis is conducted to show the advantages of the proposed framework over existing methods. The obtained results demonstrate that using the flexibility of datacenter resources will help improve the overall operational benefits of ADSs with RESs. Moreover, the improvement strategies taken for SOS are proved effective for elevating the performance of the algorithm, which makes it have faster convergence speed to find the global optima of the problem than the conventional widely-used heuristic methods.

In future studies, we will use more practical cases to verify the feasibility of the optimal power flow framework under the uncertainty of RESs and the responsiveness of data center resources. Under this research background, electric vehicles can also be incorporated into the optimal operation analysis of the power system. Besides, the SOS algorithm can be further improved to be compatible with the large-scale multi-objective optimization problems.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

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