Multi-objective Performance Optimization of Energy Internet Using Improved NSGA-II

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***Abstract*—In this paper, we proposed an improved NSGA-II algorithm to optimize the operation performance of Energy Internet. We designed the corresponding gene structure and related parameters according to the Energy Internet operation demand. Then, to increase the proportional of feasible gene samples, we designed a data sequence compensate function and adopted random compensating with different probability thresholds, which can further increase the performance compared to all samples compensating. Through this means, we got the optimal result with better operation cost, which verified the advanced performance of this improved algorithm. In the further research, we will try more system optimal indexes and get better results based on the progress of newest NSGA liked algorithms.**

Keywords—*NSGA-II, Energy Internet, compensate function, random compensating, probability threshold*

I. Introduction

Energy Internet is a new type of energy system which utilizes many forms of energy, such as wind, photovoltaic, fossil and hydrogen [1] and so on. It applies automatic management, multi-end collaboration and multi-energy complement to realize high energy utilizing efficiency, low operation cost and low carbon emission. At the same time, many other extendable targets can be considered, such as high robust characters, long-life cycle, low fault time in system operation, etc. [2]

But as many targets can't be realized simultaneously, the system needs to reach a balance state with these targets, which should make simultaneous consideration of these target factors, so multi-object optimizing can be an effect method to realize performance optimal balance. It has the demands of high number of candidate samples, large evolution space and equilibrium sample density and high global results convergence, so it can find the proper results quickly and efficiently.

Multi-object optimize can be realized through finding pareto optimal samples in NSGA (Non-dominated Sorting Genetic Algorithms) series algorithms, which is based on genetic algorithm to fulfill the task. Through genetic candidate pool, NSGA can record optimal solutions and update the results iteratively. So, through many iterations, NSGA can obtain optimal results gradually and keep the sample density evenly at the same time.

NSGA has many types of evolutions, such as NSGA-I, which sets up the foundations of multi-target optimization and realizes evenly sample density through sharing distance [3], and has the characters of high computing burden, NSGA-II is the following improvement of NSGA-I [4-7], which utilizes neighborhood distance to select proper samples through optimizing sample node distribution densities. Due to its high-performance results, it becomes one of the most popular multi-target algorithms, which can be further used in target position search [8], Hydro-Photovoltaic complementing [9], wireless charging [10], motor optimal design [11]， car trajectory planning [12],etc. Another improvement of NSGA is NSGA-III [13,14], which uses reference points based on optimized space(angular) distribution, and is especially suited for large dimensional target optimization, but its performance needs to be further verified comparing to NSGA-II [15].

In this paper, we use the NSGA-II to realize multi-objects optimization, as it has moderate computing task and is suitable for not very large data sample dimensions.

Through evolutions, the NSGA experienced many innovations, such as:

a) Founding the elite set [16], which stores not only the selected valid samples but also invalid ones with better index value or previously abandoned valid ones. These samples will be used in gene evolution. Through this means, the search space can be effectively extended.

b) Adding single optimal samples (extreme samples or complement samples) [17], so the initial data sample distribution can be improved.

c) Uniform/normalize the performance indexes, so fairly comparison can be realized [18].

d) Adding chaotic disturbance in gene mutation, doing so to increase the search space [19].

e) Adding other data handling algorithms, such as k-means [20], information entropy [21] and Taguchi method [22] to increase the gene evolution performance.

f) Select the elite samples through angle value [23].

g) Realize target decomposition for pareto optimal set [24].

Through above innovations, NSGA series algorithm can be improved for some specified scenes, and its applicability for general scenes is still to be explored.

II. SYSTEM DESIGNING

Here we use improved NSGA II algorithm to optimize the EI operation performance with multi-object optimization scheme using the concept of pareto optimal set. It includes following function modules.

A. Overall Targets Design

The simulation time is for one day operation, with the data periods of 2 hours, which include total 12*2 charge and discharge sample points in one gene sample.

The energy internet has the RES generation equipment such as distributed PV and wind. The energy internet can buy and sell the power with main grid, at the same time it can storage and emit power through energy storage equipment. The energy storage can help reduce carbon emission in their whole life cycle, which ensures the system's economic and environment protection effect.

The program has three operation targets, e.g., lowering the operation cost, maximizing the system revenue, and lowering the carbon emission. In the designed system, the wind energy profile, the photovoltaic (PV) profile and the load profile is kept invariance, the only changeable factor is the charge and discharge rate of storage equipment, grid power exchange can be varied based on this factor.

B. Specific Design Scheme

The detailed operation flow is shown as in Fig. 1, the ellipses represent the improved components. First, we need to design the gene structure according to the need of EI optimization, then we will generate the initial sample in EI, and compensate the sample to more fulfill the operation constraints. Then we will iteratively take the evolution for generating candidate gene, which also include using the compensate function to increase the proportional of valid samples. And probability compensating is executed in the compensate function to keep certain number of no-valid samples. Then we will find a robust result from the results of improved NSAG_II using the combined weight max-min selection algorithm (with max count of minimum weight combined value). Then the result can be used in EI operation and control proceedings.

C. Gene Variable Structure Design

As the experiment contains 12 time periods (every 2 hours in one day), and the gene information should include the charge amount and discharge amount for every time instant. So there contains 24 original gene value (2*12) for every sample group, which can be represented as $[charge\ 1, discharge\ 1 \ldots, charge\ 12, discharge\ 12]$, with the dimension of 1*24. And we use the reshape function to change the dimensions of every gene value sequence in data handling when needed.

There is some additional information that should be appended to original gene value in programming, such as the rank of pareto optimal samples, its neighbor crowding distance and the index value of invalid samples, which can be used in pareto sorting and gene sample selection, in the form of [charge/discharge rate, other factors].

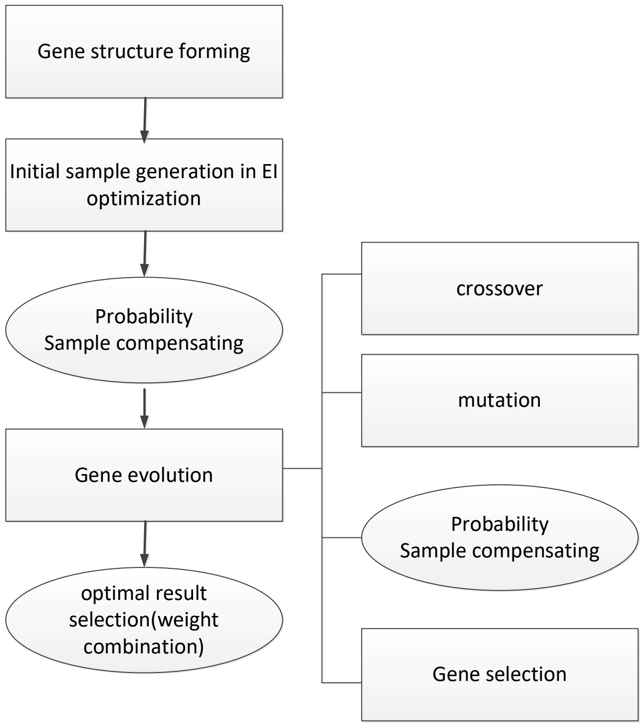

Fig. 1. EI optimization operation flow

III. SYSTEM MODELIING

A. Parameter Modeling

The operation cost includes PV operation cost, wind operation cost, grid cost (set as zero), energy storage equipment's charge cost and its discharge cost.

$$\begin{aligned} factor1 = {} & buy\_cost(1) * pv\_profile(1, hour\_number) \\ & + buy\_cost(2) \\ & * wind\_profile(1, hour\_number) \\ & + buy\_price(hour\_number) \\ & * max(grid\_real, 0) + buy\_cost(4) \\ & * (charge\_real + discharge\_real); \end{aligned}$$

The system revenue includes the electrical sell revenue, this value will be minus transformed to take related targets with minimum value as its optimal index.

$$\begin{aligned} sell\_load = {} & pv\_profile(1, hour\_number) \\ & + wind\_profile(1, hour\_number) \\ & - charge\_real + discharge\_real \\ & - load(1, hour\_number); \end{aligned}$$

$$grid\_real = -sell\_load;$$

$$\begin{aligned} factor2 = {} & sell\_price(hour\_number) \\ & * max(-grid\_real, 0); \end{aligned}$$

The carbon cost includes the wind carbon emission cost, the PV carbon emission cost, the grid carbon emission cost and energy storage charge and discharge related carbon emission cost.

$$factor3 = carbon\_cost(1) * pv\_profile(1, hour\_number) + carbon\_cost(2) * wind\_profile(1, hour\_number) + carbon\_cost(3) * max(grid\_real, 0) + carbon\_cost(4) * (charge\_real + discharge\_real);$$

In the power exchange with grid and energy internet, for the revenue purpose of main grid, the sell price to the grid should be smaller than the buy price from the grid. Here we use the proportional price, such as $sell\_price = 0.75 * buy\_price$, which may affect the system revenue.

The charge amount of energy storage equipment can be represented as below equations, which consider both the charge ratio and discharge ratio (set as 0.95):

$$for\ p = 1:11$$

$$cap2 = cap2 + round(charge1(p, 1) * 0.95) - round(discharge1(p, 1)/0.95);$$

$$end$$

B. System Constraints Modeling

The constraints of power charge and discharge can be expressed as:

if $data\_line(1)$>255||$data\_line(2)$>255||$data\_line(1)$<0||$data\_line(2)$<0

$flag$=0;

end

if $hour\_number$==12

if $abs(battery\_cap\_1)$>1%$battery\_rate$/255;

$flag$=0;

end

end

if $battery\_cap\_1$<0||$battery\_cap\_1$>255*5

$flag$=0;

end

if $charge\_real$*$discharge\_real$~=0

$flag$=0;

end

The first constraint ensures that the charge and discharge rate at every time instant should fulfill itself constraint of the storage equipment.

The second constraint ensures that the charge amount should become zero (or reach the minimum value) at the final time point of current cycle. This is an important constraint which makes energy dispatch more operable, but it greatly increases the algorithm's complexity and make energy optimal dispatch harder with less qualified samples if not applying compensate function.

The third constraint ensures that the charge amount of energy storage equipment is kept in the proper range.

The fourth constraint ensures that the charge and discharge amount can't be larger than zero simultaneously (either one for zero).

IV. Programming Improvements

A. Adjusting Programming

We first generate the candidate samples randomly, then we adjust every gene group in the positive and reverse order to make one day samples fulfill all above constraints. In this procedure, we should keep every charge and discharge rate for every time instant in the range of [0,255], and when one rate is decreased to zero/increased to maximum, we should consider increasing/decreasing the other rate. If the energy is still surpassed or deficient, we should consider its previous or following time node according to the iterative order. This task is fulfilled using the compensate function, its execution includes two iterations, i.e. positive iteration and reverse iterations. In every step of charge and discharge compensation, we should consider the operation efficiency of charge rate and discharge rate, which makes the total charge amount is always larger than the discharge amount.

The state of the energy storage equipment can be calculated as:

$$cap = cap - round((charge(i, 1) - charge1(i, 1)) * 0.95) + round((discharge(i, 1) - discharge1(i, 1))/0.95);$$

Where cap represents the capacity of energy storage equipment, and charge(i,1) and discharge(i,1) represent the charge and discharge rate before adjusting actions, and charge1(i,1) and discharge1(i,1) represent the charge and discharge rate after adjusting actions. When there is no modification of charge and discharge factors, the value cap is unchanged.

When we finish this job, we calculate the accumulated charge amount and discharge amount in positive time order and get the discharge amount of the final time instant, which must larger or equal than zero. And at the end of compensating proceeding, if these adjusted data vectors can't fulfill all the constraints, the gene will be labeled unaccepted(false). But by using our proposed compensate function, the constraints will not be break down after compensating.

B. Random Compensating

When running this algorithm, we first apply the compensate function for every generated charge and discharge sequence, this will ensure that all of the sample sequences input into this algorithm satisfy the charge and discharge constraints (here we call it the positive sequence, otherwise negative sequence). But due to the lack of negative sequences, the search range can't be diversely extended, and the finally optimal set can't be globally optimized. So, we use a trick for execute the compensate function, i.e. probability compensating. We set a threshold p, and choose a random value as $(rand(1,1))$, if it is less than threshold $(rand(1,1) < p)$, the compensate function will be executed, otherwise the data sequence keeps invariant. Through this means, the number of negative sequences can be ensured, and the search space is effectively extended than just considering positive sequences, so the performance of NSGA-II could be promoted compared to probability value 1, which gives a less performance index. This will be verified in following sections.

C. Sample Filtering

In this algorithm we filter the gene groups with the same gene samples and the gene with almost all zero samples. The almost zero samples occupy a large data space, and are not valuable to the final results, which should be omitted.

$$chrom = [chromes, unit\_index, feasible];$$

$$chrom = unique(chrom,' rows');$$

$$Chrom = delete\_zero\_function(chrom);$$

$$chromes = chrom(:,1:24);$$

$$unit\_index = chrom(:,25:27);$$

$$feasible = chrom(:,28);$$

Through this means we calculate the robust result of NSGA-II.

D. Target Sample Selection

For three fitness value, we first normalized the value, such as:

$$mean\_v = mean(Popobj(:,i));$$

$$var\_v = var(Popobj(:,i));$$

$$index(:,i) = (Popobj(:,i) - mean\_v)/max\,(sqrt(var\_v),0.01);$$

Then we set the 3-dimensional weight w1, w2, w3, which is the multiplying step of 0.05 and should be nonzero, and the weight sum equals 1. We then get the weighted average value by f1*w1+f2*w2+f3*w3. As the targets are to minimize the target indexes, we calculate the min value for every weight combination and increase the corresponding count number by one at a time if corresponding value is minimum within this weight combination. At the end of iteration, we choose the sample with max count number of the corresponding min value or the minimum value of one special index as the optimal result. If there are more than one max count numbers, we choose the value with min cost as the final value.

V. EXPERIMENT RESULTS

A. Parameter Settings:

The buy cost profile is set as (in turn for PV, wind, grid, charge and discharge):

$$buy\_cost = [0.3,0.35,0,0.23,0.23];$$

The carbon cost profile is set as (in turn for PV, wind, grid, charge and discharge):

$$carbon\_cost = [0.04,0.011,0.58,0.03,0.03];$$

The buy price and sell price profile is set as (one for two hours in one day):

$$buy\_price = [0.2259,0.2259,0.2259,0.2259,0.9647,1.0647,0.5568,0.5568,0.5568,0.9647,0.9647,0.5568];$$

$$sell\_price = buy\_price * 0.75;$$

The PV profile, wind profile and load profile are set as below, with interval of two hours:

$$pv\_profile = 1 * [0,0,0,0.25,0.5,0.62,0.8,0.6,0.23,0.03,0,0] * 1000;$$

$$wind\_profile = 1 * [0.75,0.44,0.435,0.43,0.41,0.38,0.372,0.4,0.39,0.38,0.388,0.43] * 1000;$$

$$load\_profile = 2 * [0.6,0.33,0.32,0.37,0.44,0.45,0.455,0.43,0.44,0.48,0.47,0.42] * 1000;$$

Above raw PV vectors are fetched from [25], and the wind and load profile raw data are obtained through a web figure, the multiply factors are adjusted as needed.

B. Result analyse

a) Result analyse I

The best results for different probability thresholds are shown in below table, here we choose the system cost value as the final evaluation index for performance comparison, so other indexes may not be optimal at the same time:

TABLE I. PERFORMANCE COMPARISON WITH DIFFERENT PROBABILITY THRESHOLDS

*10^3	cost	Revenue(minus)	Carbon emission	Count number
P=1	4.5715	-0.2872	1.8614	66
P=0.7	4.5604	-0.2493	1.8050	49
P=0.5	4.4149	-0.3975	1.9736	92
P=0.3	**4.2501**	-0.02695	1.8161	47
P=0.1	4.4787	-0.3783	1.9551	21
Traditional P=0	4.5634	-0.1879	1.7692	64

From above table we can see, when the probability decreases from 1 to 0.3, the cost value monotonously decreases, so its performance increases accordingly, and reach the peak value at P=0.3, while the performance of P=0.1 is also better than the situation of P=1 (all samples compensating). From related results we can also see, that the data sample with the least cost value also has the most count number in every iteration round, which shows the potential performance of weight combination in optimal sample selection.

The performance of traditional algorithm is better than that of P=1, but by applying random compensating, all the results of our proposed algorithm is better than that of traditional algorithm. And the superior performance of traditional algorithm compared to that of P=1 may be due to `modified random sampling proceeding in the initial forming samples, which will generate more positive samples at the initial step.

This makes traditional algorithm comparable but a little poor performance with random compensating.

b) Result analyse II

While the background parameter rarely changes, the curves of charge and discharge are diversly distributed due to rand gene generating function adopted in this algorithm, one typical result can be seen in below figure.

Fig. 2 shows the result of battery charge and discharge amount, and the curve of PV, wind, load and grid exchange in one day are also plotted. When grid exchange is more than zero, it will buy energy from the grid, when it is less than zero, it will sell energy to the grid.

Form the curve we can see, in the start hours, storage equipment begins to charge the energy, which has low electric price at this time instant, so the charge cost can be low, and the charge amount is high. Then the charge amount of storage equipment begins to fluctuate according to the demand of load and PV and wind energy output, which should keep the energy balance of the whole system while achieve economics target. From time points 8, the storage equipment begins to discharge until it reaches zero at the end of simulation time instant.

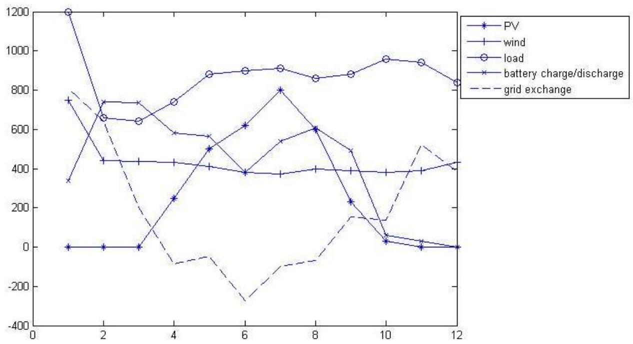

Fig. 2. Simulation results for P=0.3

From above Fig. 2, we can also see that positive grid exchange peaks occur at the start time point and near end time, and at point 6 (am 12:00), negative grid exchange peak occurs. From the global view, the profile of grid exchange roughly correlates with the trend of battery charge and discharge curve in the middle sections of simulation.

From above figure we can get that, through charge and discharge at proper time point using storage equipment, we can efficiently lower the operation cost and maximize the system revenue based on time-of-use electricity price and cut down the carbon emission at the same time. And more rational electricity price may further increase the revenue of EI.

c) Result analyse III

Here we compare the optimal set distribution for different thresholds at the final time instant as shown in below Fig. 3 and Fig. 4:

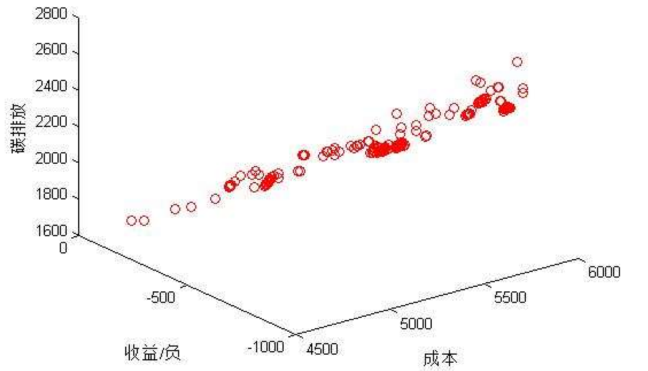

Fig. 3. Optimal set distribution without random compensating (traditional algorithm)

From above figure we can see, when P=0.3, which has the best performance, its nodes number of optimal pareto set are the largest comparing to other probability threshold, while P=1 has the least optimal pareto number, which have the worst performance accordingly. Traditional algorithm also has many optimal pareto samples, but its performance is second worst, which may due to that it doesn't use random compensating function, so it can't evolve as fast as other situations in following gene evolutions.

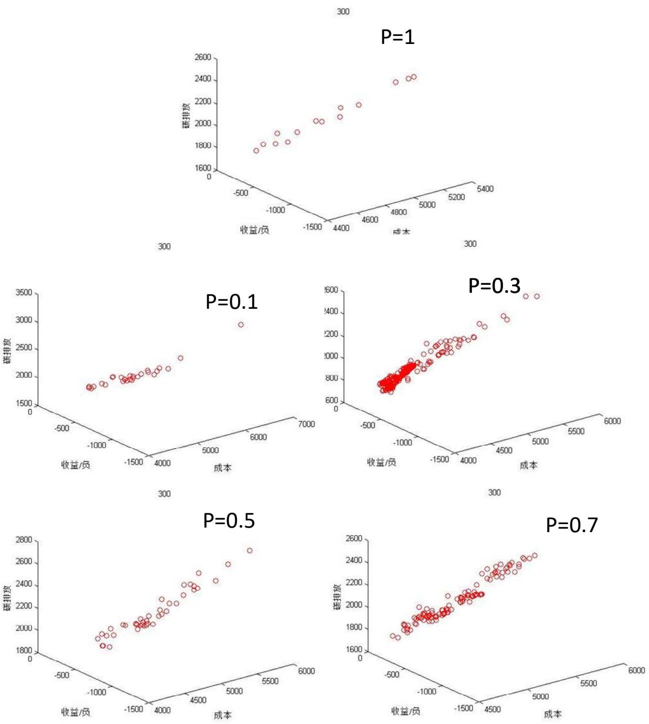

Fig. 4. Optimal set distribution with random compensating

VI. Conclusions

In this paper, we proposed an improved NSGA-II algorithm to promote the operation performance of Energy Internet. Through this algorithm, we realize the targets of minimum cost, maximize system revenue and minimize carbon emission in one day's simulation in EI expressed by optimal pareto set, which shows the potential advantages of gene evolution algorithm for solving the EI optimal multi-parameter problem. Though using compensate function and random compensating, the system's performance can be further improved, and verified through considering one specific performance index. In the further research, we can search more optimal targets (performance indexes), and make the system more robust and effective through improved optimal designs.

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