Coordinated Operation and Control in Energy Internet Using Machine Learning and Modeling Optimization

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***Abstract*—As machine learning (artificial neural network) and system modeling optimization each has individual advantages and disadvantages, some functions are complemented and can make up different shortcomings, so integrated using them may achieve performance revenues in system optimization and management. In the Energy Internet (EI) managing and control domain, we sequentially using ELM (extreme learning machine) for machine learning and PSO (particle swarm optimization) for system modeling optimization which should obey inherent operation constraints, to solve the system optimizing problem. This algorithm is tested in EI with one day before operation, and its performance is compared with that of pure PSO algorithm. The results show great running time reduction and negligible running performance degradation, and can be effectively used in cloud-edge collaboration of EI system.**

Keywords—machine learning, system modeling, PSO, ELM, Energy Internet, cloud-edge collaboration

I. Introduction

With the developing of machine learning and system modeling optimization, their combination becomes necessary and inevitable. Machine learning algorithms, represented by deep learning neural network, treating the whole system as a black box, so it can't clearly explain the inner running schemes and the obtained results may not obey the running constraints. System modeling, usually need the human defined related parameters, so it become impractical in some dynamic unsteady systems, and the deducing time maybe long due to complex mathematical computing, so it is not suited for the real time operating systems such as cloud-edge collaboration.

There are three means to combine machine learning with system modeling: "before", "in" and "after". In the "before" situations, sample data first pass the system modeling to check the system running constraints, if all related constraints are satisfied, the data example are trained in machine learning to set up related neural network models, so the result have a large probability of satisfying the running constraints, which has certain application potentials and need further innovations. In the "in" situation, the neural network model is built by injecting the sampled data and related constraints for model training at the same time, in this way, we should consider the computing data proceeding and logical state proceeding at the same time, so the related constraints can be satisfied timely and explicitly. In the "after" situation, we should first train and build up the neural network, then the tested results should pass a filter or local search function liked model to correct the results which ensures that they obey the specific running constraints. As in industry manufacturing, its running constraints should be strictly satisfied, so peoples usually consider the "in" and "after" related algorithms. Here we choose the "after" means as the research target.

In order to verify the performance of combined machine learning and system modeling optimization, we proposed an innovation algorithm for the operation and control tasks in EI. Corresponding innovations lies in effective using both techniques of PSO and ELM to make running time largely shortened while ensure EI's entire performances in the situation of existing many running constraints, whose performance is comparable to traditional algorithms such as gene algorithm and PSO. So, the algorithm can be real-time fulfilled and edge equipment affordable. It will give the EI application scenes a new technique realization means, which has broad application prospects and deserves further researches.

The following structure of this paper is as follows. In chapter II, we introduce the technique background; in chapter III, we propose designed algorithm; in chapter IV, we analyze the simulation results; in chapter V, we discuss further research directions; in chapter VI, we make the conclusion.

II. Technique Background

A. PSO

PSO is an advanced and popularly used intelligent data searching algorithm, which adopt the idea of swarm wisdom in bird eating proceedings, and can find the target quickly and robustly. In the operating proceeding, related system parameters can be adaptively changed to promote its searching precision and optimize the search time, which is still a hot research point. In [1], the author observed that the BP neural network is being trapped in local minima and has slow convergence speed problem, and quantum particle swarm can realize energy saving. In another paper, [2] proposed a new methodology named Signaled Particle Swarm Optimization (SiPSO) to address the energy resources management problem in the scope of smart grids, with intensive use of DER.

B. ELM

Deep learning neural network largely prompt the cognitive ability in the system operation by simulating the thinking way of human. But in order to reach the cognitive and deducing ability like human, the related models usually need high amount data for training and adopt a very complex network model,

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whose parameter level is at the billion level or higher, which greatly hurdles its research in laboratory.

To overcome this situation difficulties, ELM network is introduced in this paper, which is shown in Fig. 1. Though MSE (mean square error) and pseudo-inverse technique, which can largely reduce the training time and get comparable results with traditional neural networks.

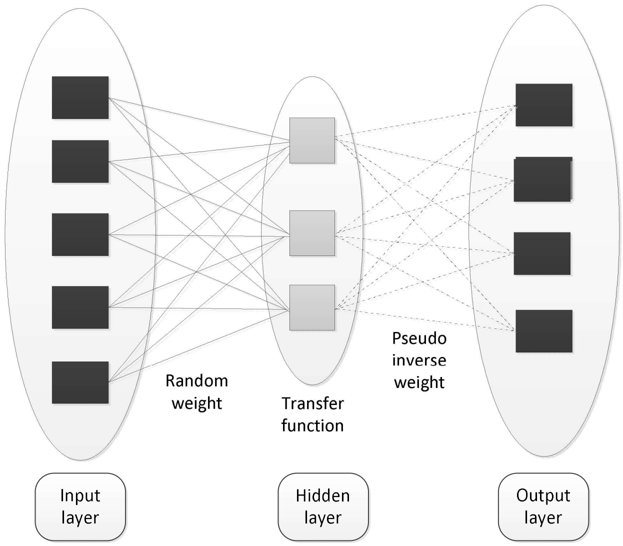

Fig.1. ELM network

In paper [3], Geng Z et al. proposed an integrated extreme learning machine approach for energy optimization in chemical processes. Following paper [4] proposed a novel load curve clustering method based on dimension reduction, which utilized ELM to embed original load sequence data set into low-dimensional space. At the same time, [5] proposed a new stochastic framework for optimal energy/power management of the interconnected MGs based on the Internet of Things (IoT) approach, which using a Generalized Extreme Learning Machine to make a model of its parameters.

C. Energy Internet Control Scheme

Through "source-network-load-storage" coordination and multi-energy complemented utilization, EI can largely promote the energy utilizing efficiencies, the energy utilizing revenue, the energy system safety, and reduce the whole operation cost of EI. The authors' related research on EI can be found in [6-8].

Year 2018 to 2021 can be seen as the hot research years of EI optimal control. In year 2018, [9] proposed a combined electricity-gas-heat Energy Internet scheduling method, whose technologies were discussed. [10] proposed a mixed energy utilization mode in regional EI. [11] proposed the concept of Integrated Energy Network, which realized the coordination and complementarity of multiple energy sources. With a large technique progress, [12] utilized ordinary differential equations (ODEs) and stochastic differential equations (SDEs) to realize stochastic optimal control.

As researches ongoing, [13] proposed five kinds of energy efficiency evaluation indexes from the energy sections of production, transmission, consumption, storage, and conversion based on the second law of thermodynamics. In [14], authors applied EI in agricultural engineering. [15] proposed an overall architecture of integrated energy management and control system with four layers, which was tested in the industrial park. Following the research of [12], [16]and [17] improved the optimal control performance of EI using deep reinforcement learning etc. techniques.

With the mature of EI, [18] introduced the intelligent management concept into EI. And the regional integrated energy system (RIES) is studied in [19]. [20] created a new EI scene: Energy-Use Internet to promote energy efficiency. In [21], author applied Non-Intrusive Load Monitoring in demand side energy management.

The viewpoint of EI control is extended gradually. To meet global energy demand, [22] scheduled the corresponding roadmap. [23] solved the system synergy challenges through matching analysis. [24] considered power consumption and air pollution in EI management. In [25], the synergetic development level of the energy Internet industry system should be evaluated and promoted. [26] adopted compressive sensing to handle the nonlinear energy storage management problem.

D. Proposed Research Direction

Though above research, the control and management performance are gradually promoted in EI, but generally, high performance scene realization usually need complex algorithm's support, which may not satisfy the low time delay or local computing sources demand. So, in this paper, we proposed a mixed algorithm combining machine learning (ELM) and system modeling (PSO), which aims to reduce the data handle time delay and can be affordable for common lab research, so the demand of many real time scenes can be fulfilled, especially for the scenes of cloud-edge collaboration system in EI control and operation.

III. Proposed Algorithms

A. Running Schemes

The simulated EI is composed of several parts, e.g., the distributed renewable energy sources (DES) like wind and PV, the energy store equipment, the user load, and the main grid, like in Fig. 2. Though DES, we can generate green power used locally and efficiently, through energy store equipment, we can ensure demand and supply balance all the time, and reduce the risk for power outage. The main grid with a robust power source can also ensure higher quality power supply and participate with systematic source-network-load-storage collaboration.

The load can be roughly predicted and can be seen as unchangeable in devised scene without demand side management. The generated power of DES heavily relied on weather change, which can't be randomly controlled in spirit, but the charge and discharge state of energy store can be humanly intervened, and when there is lack or surplus of grid power, system can interact with main grid to sell or buy electrical power in real time. So, the only changeable data items in this scene should be the charge/discharge state (rate) of power storage equipment.

We set one day as a simulate period and two hours as one basic time interval, so there will produce 12 charge and discharge data in one period. At the beginning and end time point of the one-day period, the storage capacity should reach 0, this constraint along with max and min charge rate and max storage capacity requirements can be seen as the constraints of running EI.

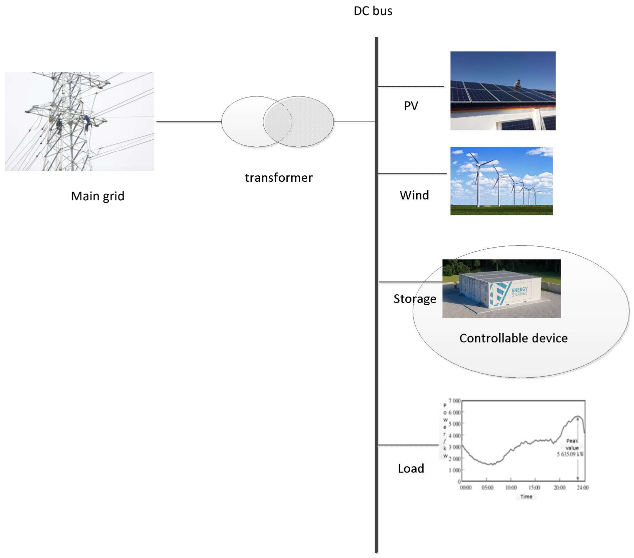

Fig. 2. Typical EI topology

The max benefit (revenue minus cost) can be seen as the optimal value of PSO, which will be used in the performance evaluating and comparison with pure PSO algorithms.

B. Algorithm Proceedings

We sequentially using PSO algorithms and ELM model, which is represented as PSO+ELM.

As in Table I, to obtain the raw data for ELM input, we random generate the input data for PSO, and use PSO to search their optimal result with inherent constraints. When enough data samples and related optimal results are collected, we train the ELM model to obtain the relationship between input data with the optimal control value, which are then used for new data sample estimation, and the obtained value will be checked for its related constraints. If the constraints can't be fulfilled, a local search with PSO will be executed to update the found results. Through this means, a near optimal result satisfying related constraints can be obtained.

TABLE I. THE PROCEEDING OF PSO-ELM ALGORITHM

Step 1	Randomly generate raw sample data and select related parameters.
Step 2	Using sample data to obtain optimal value in PSO which should fulfill the inner constraints.
Step 3	Training the ELM with PSO output.
Step 4	Using ELM to predict the optimal value of test examples.
Step 5	Check the constraints of test result.
Step 6	If the constraints are satisfied, go to step 8, otherwise step 7.
Step 7	Local search optimal value with PSO.
Step 8	Compare the result with pure PSO algorithm, with the computing time and predict performance.

C. Technique Details

In step1, the positive value of charge vector represents charge rate in one time interval, the negative ones represent discharge rate in one time interval. The capacity should obey below equation:

$$capacity_t = capacity_{t-1} + \max(charge, 0) * ratio \\ + \min(charge, 0)\ /ratio$$

In step 1, for the initial data sample generation, we first randomly generate 40 samples for first PSO handling, and generate 10 examples for testing. The generated samples satisfy uniform distribution in the designed data range.

In step2 and following steps, the detailed expression of optimal evaluation target is:

$$sell\_load = pv\_profile(hour\_number, 1) \\ + wind\_profile(hour\_number, 1) \\ - charge\_real(hour\_number, 1) \\ - load(hour\_number, 1);$$

$$factor1 = buy\_cost(1) * pv\_profile(hour\_number, 1) \\ + buy\_cost(2) \\ * wind\_profile(hour\_number, 1) \\ + buy\_price(hour\_number, 1) \\ * max(-sell\_load, 0) + buy\_cost(4) \\ * \ abs(charge\_real\ (hour\_number, 1))\ ;$$

$$factor2 = sell\_price(hour\_number, 1) * max(sell\_load, 0) \\ + buy\_price(hour\_number, 1) \\ * load(hour\_number, 1);$$

$$total\_value = total\_value + factor1 - factor2;$$

Where $pv\_profile$ represents the PV generating power profile, $wind\_profile$ represents the wind generating power profile, $charge\_real$ represents the charge/discharge rate of energy storage, $load$ represents the power profile of load consuming. While buy_cost is the cost of different power generating type, buy_price is the price of buying power from main grid, $sell\_price$ is the price of selling power to main grid. And $hour\_number$ is related time point. The smaller the $total\_value$, its performance is better.

In step 2, the element of charge vector should fulfill the physical constraints of energy store equipment, such as the max and min charge/discharge rate, the max and min storage capacity limit, and the begin and end time point zero storage capacity constraints, such as shown below:

$$x_{min} \le charge_{rate} \le x_{max}$$

$$0 \le capacpity \le y_{max}$$

$$capacity = 0\ when\ t = 0\ or\ N$$

In order to satisfy the latter two constraints, we designed a compensate function module. Its basic idea is, if the capacity passes the max value, we need do more discharge operation or less charge operation. If the capacity is below the min value, we need do more charge operation or less discharge operation. The operation is iterated until all constraints are satisfied. In the proceedings of increase or decrease the charge rate, the charge and discharge efficiency ratio should be considered, and preliminarily set as 0.95.

The related parameters are shown in below Table II.

TABLE II. SIMULATION PARAMETER SETTING

Sample dimensions	12*N	ELM training sample number	40
PSO swarm number	30	ELM simulation sample number	10
PSO learning rate	1.5	Max PSO velocity	25
Energy rate range	[-255,255]	Sample distribution model	Uniform distribution
Energy store capacity	4*255	Buy price/sell price	1.25

IV. SIMULATION RESULTS

A. Simulation Conditions

This simulation is executed in windows 7 with intel i5, the memory is 4GB with 4 cores, and the simulation software adopts MatLab 2014a. There are two simulation algorithms, "pure PSO" represents the PSO only algorithm as the reference algorithm, "PSO-ELM" represent our proposed algorithm. The initial data is fetched from corresponding web site.

B. Simulation Analysis

- Component performance analysis

The performance of PSO is showed in Fig. 3. From this figure we can see, as the iteration runs, its performance is gradually decreasing (becoming better), and finally reach the performance floor.

For one turn of iteration, we can get the optimal vector as:

The best solution obtained by PSO for one sample is: [255,255,193.4174,255,-106.6255,-255,0.7196922,1.19026,-0.3315107,-250.817,-255,0]. The best optimal value of the objective function found by PSO is: -1229.1473.

From this result we can see, at the begin time of simulation, as the capacity of energy store equipment begins with zero, and the buy price of that time period is low, so the system will charge the energy form the main grid. When the time period in the middle range, system charge and discharge the energy according to the optimal minimize cost target and demand and supply balance. At the end of the simulation period, the store equipment needs to clear the capacity, the system begins to discharge the energy, but at the last interval, as the energy is totally discharged, system don't charge and discharge at the final time point.

In the proceeding of PSO, designed compensate function may change the distributions of particle samples, so that proposed algorithm may not always point to the best possible location area to find the best target, whose entire performance may be curtailed and need more carefully technique handling, which will be one of future research directions in this related work.

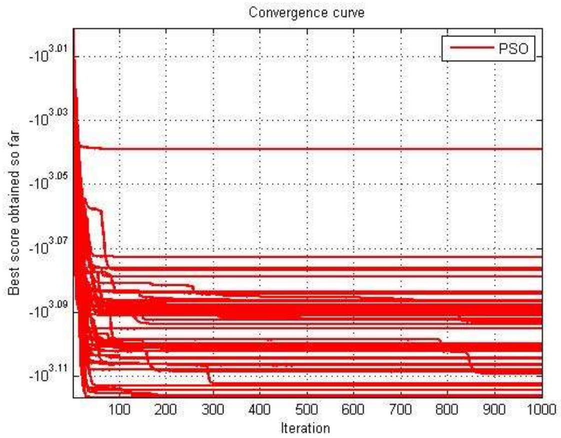

Fig. 3. The convergence performance of PSO.

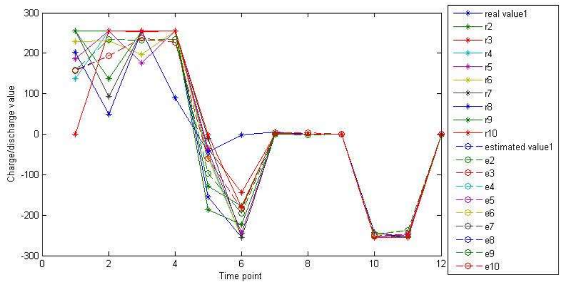

Fig. 4. The performance of ELM

Fig. 4 showed the performance of ELM, where r_n represents that of real value, e_n represents that of estimated value. In this simulation, its training MSE (mean square error) accuracy value is 46.3030, whose error precision is about 10.3% (52.6141/510). Although the difference between real value and estimated value looks a little large for some time points of some samples, especially at the beginning time points, but the final result of the whole algorithm can be accepted, as shown in below figures.

- Executing time analysis:

For a sample of 30 iterations of local PSO search in pure PSO, its executing time of pure PSO is 207 seconds with total 50 running samples, and the test time of pure PSO is 38.59375 seconds with 10 test samples, the train time of PSO-ELM is 207.7656 seconds, its test (predict) time is 1.828125 seconds. From this result we can see, the total running time of PSO-ELM is a little larger than that of pure PSO, but its executing time is far less than that of pure PSO for the same sample number, so the computing complexity at the user side can be largely reduced through cloud-edge coordination. With the increasing of test samples (*100 or *1000), the total time of PSO-ELM will also become less than pure PSO.

- Optimize performance analysis

The result is shown in Fig. 5, where the local search turns of PSO is changed with iteration value [30,40,50,60], from the figure we can see, all the function value of PSO-ELM is approaching that of pure PSO, which verified our intuition and that the performance of this algorithm is acceptable (max performance degradation of 1.6% for optimal value). In some time points, the performance of PSO-ELM is even superior to that of pure PSO, which may due to that PSO can't always find the optimal value through random search, and local search may prompt its performance effectively. And as turn number changes, the results do not show very regular results.

We also compare the performance of one typical gene algorithm(NSGA-II) with our algorithm, where the adopted performance indexes of NSGA-II include cost, revenue and carbon emission, whose performance is better when the value of three indexes being less, and finally we choose the sample with least value of cost minus revenue as the algorithm output. From Fig. 6 we can see, the performance of Gene algorithm is far less than the proposed PSO-ELM algorithm, which preliminarily verified our hypothesis. And the reason of inferior performance with NSGA-II may due to that it considers many complex constraints in sample searching, to compensate this condition , it needs more irregular samples, which potentially cut down the searching efficiency and make optimization harder.

From Table III we can see, in this simulation, 4 in 10 samples satisfy the system constraints, and other samples should perform local search further. For the constraints check passed samples, the performance of PSO-ELM is usually worse than that of pure PSO(except sample 2). And for other local search samples, pure PSO also shows better performance in most samples (about 3 in 6). From more simulations, we could get that local search with turns number 60 usually have better performance than that with turns number 30 in some simulations.

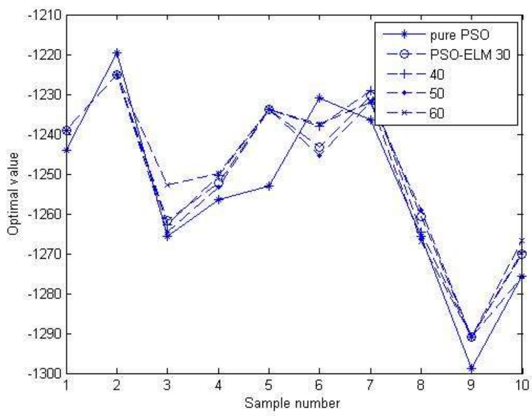

Fig. 5. The performance of pure PSO and PSO-ELM

V. FURTHER RESEARCH DIRECTIONS

A. Higher Performance Neural Networks with Affordable Complexity.

As so far, the performance of ELM may be inferior to large scale deep learning neural network, which may reduce the whole performance of proposed algorithm, but the result is convincing. So, in order to improve system performance, laboratory affordable low complexity neural network model deserves more researched, especially for multi-input and multi-output neural network.

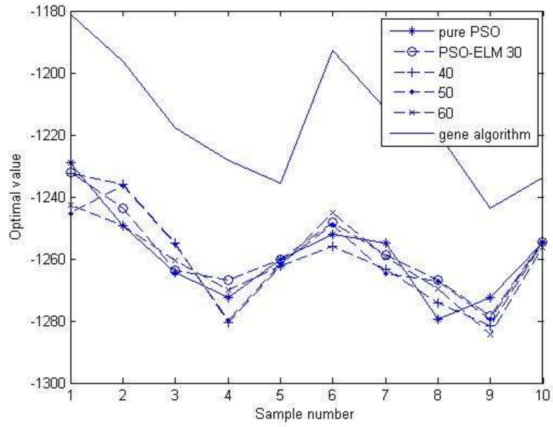

Fig. 6. The performance of gene algorithm (NSGA-II) and PSO-ELM

TABLE III. THE RUNNING RESULTS OF TWO ALGORITHMS IN OPTIMAL TARGET VALUE

turns	(Optimal value) results*1000									
30	-1.2391	-1.2250	-1.2617	-1.2523	-1.2339	-1.2433	-1.2303	-1.2607	-1.2909	-1.2701
40	-1.2391	-1.2250	-1.2628	-1.2504	-1.2339	-1.2380	-1.2291	-1.2646	-1.2909	-1.2695
50	-1.2391	-1.2250	-1.2646	-1.2533	-1.2339	-1.2454	-1.2321	-1.2591	-1.2909	-1.2760
60	-1.2391	-1.2250	-1.2529	-1.2498	-1.2339	-1.2375	-1.2319	-1.2671	-1.2909	-1.2666
Pure-PSO	-1.2442	-1.2197	-1.2656	-1.2565	-1.2530	-1.2309	-1.2363	-1.2656	-1.2989	-1.2757

B. Adapting Adjust the Related Parameters to Improve the System

In PSO and ELM, there are large number of parameters which need to be quantified, and their influences to the proposed algorithm are still unclear and can't be theoretic analyzed and can only be manually modified, which need further technique and theory innovations for parameter adjusting techniques.

C. A More Mature EI Systems

As the domain of EI is not limited to electrical power, the further simulations of EI should also consider hot, cold and gas, and related influence on EI operation. The related model should be more comprehensive and collaborated. To set up corresponding model, the robust of energy supply should be firstly considered, while considering the influences of energy trade and demand side management at the same time, and also set the whole revenue and operation cost as the final target.

VI. CONCLUSIONS

In order to reduce the execution time and the algorithm's complexity, and utilize the advanced performance of machine learning and system modeling optimization, we combinedly using PSO and ELM to optimize the operation and control of EI through charge and discharge control for energy store equipment. In this way, the execution time delay can be largely reduced, while the optimal precision is comparable with traditional PSO algorithm, which is suited for cloud-edge collaboration liked tasks, and will become further broadly applied in EI control and management.

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