Optimal Battery Charging Strategy Based on Complex System Optimization

Haiping Ma[1,2](✉), Pengcheng You[1], Kailong Liu[3], Zhile Yang[3], and Minrui Fei[4]

[1] State Key Laboratory of Industrial Control Technology, Department of Control, Zhejiang University, Hangzhou, China
Mhping1981@126.com, pcyou@zju.edu.cn
[2] Department of Electrical Engineering, Shaoxing University, Shaoxing, Zhejiang, China
[3] School of Electronics, Electrical Engineering and Computer Science, Queen's University Belfast, Belfast, UK
{kliu02, zyang07}@qub.ac.uk
[4] Shanghai Key Laboratory of Power Station Automation Technology, School of Mechatronic Engineering and Automation, Shanghai University, Shanghai, China

Abstract. This paper proposes a complex system optimization method to obtain an optimal battery charging strategy. First, a real-world lithium-ion battery charging model is built as a complex system problem, which includes electric subsystem and thermal subsystem. The optimization objectives of electric subsystem includes battery charging time and energy loss, and the optimization objectives of thermal subsystem includes battery internal temperature rise and surface temperature rise. Then a called biogeography-based complex system optimization (BBO/Complex) algorithm is introduced, which is a heuristic method for complex system optimization. Finally, BBO/Complex is applied to the complex system of battery charging strategy, and the results show that the proposed method is a competitive algorithm for solving batter charging problem studied in this paper.

Keywords: Battery charging · Complex system · Heuristic algorithm · BBO/Complex

1 Introduction

In recent years, portable electronic devices have been widely used in many domains. Lithium-ion batteries are tending to replace the traditional rechargeable batteries such as lead-acid batteries used in these devices, because they show some outstanding performance such as high power and energy densities, broad operating temperature range, long-life cycles, and low self-discharge rate [1]. These merits of lithium-ion batteries make them become a very promising primary power source for electronic devices in the future. Therefore, for the applications of lithium-ion batteries, a well-designed battery charger plays a vital role for sustaining battery performance and lifespan, and the key is to obtain a proper battery charging strategy including the

K. Li et al. (Eds.): LSMS/ICSEE 2017, Part III, CCIS 763, pp. 371–378, 2017.
DOI: 10.1007/978-981-10-6364-0_37

selection of charging current pattern, the control and termination of charging process, and the safety and behavior of the battery.

In the past years, a lot of approaches have been developed to improve the battery charging performance. Some of the approaches involve computation intelligence including neural networks [2, 3], grey prediction [4], and fuzzy control [5]. Some of strategies take the battery charging behaviors as an optimization problem which is further solved using heuristic methods. In [6], genetic algorithm (GA) is used to manage online battery charging state for electric and hybrid vehicle applications. In [7], particle swarm optimization (PSO) is employed to obtain optimum battery energy storage system considering dynamic demand response for micro grids. But these studies only consider battery charging performance as a single-objective or multi-objective optimization problem. In fact, the battery temperatures including the surface and internal temperatures also consist of a system optimization problem, and they are important factors during the battery charging process, because too high or low temperature would be harmful to the battery charging safety and behavior. Undoubtedly, it becomes more complex than ever before, and the optimization becomes more difficult under considering battery temperatures. In this situation, battery charging strategy cannot be treated as a typical single-objective or multi-objective optimization problem any long. Strictly, it is taken as a complex system, which contains multiple subsystems, each of which contains multiple objectives, multiple constraints and multiple variables. So it is necessary to build new heuristic methods to tackle the battery charging problem under new circumstances.

Complex system optimization is a class of optimization methods dedicated to solving complex problems with multiple subsystems, multiple objectives, and multiple constraints. Traditional complex system optimization methods includes multidisciplinary feasible (MDF), individual discipline feasible (IDF) and collaborative optimization (CO), which are popular in engineering domain [8, 9]. But these methods only provide conceptual frameworks without involving the detailed algorithms, which are usually specified based on the user's preference. Recently, a heuristic method, called biogeography-based complex system optimization (BBO/Complex) is proposed by Simon and Du [10] to solve complex problems. Some literatures showed that BBO/Complex had obtained good performance for the virtual machine placement [11], the economic emission load dispatch [12], the speed reducer problem, the power converter problem, the heart dipole problem and the propane combustion problem [10].

For battery charging management, an important but challenging problem is to achieve optimal charging performance considering various factors including efficiency, reliability and safety. Motivated by these considerations, this paper adopts BBO/Complex to obtain the optimal battery charging strategy. The remainder of this paper is organized as follows. Section 2 builds a battery charging model for complex system optimization. Section 3 reviews BBO/Complex as a complex system optimization method. Section 4 applies BBO/Complex to solve battery charging model and presents optimization results. Section 5 provides conclusions and suggests directions for future work.

2 Problem Formulation of Battery Charging

The complex system model of battery charging is formulated as two subsystems, each of which includes two objective functions. One is the electric subsystem with two objectives of battery charging time and energy loss. Another is the thermal subsystem with two objectives of battery internal temperature rise and surface temperature rise.

2.1 Battery Electric Subsystem

In the electric subsystem, the charging time during battery charging is an important optimization indicator. Generally, the shorter the charging time is, the better the performance is. Another important optimization indicator is the battery energy loss. The smaller energy loss is, the higher the battery charging efficiency is.

The objective functions of the battery charging time and energy loss are defined as

$$J_{CT} = t_s \cdot k_{tf} \tag{1}$$

$$J_{EL} = t_s \cdot \sum_{k=0}^{k_{tf}} \left(i^2(k) \cdot R(k) + \frac{V_1^2(k)}{R_1(k)} + \frac{V_2^2(k)}{R_2(k)} \right) \tag{2}$$

where t_s is the sampling time interval during the battery charging process, k_{tf} is the number of sample when the capacity of battery reaches its target, i is the charging current, which remains constant during a given sample time internal, R, R_1 and R_2 are the battery diffusion resistances, and V_1 and V_2 are the battery RC network voltages.

2.2 Battery Thermal Subsystem

In the thermal subsystem, the battery internal temperature rise and surface temperatures rise are key performance indicators during the charging process. The higher the temperature is, the more serious the damage is for the service life of the battery.

The objective functions for the battery internal temperature rise and surface temperature rise can be defined as

$$J_{ITR} = t_s \cdot \sum_{k=0}^{k_{tf}} T_{IT}(k) \tag{3}$$

$$J_{STR} = t_s \cdot \sum_{k=0}^{k_{tf}} T_{ST}(k) \tag{4}$$

where T_{IT} and T_{ST} represent the battery internal and surface temperature respectively.

2.3 Optimization and Constraints

Optimal battery charging strategy is to find the appropriate charging current i to simultaneously minimize objective functions J_{CT} and J_{EL} in battery electric subsystem and objective functions J_{ITR} and J_{STR} in battery thermal subsystem. It is defined as

$$\text{minimize } \{J_{CT},\ J_{EL},\ J_{ITR},\ J_{STR}\}. \tag{5}$$

Furthermore, during the battery charging process, some constraints and updates need to be satisfied for the battery parameters such as voltage and current, which are described as follows:

$$\begin{gathered} V_1(k) = a_1 \cdot V_1(k-1) - b_1 \cdot i(k-1) \\ V_2(k) = a_2 \cdot V_2(k-1) - b_2 \cdot i(k-1) \\ V(k) = V_1(k) + V_2(k) + i(k) \cdot R(k) \\ T_{IT}(k) = (1 - t_s{\cdot}k_1/D_1) \cdot T_{IT}(k-1) + (t_s \cdot k_1/D_1) \cdot T_{ST}(k-1) \\ \qquad\qquad + t_s \cdot R(k-1) \cdot i^2(k-1)/D_1 \\ T_{ST}(k) = (t_s{\cdot}k_1/D_2) \cdot T_{IT}(k-1) + (1 - t_s{\cdot}(k_1+k_2)/D_2) \cdot T_{ST}(k-1) \end{gathered} \tag{6}$$

and

$$\begin{gathered} T_{IT}(0) = 0,\ \ T_{ST}(0) = 0 \\ a_j = \exp\left(-t_s/R_j\right),\ j = 1,\ 2 \\ b_j = R_j \cdot \left(1 - a_j\right) \\ i_{\min} \le i(k) \le i_{\max} \\ V_{\min} \le V(k) \le V_{\max} \end{gathered} \tag{7}$$

where $k_1,\ k_2,\ D_1$ and D_2 are pre-defined parameters, $i_{\min}$ and $i_{\max}$ are the minimum and maximum values of charging current i, $V_{\min}$ and $V_{\max}$ are the minimum and maximum values of the voltage V.

3 Biogeography-Based Complex System Optimization

This section provides an overview of BBO/Complex for complex system [10]. Before we introduce the details of BBO/Complex, there are some notations we need to clarify. BBO/Complex is an extension to the standard BBO, but it is different to BBO. Standard BBO is a single-objective or multiple-objective optimization algorithm, which is suitable to a single system. BBO/Complex is a complex system optimization algorithm, and it is suitable to a complex system with multiple subsystems, each of which contains multiple objectives and multiple constraints. On the other hand, some definitions and operating strategies of standard BBO, including migration and mutation, are reserved, which are not described repeatedly in this paper.

Now we introduce some new BBO/Complex notations which are different with standard BBO. Let $P = \{A_1,\ A_2,\ A_3,\ \ldots\}$ denote an ecosystem that is comprised of archipelagos, each of which corresponds to one subsystem. $A_h = \{O_{h1},\ O_{h2},\ O_{h3},\ \ldots;$ $C_{h1},\ C_{h2},\ C_{h3},\ \ldots;\ I_{h1},\ I_{h2},\ I_{h3},\ \ldots\}$ represents an arbitrary archipelago, which is comprised of objective O_{hi}, constraints C_{hi} and candidate solutions I_{hi}. $I_{hi} = \{S_{hi1}, S_{hi2}, S_{hi3}, \ldots\}$ represents an arbitrary candidate solutions, which is comprised of independent variables S_{hij}.

Based on the original paper [10], the framework of BBO/Complex is shown in Fig. 1, which includes within-subsystem migration, cross-subsystem migration and mutation.

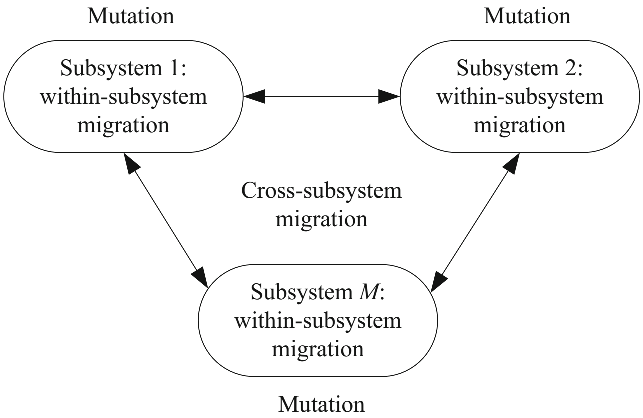

Fig. 1. Framework of BBO/Complex, including within-subsystem migration, crossover-subsystem migration, and mutation.

The main steps of BBO/Complex are depicted as follows.

Step 1: Initialize the population and parameters;
Step 2: Perform within-subsystem migration for each subsystem;
Step 3: Perform cross-subsystem migration for selected subsystem pairs;
Step 4: Perform probabilistic mutation for each candidate solution;
Step 5: Terminate if the termination condition is satisfied, otherwise, generate the next population and go to Step 2.

In step 1, BBO/Complex parameters include the number of subsystems, the number of candidate solutions in each subsystem, the maximum immigration rate and emigration rate, the mutation probability and stopping criterion.

In step 2, within-subsystem migration is very similar to standard BBO migration. For standard BBO, the calculation of migration rates is based on the solution fitness, and for BBO/Complex, the calculation of migration rates is based on the solution rank. Note that solution rank in BBO/Complex combines all information of objectives and constraints to calculate the migration rates, and the calculation method is the same to non-dominated sorting [13]. The process of within-subsystem migration shows as follows: first, probabilistically choose the immigrating solution based on immigration rate, and use roulette-wheel selection based on emigration rates to select the emigrating solution. Immigration rate and emigration rate linearly related to the solution rank, which are calculated as

$$\lambda = \frac{k}{K}, \quad \mu = 1 - \lambda \tag{8}$$

where λ and μ are the immigration rate and emigration rate respectively, k and K are the solution rank and total number of solutions in a subsystem respectively.

Finally, migration is performed from the chosen emigrating solution to the corresponding immigrating solution, and each independent variable in an immigrating solution will have a chance to be replaced by an independent variable from an emigrating solution.

In step 3, cross-subsystem migration is carried out only on selected subsystem pairs. First, calculate the constraint similarity level and objective similarity level between every two subsystems, which is based on fast similarity level calculation (FSLC) [14]. Next calculate Euclidian distance between each pair of solutions from two selected subsystems. Finally perform cross-subsystem migration: probabilistically find suitable pair of subsystems to migrate based on the obtained similarity levels. After that, we need to choose emigrating solution for each immigrating solution. We use roulette-wheel selection to select the emigrating solution based on Euclidian distances of solutions. Solutions with better distances will have better chance to be selected as the emigrating solution. Each independent variable in an immigrating solution will have a chance to be replaced by an independent variable from an emigrating solution.

In step 4, probabilistically perform mutation on each solution based on the mutation probability, which is the same as that in the standard BBO algorithm.

Based on the above description, we find that the two most important components are within-subsystem migration and cross-subsystem migration for BBO/Complex. In standard BBO, migration is a simple operator because only one subsystem evolves in the entire system. But in complex system, it has multiple subsystems. We need to combine all information within and cross subsystems, including objectives, constraints, and solution variables, to determine to migration.

4 Simulation Results

In this section, we use BBO/Complex to solve the proposed battery charging problem. The purpose of this simulation is to show the feasibility and effectiveness of BBO/Complex to solve real-world complex systems. So we compare BBO/Complex with CO, MDF, and IDF [10], which are well-known traditional complex system optimization methods. But we do not compare it with other evolutionary algorithms such as GAs, PSO and so on.

The battery charging parameters are set as follows: $t_s = 1s$, $R = 0.0152\Omega$, $R_1 = 0.0037\Omega$, $R_2 = 0.0034\Omega$, $k_1 = 1.6423$, $k_2 = 0.3102$, $D_1 = 286.35$, and $D_2 = 30.9$. In addition, the minimum and maximum values of charging current and voltage are $i_{\min} = -30A$, $i_{\max} = 0A$, $V_{\min} = 2.6V$, $V_{\max} = 3.65V$ respectively. The more detail of the parameters of battery charging model refers to [15]. The performance criteria is based on the cost values of battery charging time, energy loss, internal temperature rise and surface temperature rise, and the optimization goal is to find the minimum values of these costs.

The parameters of BBO/Complex have been manually tuned for optimal performance. For BBO/Complex and the complementary methods in CO, MDF, and IDF, the size of population is 10, mutation rate is 0.01 per independent variable in solution, and the number of Monte Carlo simulations is 20, with a maximum number of function evaluations equal to 1000 for each Monte Carlo simulation. The optimization results are shown in Table 1.

Table 1. The optimization results of the battery charging model for CO, MDF, IDF and BBO/Complex.

Objective functions	Complex system optimization			
	CO	MDF	IDF	BBO/Complex
Charging time J_{CT}	1342	1388	1524	1252
Energy loss J_{EL}	17875	17912	18807	16908
Internal temperature rise J_{ITR}	10245	10107	11823	9805
Surface temperature rise J_{STR}	3428	3473	3612	3349

From Table 1, we see that BBO/Complex has the smallest cost value of charging time, the smallest cost value of energy loss, the smallest cost value of internal temperature rise and smaller surface temperature rise. That is, BBO/Complex has better performance than traditional complex system optimization methods including CO, MDF, and IDF. This is because BBO/Complex improves the diversity of solutions by employing cross-subsystem migration and within-subsystem migration to enhance optimization performance. According to these results, we conclude that BBO/Complex has good complex system optimization performance for battery charging problem studied in this paper.

5 Conclusions

In this paper, we propose a model of real-world lithium-ion battery charging, which is formulated as a complex system with two subsystems, each of which includes two objectives. Then, we introduce BBO/Complex, which includes within-subsystem migration, cross-subsystem migration and mutation, to satisfy the structure of complex systems. Finally, we apply BBO/Complex to the proposed battery charging model, and the simulation results demonstrate that BBO/Complex can effectively obtain the optimal battery charging strategy, which shows it is a competitive complex system optimization algorithm.

This paper shows that BBO/Complex has good optimization performance for solving battery charging problem, but it still opens other research directions for additional development and empirical investigation. First, we consider some real-world charging circumstance constraints into battery charging model, which are important factors for charging performance. Second, we consider adjusting cross-subsystem migration strategy to improve BBO/Complex optimization performance for complex system problems.

Acknowledgments. This research was supported by the National Natural Science Foundation of China under Grant Nos. 61640316 and 61633016, and the Fund for China Scholarship Council under Grant No. 201608330109.

References

1. Vo, T., Chen, X., Shen, W., Kapoor, A.: New charging strategy for lithium-ion batteries based on the integration of Taguchi method and state of charge estimation. J. Power Source **273**, 413–422 (2015)
2. Xu, L., Wang, J., Chen, Q.: Kalman filtering state of charge estimation for battery management system based on a stochastic fuzzy neural network battery model. Energy Convers. Manag. **53**(1), 33–39 (2012)
3. Sun, M., Ni, S., Ma, H.: Delay-dependent robust H∞ control for time-delay systems with polytopic uncertainty. In: Proceedings of the 48th IEEE Conference on Decision and Control with the 28th Chinese Control Conference, pp. 280–284. Shanghai, China (2009)
4. Chen, L., Hsu, R., Liu, C.: A design of a grey-predicted Li-ion battery charge system. IEEE Trans. Ind. Electron. **55**(10), 3692–3701 (2008)
5. Li, C., Liu, G.: Optimal fuzzy power control and management of fuel cell/battery hybrid vehicles. J. Power Sources **192**(2), 525–533 (2009)
6. Chen, Z., Mi, C., Fu, Y., Xu, J., Gong, X.: Online battery state of health estimation based on genetic algorithm for electric and hybrid vehicle applications. J. Power Sources **240**, 184–192 (2013)
7. Kerdphol, T., Qudaih, Y., Mitani, Y.: Optimum battery energy storage system using PSO considering dynamic demand response for micro-grids. Int. J. Electr. Power Energy Syst. **83**, 58–66 (2016)
8. Allison, J.: Complex system optimization: a review of analytical target cascading, collaborative optimization, and other formulations. M.S. Thesis, University of Michigan, Ann Arbor, MI (2004)
9. Ma, H., Su, S., Simon, D., Fei, M.: Ensemble multi-objective biogeography-based optimization with application to automated warehouse scheduling. Eng. Appl. Artif. Intell. **44**, 79–90 (2015)
10. Du, D., Simon, D.: Complex system optimization using biogeography-based optimization. Math. Probl. Eng. **2013**, 17 p. (2013). Article ID 456232
11. Zheng, Q., Li, R., Li, X., Shah, N., Zhang, J., Tian, F., Chao, K.-M., Li, J.: Virtual machine consolidated placement based on multi-objective biogeography-based optimization. Future Gener. Comput. Syst. **54**, 95–122 (2016)
12. Ma, H., Yang, Z., You, P., Fei, M.: Complex system optimization for economic emission load dispatch. In: Proceedings of 11th UKACC International Conference Control, pp. 1–6. Belfast, UK (2016)
13. Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.: A fast and elitist multi-objective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. **6**(2), 182–197 (2002)
14. Hathaway, R., Bezdek, J.: Fuzzy c-means clustering of incomplete data. IEEE Trans. Syst. Man Cybern. **31**(5), 735–744 (2001)
15. Liu, K., Li, K., Yang, Z., Zhang, C., Deng, J.: An advanced Lithium-ion battery optimal charging strategy based on a coupled thermoelectric model. Electrochim. Acta **225**, 330–344 (2017)