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Ev Battery Controller Tuning For Efficient Thermal Management Based On Grasshopper Algorithm And Particle Swarm Optimization Algorithm

Allif Nazmie[1], Driman bin Hanafi[2]
[1, 2]Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia

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ABSTRACT

Electric Vehicles (EVs) offer low emissions and reduced fossil fuel dependence but require efficient battery thermal management to ensure performance and safety. This research aims for tuning proportional-derivative(PD), proportional-integral(PI) and proportional-integral-derivative (PID) controller for Electrical Vehicle (EV) Thermal Management System using Particle Swarm Optimization (PSO) and Grasshopper Optimization Algorithm method (GOA) method to optimize the compressor power consumption to contribute to the development of better EV battery thermal management systems. By minimizing and maximizing the factors involved in the challenges, optimization is the process of identifying the best way to make something as useful and effective as feasible. Simulation results show that GOA outperforms PSO for all controllers. Objective function values for GOA are lower, 1.6783 (PD), 0.8517 (PI), and 0.8114 (PID), compared to PSO, 1.7578, 0.8665, and 0.8254, respectively. Improvement percentages of GOA over PSO are 4.73% (PD), 1.70% (PI), and 1.65% (PID). The PID controller achieved the best performance overall, showing 51.65% improvement over PD and 4.91% over PI. The findings confirm that GOA is more effective than PSO in optimizing controller performance, and that PID is the most suitable for stable and efficient EV battery thermal management.

Corresponding Author:

Dirman Hanafi,
Faculty of Electrical and Electronic Engineering,
Universiti Tun Hussein Onn Malaysia,
Email: dirman@uthm.edu.my
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1. INTRODUCTION

Electric Vehicles (EVs) have emerged as a promising alternative to internal combustion engine (ICE) vehicles, primarily due to their lower emissions, energy efficiency, and environmental sustainability. However, one of the persistent challenges in EV adoption is the effective management of battery temperature during operation [1]. Poor thermal control can lead to degraded battery performance, reduced lifespan, and in severe cases, thermal runaway or safety [2]–[5].

A Battery Thermal Management System (BTMS) is essential to maintain battery cell temperature within the ideal operational range of 15°C to 35°C, with optimal efficiency around 21.5°C [6]–[10]. Traditional BTMS designs rely on passive methods or fixed-parameter controllers, which may not adapt well to dynamic driving conditions and thermal loads. As a result, modern approaches explore intelligent controller tuning and optimization to achieve responsive and efficient BTMS performance [11]–[13].

Recent studies have investigated the use of metaheuristic algorithms for optimizing controller parameters. Particle Swarm Optimization (PSO) has been widely used in engineering applications due to its simplicity and fast convergence [14], [15]. However, it tends to get trapped in local optima, limiting its effectiveness in complex nonlinear systems like BTMS [13]. To overcome these limitations, newer algorithms such as the Grasshopper Optimization Algorithm (GOA) have been introduced, offering improved exploration capabilities and robustness in avoiding premature convergence [16].

Previous research has applied PSO to tune PID controllers for thermal systems with notable success in reducing overshoot and settling time [17]. However, limited studies have compared PSO with GOA in the context of EV BTMS optimization. Furthermore, while some studies focused solely on battery temperature, few considered the balance between compressor power consumption and thermal regulation, which is critical for EV range and efficiency [4], [18].

In summary, although intelligent algorithms have been used to improve controller performance, a few researchers focused on optimizing both compressor power and battery temperature simultaneously. There have been limited studies concerned with comparing the performance of PSO and GOA in EV thermal management systems under the same conditions.

Therefore, this research intends to apply and compare PSO and GOA in tuning PD, PI, and PID controllers for an EV BTMS. The objectives of this research are:

- To investigate the power consumption performance of the EV BTMS during controller tuning.
- To evaluate the impact of PD, PI, and PID controller variation on compressor behavior and battery thermal response.
- To integrate PSO and GOA for optimizing the controller parameters and achieving a target battery temperature of 21.51°C.

2. METHOD

This study uses MATLAB/Simulink to simulate an Electric Vehicle (EV) Battery Thermal Management System (BTMS) that includes compressor, radiator, chiller, and heat exchange components. A Simulink model replicates the thermal behavior of an EV battery pack, with control blocks assigned for PD, PI, and PID controllers. The controller parameters are tuned using two metaheuristic algorithms: Particle Swarm Optimization (PSO) and Grasshopper Optimization Algorithm (GOA). PSO mimics swarm intelligence for global optimization, while GOA imitates grasshopper swarming behavior to balance exploration and exploitation in the search space [14], [16]. Custom MATLAB `.m` files were written for both PSO and GOA to optimize objective functions based on system response metrics, compressor power consumption, overshoot, settling time, and battery temperature. These optimization scripts are interfaced with the Simulink model using MATLAB's built-in function block.

Each controller is tuned independently under both algorithms. Simulations are run until convergence or a maximum number of iterations is reached. The best-performing parameters are recorded and compared. This approach follows standard optimization techniques, with modifications adapted from [13], [19]. to fit EV BTMS use cases.

3. RESULTS AND DISCUSSIONS

The optimization results using both PSO and GOA for PD, PI, and PID controllers were analyzed based on compressor power consumption and battery temperature control. The system was simulated in MATLAB/Simulink, and the performance was evaluated through convergence graphs, objective function values, and time-domain response.

Figures 1 to 3 show the convergence curves of the objective functions for PD, PI, and PID controllers, respectively. GOA demonstrated faster and smoother convergence in all controller types compared to PSO, which showed more fluctuation before stabilization.

For convergence graph of PD controller as shown in Figure 1, it shows that the GOA has lower value of objective function compared to PSO and this indicates that the GOA are better in tuning the PD controller in order to keep the battery temperature closer to the ideal range, fluctuations, and less energy using by the controller which can improves overall performance of the vehicle.

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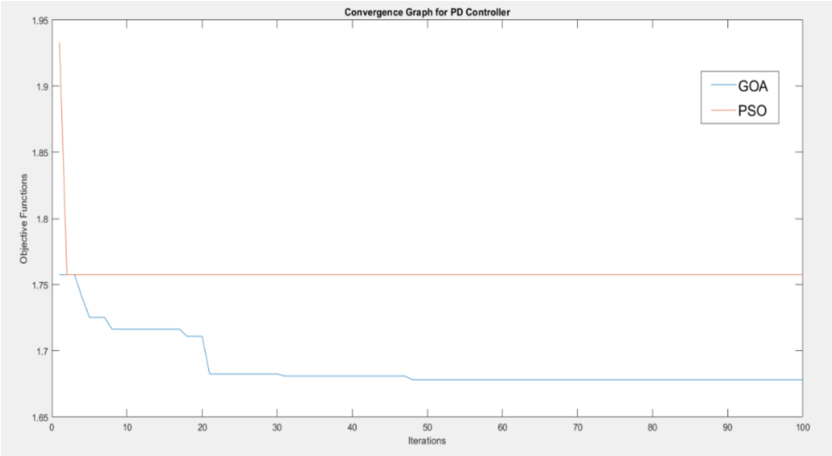

Figure 1. Convergence graph for PD controller

For convergence graph of PI controller as shown in Figure 2, GOA has lower value of objective function compared to PSO. This portrays that GOA tune the PI controller better than PSO to keep the battery temperature stable and within the ideal range of 21.5oC while using lower energy, which can improve overall performance of the vehicle. PSO starts with higher objective function compared to GOA and relatively rapid decrease. GOA converge faster and reach lower final objective function while PSO take longer time to converge. GOA achieved a lower final objective function and this indicates GOA is more effective to tune the controller.

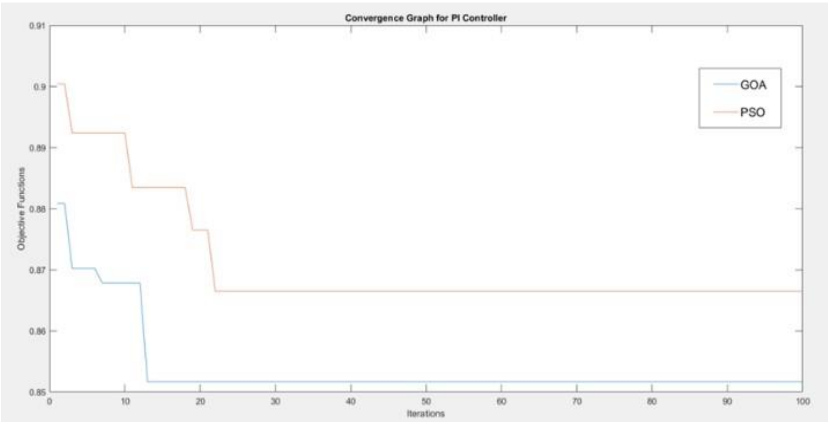

Figure 2. Convergence graph for PI controller.

Figure 3 shows a convergence graph for PID controller. PSO starts with higher objective function while GOA starts lower objective function. Both exhibits a steep initial drop. For convergence, GOA is faster and finally stabilizing around 35 to 38 iterations while PSO decreases more gradually and stabilizing around 25 iterations. GOA has a lower final objective function that indicates that it is more effective to tune the controller.

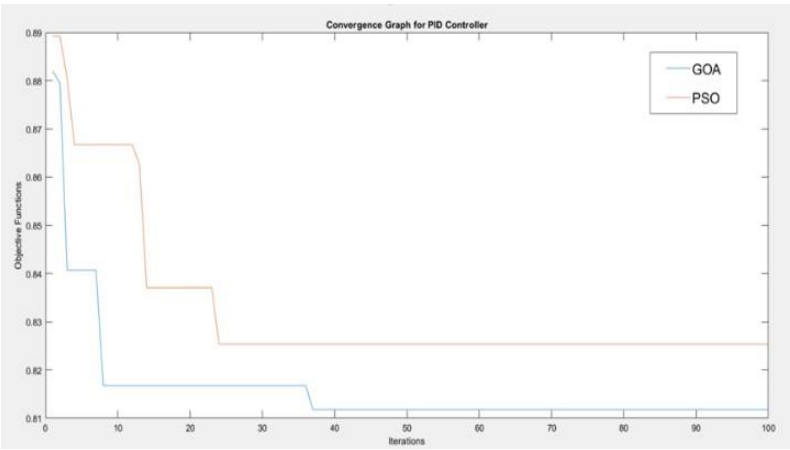

Figure 3 Convergence graph for PID controller

Table 1 summarizes the compressor power consumption values obtained after optimization. GOA consistently achieved lower values across all controller types, indicating more efficient tuning. The PID-GOA configuration recorded the lowest power consumption.

Tabel 1. Compressor power consumption for each controller

Controller	PSO (kW)	GOA (kW)
PD	1.7578	1.6783
PI	0.8665	0.8517
PID	0.8254	0.8114

Battery temperature response for each controller is shown in Figures 4 to 9. GOA tuning achieved faster settling time and less overshoot compared to PSO. The PID controller maintained battery temperature closest to the target value of 21.51°C.

Figure 4 shows the battery temperature with PSO-PD optimization. The initial temperatures are around 30 to 35oC because of the air and surrounding temperature or after a long period of discharge. Then the temperature drops from initial point indicates that the BTMS are engaging in the cooling system. After that, the temperature reach the yellow line which represents the ideal temperature for the battery. There are oscillations due to controller behaviour trying to reach and stabilize the temperature within the ideal range.

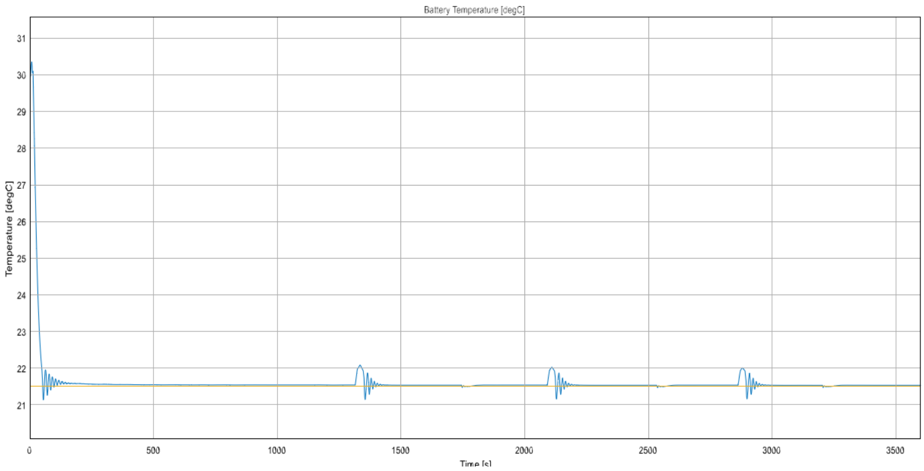

Figure 4. Battery temperature for PSO-PD

Figure 5 shows the battery temperature with GOA-PD optimization. The initial temperatures are around 30 to 35oC because of the air and surrounding temperature or after a long period of discharge. Then the temperature drops from initial point indicates that the BTMS are engaging in the cooling system. After that, the temperature reaches the yellow line which represents the ideal temperature for the battery. There are oscillations due to controller behaviour trying to reach and stabilize the temperature within the ideal range.

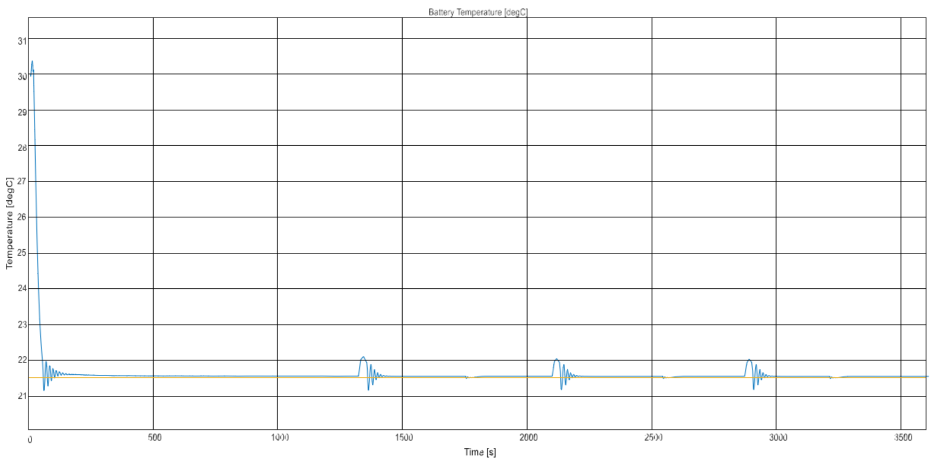

Figure 5. Battery temperature for GOA-PD

Figure 6 shows the battery temperature with PSO-PI optimization. The initial temperatures are around 30oC because of the air and surrounding temperature or after a long period of discharge. Then the temperature drops from the initial point indicates that the BTMS are engaging in the cooling system. After that, the temperature reaches the yellow line which represents the ideal temperature for the battery. There are oscillations due to controller behaviour trying to reach and stabilize the temperature within the ideal range.

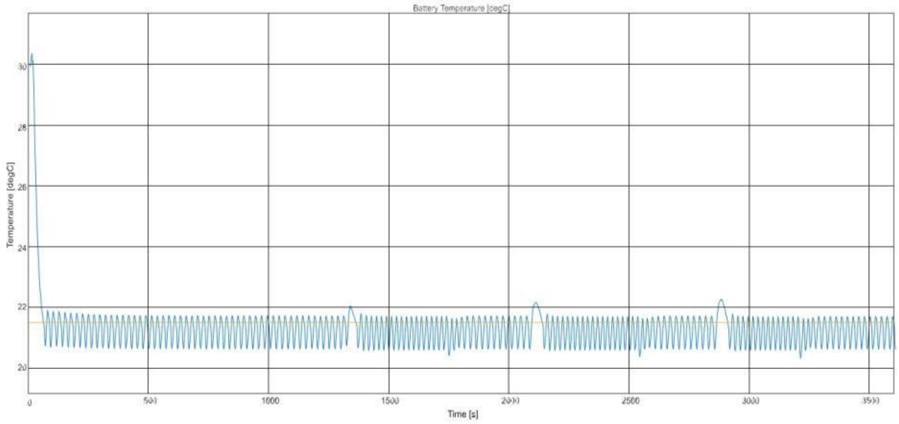

Figure 6. Battery temperature for PSO-PI

Figure 7 shows the battery temperature with GOA-PI optimization. The initial temperatures are around 30oC because of the air and surrounding temperature or after a long period of discharge. Then the temperature drops from the initial point indicates that the BTMS are engaging the cooling system. After that, the temperature reaches the yellow line which represents the ideal temperature for the battery. There are oscillations due to controller behaviour trying to reach and stabilize the temperature within the ideal range.

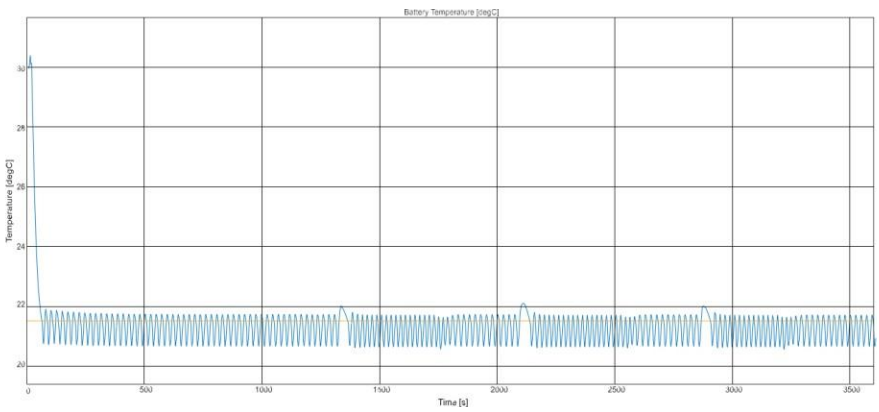

Figure 7. Battery temperature for GOA-PI

Figure 8 shows the battery temperature with PSO-PID optimization. The initial temperatures are around 30oC because of the air and surrounding temperature or after a long period of discharge. Then, the temperature drops from the initial point indicates that the BTMS are engaging in the cooling system. After that, the temperature reaches the yellow line which represents the ideal temperature for the battery. There are oscillations due to controller behaviour trying to reach and stabilize the temperature within the ideal range.

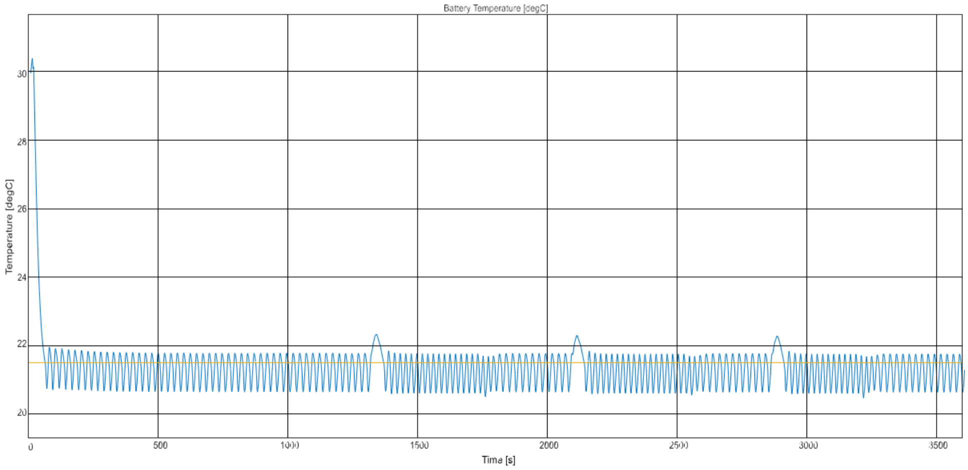

Figure 8. Battery temperature for PSO-PID

Figure 9 shows the battery temperature with GOA optimization. The initial temperatures are around 30oC because of the air and surrounding temperature or after a long period of discharge. Then the temperature drops from the initial point indicates that the BTMS are engaging the cooling system. After that, the temperature reaches the yellow line which represents the ideal temperature for the battery. There are oscillations due to controller behaviour trying to reach and stabilize the temperature within the ideal range.

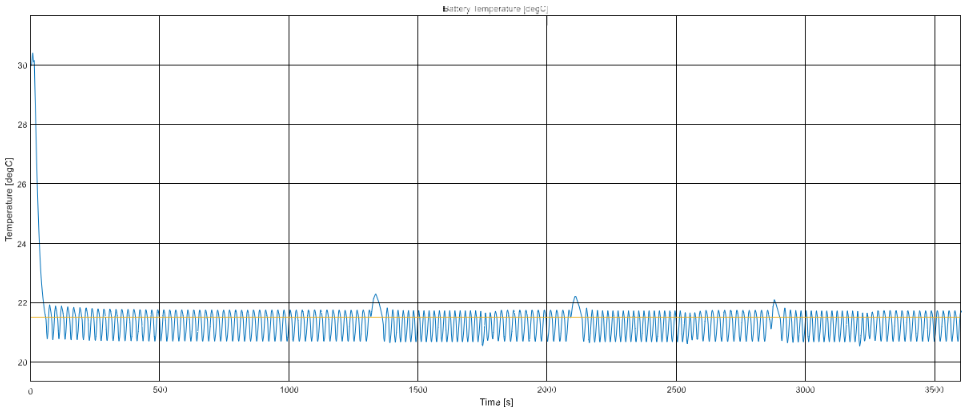

Figure 9. Battery temperature for GOA-PID

Overall, the GOA outperformed PSO in terms of convergence speed, power efficiency, and thermal stability. The PID controller was the most effective among the three, reducing compressor load by 51.65% compared to PD, and 4.91% compared to PI. These results confirm the suitability of GOA and PID for BTMS optimization in EV applications.

4. CONCLUSION

This study aimed to optimize the battery thermal management system (BTMS) in electric vehicles (EVs) by tuning PD, PI, and PID controllers using Particle Swarm Optimization (PSO) and Grasshopper Optimization Algorithm (GOA). The objective was to reduce compressor power consumption while maintaining battery temperature at the ideal value of 21.51°C. The results demonstrated clear alignment with these objectives. GOA outperformed PSO in terms of convergence speed and optimization accuracy. The PID controller, when tuned using GOA, provided the most efficient thermal regulation and lowest power usage. These findings confirm that intelligent optimization of controller parameters can significantly improve BTMS performance in EVs. The outcomes validate the proposed method and suggest strong potential for real-world application. Future research should explore hardware implementation and real-time simulations to further validate the model. Additionally, hybrid optimization strategies or adaptive control methods could be investigated to enhance performance under dynamic driving conditions.

REFERENCES

[1] A. M. Andwari, A. Pesiridis, S. Rajoo, R. Martinez-Botas, and V. Esfahanian, “A review of Battery Electric

Vehicle technology and readiness levels," *Renew. Sustain. Energy Rev.*, 2017.

[2] R. Zhao, J. Gu, and J. Liu, "An experimental study of heat pipe thermal management system with wet cooling method for lithium ion batteries," *J. Power Sources*, vol. 273, pp. 1089–1097, Jan. 2015.

[3] A. J. Bhosale and V. N. Deshmukh, "Efficient ways of thermal management of an EV battery," *Mater. Today Proc.*, vol. 72, pp. 1434–1445, Jan. 2023.

[4] A. Steiner and A. Mladek, "Reducing the energy consumption for comfort and thermal conditioning in EVs," in *12th International Conference on Ecological Vehicles and Renewable Energies (EVER 2017)*, 2017.

[5] Z. Rao and S. Wang, "A review of power battery thermal energy management," *Renew. Sustain. Energy Rev.*, vol. 15, no. 9, pp. 4554–4571, Dec. 2011.

[6] I. Naik and M. Nandgaonkar, "Review of the Approaches and Modeling Methodology for Lithium-Ion Battery Thermal Management Systems in Electric Vehicles," in *Lecture Notes in Mechanical Engineering*, 2021, pp. 75–109.

[7] C. Argue, "To what degree does temperature impact EV range?" 2025.

[8] F. Duffner, N. Kronemeyer, J. Tübke, J. Leker, M. Winter, and R. Schmuch, "Post-lithium-ion battery cell production and its compatibility with lithium-ion cell production infrastructure," *Nat. Energy*, vol. 6, no. 2, pp. 123–134, Feb. 2021.

[9] W. Liu, T. Placke, and K. T. Chau, "Overview of batteries and battery management for electric vehicles," *Energy Reports*, vol. 8, pp. 4058–4084, Nov. 2022.

[10] Q. Wang, B. Jiang, B. Li, and Y. Yan, "A Critical Review of Thermal Management Models and Solutions of Lithium-ion Batteries for the Development of Pure Electric Vehicles," —, 2020.

[11] N. Selvanathan and W. J. Tee, "A Genetic Algorithm Solution to Solve the Shortest Path Problem in OSPF and MPLS," 2003.

[12] A. Lambora, K. Gupta, and K. Chopra, "Genetic Algorithm — A Literature Review," in *International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon 2019)*, 2019, pp. 380–384.

[13] C. K. Dimou and V. K. Koumousis, "Investigation of the robustness of PSO algorithms in reliability optimal design problems," 2009.

[14] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of ICNN'95 - International Conference on Neural Networks*, 1995, vol. 4, pp. 1942–1948.

[15] G. Pereira, "Particle Swarm Optimization." 2014.

[16] S. Saremi, S. Mirjalili, and A. Lewis, "Grasshopper Optimisation Algorithm: Theory and application," *Adv. Eng. Softw.*, vol. 105, pp. 30–47, Mar. 2017.

[17] S. Padhy and S. Panda, "A hybrid stochastic fractal search and pattern search technique based cascade PI-PD controller for automatic generation control of multi-source power systems in presence of plug in electric vehicles," *CAAI Trans. Intell. Technol.*, vol. 2, no. 1, pp. 12–25, Mar. 2017.

[18] G. Zhao, X. Wang, M. Negnevitsky, and C. Li, "An up-to-date review on the design improvement and optimization of the liquid-cooling battery thermal management system for electric vehicles," *Appl. Therm. Eng.*, vol. 219, p. 119626, Jan. 2023.

[19] S. Padhy, S. Panda, and S. Mahapatra, "A modified GWO technique based cascade PI-PD controller for AGC of power systems in presence of Plug in Electric Vehicles," *Eng. Sci. Technol. an Int. J.*, vol. 20, no. 2, pp. 427–442, Apr. 2017.