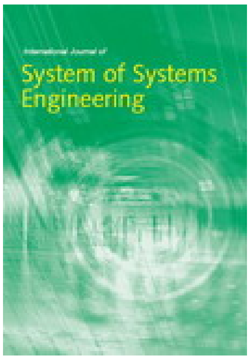

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Battery ageing management using war optimisation in electric vehicle applications

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Abstract: The growing interest in electrical vehicles (EVs) opens new possibilities in the use of lithium-ion batteries (LIB) to provide ancillary grid services while they are plugged into recharging stations. The equivalent circuit model is a type of LIB model that is widely used in EV battery management systems (BMS), which is an essential component of the LIB for managing power and safe operation. The LIB's health may be affected by some factors as abnormal charging-discharging cycles, operating temperature, charge/discharge rate, and ageing. The whole life cycle depends on accurate state of charge (SOC) estimation, and the capacity of a wide temperature range must be surpassed. In this paper, the SOC and state of health (SOH) joint estimation method with a war optimisation strategy (WOA)-based efficient battery ageing model is proposed. The depth of discharge (DOD), maximum battery current, and SOC are considered for achieving the battery ageing model, which uses the multi-objective WOA.

Keywords: BMS; battery management system; SOC; state of charge; DOD; depth of discharge; WOA; war optimisation strategy; battery capacity and temperature.

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1 Introduction

Lithium-ion batteries (LIBs) are key solutions as power storage systems for several applications including portable devices, aviation, space, and electrified vehicles. This electrification raises the issue of energy storage (Corno and Pozzato, 2019; Du et al., 2020). However, energetic and power performance of LIBs is known to decrease during their service lifetime (Xiong et al., 2018). One drawback of LIB is their durability: lithium batteries' energy and power capability decrease over time. The degradation rate is sensitive to operating conditions (Lu et al., 2020). In fact, battery temperature, SOC, voltage, DOD and current magnitude are the most influential and studied ageing factors (Karlsen et al., 2019). The first refers to the ageing of the battery, whereas the second is due to the charge/discharge of the battery, i.e., its usage as in the area with the system of systems engineering. Calendar ageing, in particular, depends on the temperature and SOC as function of the time (Xiong et al., 2020; Zhou et al., 2020). This means that understanding the mechanisms of battery ageing is a very difficult task because many factors contribute to the ageing.

Most studies focus on EV's energy efficiency and mileage, while battery wear during vehicle operation is not considered equal (Anselma et al., 2021; Han et al., 2020). This may be necessary for reasons such as the resale value of EVs being negligible and the relative mileage and class of motor vehicles. In this manner, all battery wear, energy usage, etc. during vehicle operation should be researched and defined (Kuang et al., 2020). Different caring battery management methods can be obtainable and remain industrialised through authors.

In recent years, the artificial intelligence (AI) based battery ageing organisation can be industrialised for empowering the battery life in electric vehicle applications. The ageing of the battery can be attained by seeing the multi-objective function that can be resolved through with optimisation technique whale optimisation technique (WOT), grey wolf optimisation (GWO), genetic algorithm (GA), and particle swarm optimisation (PSO), and so on. These techniques are affected by convergence problems. Hence, an efficient technique is introduced in the paper for managing the battery ageing model. The main contribution and organisation of the paper can be presented as follows.

1.1 Contribution of the paper

- This work is developing a WOA based battery ageing model for managing the battery capacity with the consideration of drivability and recharge time.
- To achieve the battery ageing model, the depth of discharge (DOD), state of charge (SOC), and maximum battery current are considered. Additionally, a multi-objective function is considered to achieve a battery ageing model, which is solved by using WOA.
- Based on the electric load cycle, the battery control variables are upgraded with the consideration of weight updating in the battery model.
- The proposed method is implemented in MATLAB/Simulink and presentations can be examined with different parameters such as the ageing and capacity of the model, charging current and temperature and discharging current, SOC and temperature, and voltage with a current of the battery model.

The residual portion of the paper is pre-arranged as follows. Section 2 gives the conventional works of the battery ageing model. The projected system battery model is presented in Section 3. The outcome evaluation of the projected model is presented in Section 4. The summary of the system is given in portion 5.

2 Literature review

In the literature, many batteries ageing management of electric vehicles are developed by researchers. Few works are reviewed in this section.

Li et al. (2022) introduced an original vehicle to grid (V2G) reservation strategy for using near-stationary power in microgrid by using a hybrid learning framework. It was the primary effort to focus battery defence on board charging GEVs in a fixed power configuration. Battery shielding processes are determined through a sophisticated run planning process where the V2G board is shown to be a compelling scaling problem because of the estimated microgrid and GEVs positions. In the interim, a web-based V2G controller has been worked on to work with the current management of GEVs charging. Extreme learning machine (ELM) computation was used to prepare the web-based controller by deriving rules from sophisticated operating systems.

Anselma et al. (2021) have introduced an efficient, multi-objective battery state of health (SOH)-sensitive disconnected Hybrid EV control technique that relies on dynamic programming (DP) and was tentatively authenticated on the predictive ability of battery lifetime. An exploratory task was performed to age cells with present outlines aimed at three dissimilar expected life events. The accuracy of the battery maturation model remains better through counting the result of temperature and then informing the observational maturation curve. A highly mature perfect was rummage-sale toward evaluating Hybrid EV operation aimed at various high-voltage battery pack sizes than control purposes up to efficiency and battery lifetime.

Xu et al. (2021) introduced a Q-learning-based system to control battery wear and power consumption. Besides Q-learning, two heuristic energy board strategies have been proposed and optimised using molecular multitude optimisation computation. A vehicle driver configuration model was first introduced, where the severity factor battery debasement model was considered and tentatively validated with the help of genetic computation. In the final test, Q-learning was first realised with the best strategy map in the context of learning. Then, the effect of the vehicle without an ultra-capacitor is used as a pattern, which was different and the effects of the vehicle with an ultra-capacitor used Q-learning, and two heuristic techniques were used as the power of the board.

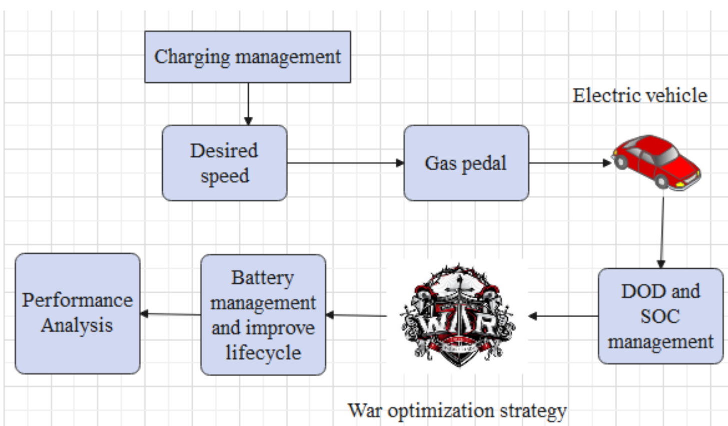
Zhang et al. (2021) have introduced a reasonable versatile battery range estimation strategy for random charging voltage range in light of incremental capacity (IC) selection and information-based procedures. All charging conditions of EVs are divided into three classes as indicated by the charging voltage range. Three information-based evaluation sub-strategies with continuous application requirements are designed separately for three charging conditions, including brain network information generation by IC pinnacle, learning accumulation by adjacent high IC curve, and direct regeneration with ampere-hour integration. To work on diversity, this technique relies on the information obtained to choose a reasonable estimation sub-strategy under different charging conditions.

Li et al. (2021) have introduced a multi-objective anticipatory energy board procedure that can find the compromise between helper power unit fuel cost controls, fuel cost control, and battery degradation cost control. Initially, the multi-purpose power of the executives was created to control the cost of work. Based on the existing multi-objective predictive control model predictive control, the team structure was intended to fulfil the continuous power of management control. Furthermore, the board developer proposed to continuously implement an original energy web-based optimisation process from the point of view of straightforward infinite shooting strategy and continuous quadratic programming calculation.

3 Proposed system model

Battery ageing can be a major problem in EV applications. The battery lifetime management is an open problem in the EV load drive cycle requirement. Many researches are focused to consider the battery ageing management in EV applications. In this process, the ageing problem is main concern which affects the whole efficiency of the electric vehicle. Additionally, hybrid electric applications, the battery are managing the whole requirement by powering the system. The EV contains one powerhouse which related to the battery ageing management and which connected to the requirements of EV. In this aim, the proposed battery ageing management technique for an electric vehicle can be correlated with vehicle dynamics. To manage the SOC in the battery, the residual battery capacity is computed and it is considered for battery ageing characteristics by using DOD and maximum cell current. In battery ageing, the major objective can be minimising battery capacity dilapidation. Additionally, to solve the battery issues in the EV, optimisation techniques are considered. In this paper, the WOA is introduced for managing SOC condition in the battery with the EV applications. The proposed complete architecture is presented in Figure 1.

Figure 1 Projected complete architecture (see online version for colours)



The proposed method can be developed with the multi-objective formulation,

$$OF_{min} = \alpha_1 J_{Life} + \alpha_s J_{speed} + \alpha_c J_{charge} - \alpha_r J_{range} \tag{1}$$

Here, J can be defined as various objectives. The initial measure penalises the capacity degradation over the travelled kilometres, N.

$$J_{Life} = \frac{q(0) - q(N)}{N} \tag{2}$$

Here, $q(0) = q_{nom}$ is defined as nominal capacity. J_{speed} can be defined as the error among the actual vehicle speed ($V(\tau)$) and desired speed ($V_{ref}(\tau)$).

$$J_{speed} = \sqrt{\frac{1}{t(N)} \int_0^{t(N)} \left(V_{ref}(\tau) - V(\tau)\right)^2 \mathrm{d}\tau}$$

Here, $t(N)$ can be defined as the time horizon, that is travel based on time with N kilometres. The variable of J_{charge} and J_{range} presented as an account of driving range and charging time.

$$J_{charge} = \sqrt{\frac{1}{\varepsilon(N)} \sum_{i=1}^{\varepsilon(N)} t_c(i)^2} \tag{4}$$

$$J_{range} = \sqrt{\frac{1}{\varepsilon(N)} \sum_{i=1}^{\varepsilon(N)} d_r(i)^2} \tag{5}$$

Here, d_r can be defined as the travelled distance between two charging events presented in kilometres, t_c can be defined as the charging period for every event denoted in minutes and $\varepsilon(N)$ can be defined as the complete number of charging events over N. In the optimisation problems, the weights are denoted as $\alpha_1, \alpha_s, \alpha_c, \alpha_r$ which plays an essential role in balancing the various objectives. This choice can be defined as non-trivial. The changes of DOD are a generally a great impact on the vehicle range and on the charging period but in general no effect on the vehicle speed as long as battery operated in the linear area of the open circuit voltage curve. From the above discussion, the control algorithm of WOA technique is avoids operating the battery outside this period to reduce excessive charging. Additionally, the higher DOD, higher range and charging time is managed. Conversely, the changes of maximum cell current are containing a negligible impact on the range and affect only the vehicle charging period and reducing the charging current and vehicle speed. A detailed explanation of the proposed methodology is explained in the below section.

3.1 Modelling of EV

Normally, the electric vehicle consumes high energy based on their vehicle energy requirements because of vehicles moving at various speeds and considerable count of energy output from the requirements to accelerate and brake. Additionally, the moving vehicles are pretended through the force's outcomes from the rolling friction force and aerodynamic resistance. In the electric vehicle (Singh et al., 2021), forces are related to different factors such as vehicle shape, frontal surface, pavement type, tyre width, and pressure. In the electric vehicle, the resultant force is managed and generates the vehicle velocity with different considerations. Additionally, the energy demand computation of vehicles is normally validated through initiating with the basis of driving force (DF). The driving force of an electric vehicle is described as the variation among rolling resistance (RS), resultant force (RF), and aerodynamic resistance (AR).

$$SF = RF - AR - RR \tag{6}$$

In the electric vehicle, the rolling resistance is computed based on the below formulation,

$$RR = Mgfto\left(1 + kv^2\right) \tag{7}$$

Here, fto can be described as low-speed resistance coefficient, g can be described as standard gravity acceleration, v can be described as the speed of the vehicle, M can be defined as the vehicle mass, k can be defined as the extra rolling resistance coefficient. The low-speed resistance coefficient is computed as follows,

$$fto = \frac{vb^2}{2gs_t} \tag{8}$$

Here, vb can be defined as the initial speed of the vehicle, s_t can be defined as the rolling distance of the vehicle. In the electric vehicle, normal moving on the road, rolling resistance coefficient with low speed can be expected to period between 0014 and 0012.

$$SF(a) = \frac{1}{2}\rho C_X av^2r \tag{9}$$

$$E = \frac{SFM}{\eta} \tag{10}$$

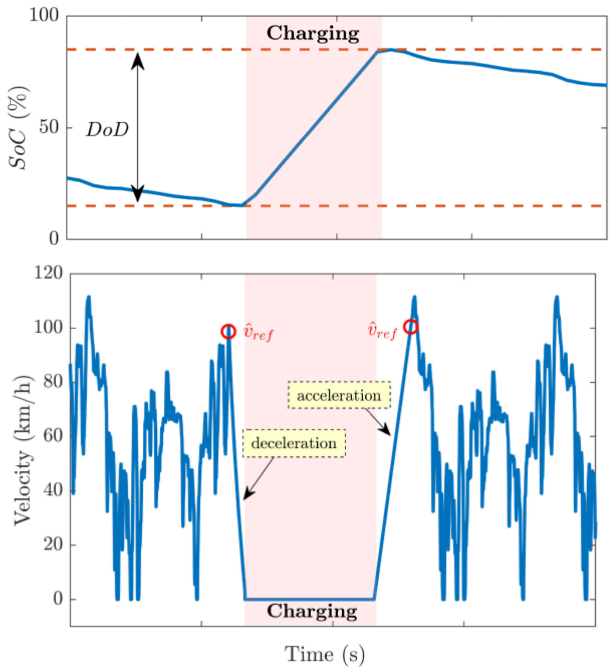
$$P = \frac{SFv}{\eta} or\, P = \frac{E}{T} \tag{11}$$

Here, ρ can be defined as the air density, C_X can be defined as the longitudinal direction with a coefficient of air resistance to vehicle ranges and shapes between 25% and 45%, a can be defined as the vehicle coefficient of a frontal surface location and v^2r is defined as the vehicle speed which correlated with the air. The thermal resistance parameter and instantaneous velocity of the car and presumptuous the drive system accuracy give level η that are utilised for computing the driving force of the electric vehicle with the energy (E) and instantaneous power (P) necessity to validate the route M in a specific period T.

3.2 Charging organisation

In the electric vehicle lifetime, the battery can be invigorated at different periods with the baits of charging behaviour usually operating on the SOC in addition geographical location of the charging locations (Corno and Pozzato, 2019). In this research, fast charging is considered to be always presented along the trip. Therefore, the battery achieves the limit SOC, the vehicle is decelerated from the present reference speed to 0 and recharged at a power controlled by the maximum cell current. The charging behaviour of the battery is illustrated in Figure 2.

Figure 2 Analysis of charging management (see online version for colours)



Once complete the charging process, the vehicle can be accelerated again. Compared with the reasoning in terms of the state of charging, the ageing technique manages the DOD and can be defined as a control variable. Here, defines the DOD is symmetric with the related the condition of SOC 50%. For example, a DOD of 70%, battery SOC varying between 15% and 85% in EV applications.

3.3 *Modelling of a battery cell*

In the modelling of a battery cell, the design ageing principle is a difficult operation; most contribution depends on semi-empirical designs. In the system, manage a similar path to develop a control-designed model (Hussain et al., 2019). This model is consisting of various assumptions which are presented as follows,

- the presence of battery management provides the balancing of complete cells in the battery pack
- additionally, design an equivalent design that deletes cell polarisation
- additionally, the temperature can be taken for the design and assume the battery management toward being armed with an energy management scheme.

Based on the expectations, the battery pack is designed as a solitary great cell with its electrical equivalent circuit. The resistance and voltage source are utilised for managing the joule losses. The battery open circuit voltage is operated with the condition of the SOC during its resistance is normally related to ageing and temperature (Ayyarao et al., 2022). Hence, the current of the cell is presented as follows,

$$Cell(i)=\frac{Voc-\sqrt{Voc^2-4RcellPcell}}{2Rcell} \tag{12}$$

Here, $Rcell$ is described as the resistance, Voc is described as the open circuit voltage. The SOC dynamics of battery cell is formulated as below expression,

$$SOC=-\frac{cell(i)}{Q} \tag{13}$$

Here, Q is defined as the cell capacity and its decreasing with ageing. The battery ageing model is considered from the electric vehicle condition from the initial situation. Hence, the range of capacity loss related to the treated Ah can be presented as follows,

$$\begin{cases} \dfrac{dq}{sAh}=\dfrac{z}{100}\propto SOC\,exp\left(\dfrac{-E_{\propto}+\eta\,|\,Cell\,|}{R_g(273.15+t)}\right)Ah^{z-1} \\ \qquad Ah=\dfrac{1}{3600}\,|\,cell\ (i)\,|\,q_{nom} \end{cases} \tag{14}$$

With the basis of equation modelling the Ah throughput as the complete current processed by the cell. The variables R_g and E_α is the activation energy which is equal to 31.5 (KJ/mol) and the universal gas constant. z and η is detected from experimental information. α_{SOC} is defined as a penalising factor that quickens the ageing aimed at high and low SOC as shown in Figure 3.

$$\alpha_{SOC}=D\left(1+Ce^{b(SOC\,min-SOC)}\right)(1+Ce^{b(SOC-SOCmax)} \tag{15}$$

Here, $SOCmax, SOC\,min, b, c\,and\,d$ is defined as computed shaping variables. The major stress parameters are moving the cell ageing characteristics remain its C-rate, temperature T then SOC. Additionally, the operating current regularised with the consideration of normal cell capacity Q_{nom}. Battery ageing improved also to an improvement of the internal resistance. Hence, the subsequent linear association among capacity decrement (ΔQ) and resistance increment (ΔR_{cell}) is developed.

$$\Delta R_{cell}=-K_{res}\Delta Q \tag{16}$$

Additionally, recalling the temperature depends on the cell's internal resistance is presented as follows,

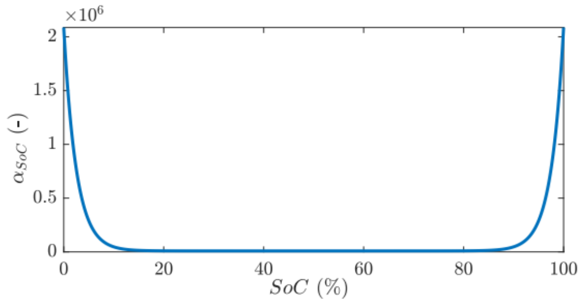
$$R^1_{cell}=R_{cell},0,e^{\left(\frac{T_1}{T-T_2}\right)} \tag{17}$$

Here, $R_{cell},0$ is defined as nominal cell resistance, T_1,T_2 is defined as the detected parameters which are achieved below,

$$R_{cell}=R^1_{cell}+\Delta R_{cell} \tag{18}$$

It must be noted that the projected system is empirical in normal in addition thus related to variations related on the general behaviours of the cell in use. The design, during requires an ageing model, does not exploit any specific characteristics of the proposed model.

Figure 3 SOC penalising factor (see online version for colours)



3.4 *War optimisation strategy*

In each cycle, each player has an equal chance of becoming a ruler or a power contingent on their fighting strength (well-being value). Together the rulers then the commander go as vanguards on the battlefield. A Lord and Commander grow in the field of conflict to lead other players. Chances are the lord or officer will face stiff opposition from a rival warrior (adjacent optima) who has enough cohesion to trick the vanguard. To evade this, combatants are guided by the situation of the ruler or alternate commander, and additionally by their integrated development strategies (Ayyarao and Kumar, 2022).

3.4.1 *Initial population*

In the initial population, the weighting parameters of the battery are initialised. First, the population is forced according to the lower bound and upper bound of the problem using the condition,

$$X_{I,J} = I_J + RAND.(U_J - L_J), I = 1, 2, \ldots, N, J = 1, 2, \ldots, M \tag{19}$$

Here, U_J can be defined as the upper bound of problem variables, L_J can be defined as the lower bound, $RAND$ can be defined as random number, M can be defined as the number of problem variables, N van be defined as the count of population members, $X_{I,J}$ can be defined as the parameter of the *j*th parameter defined by the candidate solution.

3.4.2 *Fitness evaluation*

In the projected organisation, the WOA is used to improve the ageing of the battery lifetime. To empower the battery lifetime is the objective function.

3.4.3 *Attack strategy*

We have shown binary collision techniques. In the main case, each combatant updates its location by considering the positions of the ruler and the administrator. The Lord is looking for a precious situation to send a terrible attack on the opposition. Accordingly, the officer with the best offensive power or health is seen as the ruler.

$$X_I(t+1) = X_i(t) + 2\times\rho\times(c-k) + RAND\times(w_i\times k - X_i(t)) \tag{20}$$

Here, k can be defined as the king position, c can be defined as the previous position of the commander, $X_I(t+1)$ can be a new position, w_i can be defined as the weight.

3.4.4 Updating rank and weight

Each search specialist's status update depends on the communication of the commander, commandant, and position of each troop. The rank of every soldier related on their success history in the war field managed by equation (23). The rank of every soldier related on their success history in the war field managed by equation (23), which will subsequently influence the weighting factor. The rank of every soldier manages how near to solider is to the highest.

$$X_I(t+1) = X_I(t+1)\times(f_n \ge f_p) + X_I(t)\times(f_n < f_p) \tag{21}$$

The fitness of the new position f_n is compared with less than the last location f_p, the soldier considered as a previous location. If the soldier upgrades the location efficiently, the rank R_i of the soldier is promoted (Ayyarao and Kumar, 2022),

$$R_I(t+1) = (R_I+1)\times(f_n \ge f_p) + R_I\times(f_n < f_p) \tag{22}$$

Related to the rank, the new weight can be computed as follows,

$$w_i = w_i\times\left(1 - \frac{R_I}{Maximum\,iteration}\right)^a \tag{23}$$

3.4.5 Defence method

Subsequent tech-level upgrades depend on the levels of the Lord, Warlord, and Irregular Troops. Here, weighting updating and ranking is achieved by below equation.

$$X_I(t+1) = X_i(t) + 2\times\rho\times(c - Xrand(t)) + RAND\times(w_i\times c - X_i(t)) \tag{24}$$

This combat mode explores more hunting space as opposed to the previous mode as it involves an arbitrary combatant's location. For great improvements Wi, the troops make great strides and improve their conditions. For minor advancements, Wi Warriors makes minor advancements when they refresh the status.

3.4.6 Spare/transfer of weak sold

For each priority, classify the most brutally weak fighter's fitness,

$$X_w(t+1) = LB + RAND\times(UB - LB) \tag{25}$$

Subsequent steps move the weaker warrior closer to the middle of a full armed force on a conflict field. This method further recovers the assembly performance of the computation.

3.4.7 Exploration and exploitation

Inquiry (for Global Optima) and Dual Contract (for assembly) are the two basic steps for any metaheuristic progress calculations. A decent compromise between these two characteristics would make the calculation heartier. Attack technique defined as the exploitation during defence technique defined as the exploration. The common advantages of the WOA are presented as follows,

- The proposed algorithm makes a great compromise between exploitation and exploration.
- Each provision (officer) has an interesting weight in light of his position.
- In the update step, each fighter's weight is updating assuming the fighter is working effectively on his health. In this way, weight regeneration is completely dependent on a molecular position relative to lords and lordship.
- Loads change non-linearly. The loads vary in large increments during the initial stress and in smaller increments during the last cycles. This empowers to faster convergence to the global optimum parameter.
- The stage regeneration cycle involves two phases. It further enhances the investigative capacity for global best arrangement.
- The proposed technique is straightforward and requires less computational weight.

Based on this algorithm, SOC management is achieved in the battery cell. The battery is mainly utilised to operate electric vehicle applications. In the application, the ageing of the battery is enhanced by managing the SOC in the system. The management of the SOC is achieved by utilising the WOA. Table 1 shows the implementation parameters.

Table 1 Implementation parameters

S. No.	*Description*	*Parameters*
1	Maximum capacity	40 Ah
2	Cut off voltage	10.5 V
3	Fully charged voltage	13.8 V
4	Nominal discharge current	20 A
5	Internal resistance	0.015 ohms
6	Capacity	30.14 Ah
7	Nominal voltage	12.6 V
8	Rated capacity	40 Ah
9	The initial state of charge	100
10	Battery response time	90 ms

4 Outcome evaluation

The performance of the proposed methodology is implemented and validated in this portion. The proposed method can be implemented in MATLAB/Simulink in addition presentations were assessed. The projected technique is validated with the development of battery ageing model and proposed controller. The proposed method is implemented on 32 GB of RAM in addition to a 4 GHz Intel core i78 system. The projected controller can be intended to manage the ageing condition of batteries in electric vehicle applications. The proposed controller is utilised to empower the battery operating conditions in the electric vehicle applications. The battery ageing model is empowering the lifetime of the battery by using the WOA technique. The proposed method is designed in the Simulink diagram which is presented in Figures 4 and 5.

Figure 4 Flowchart of the proposed methodology (see online version for colours)

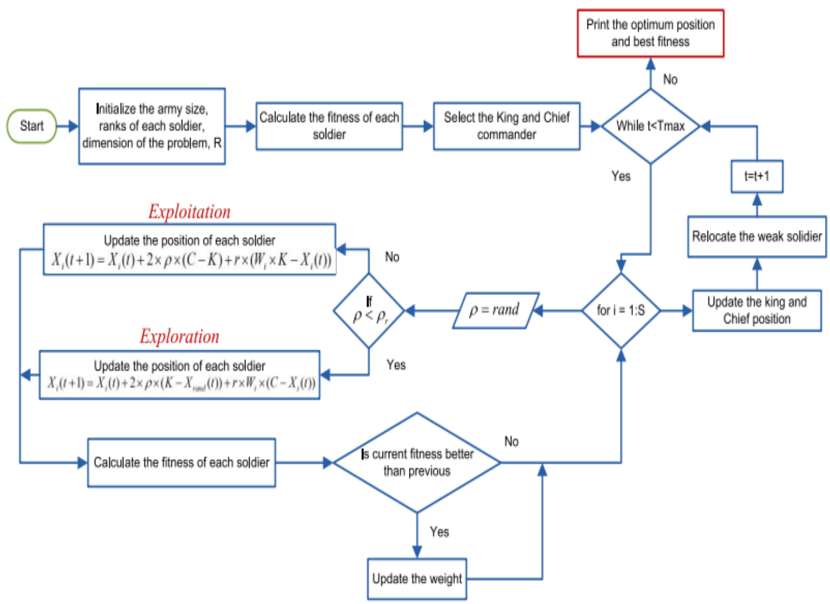
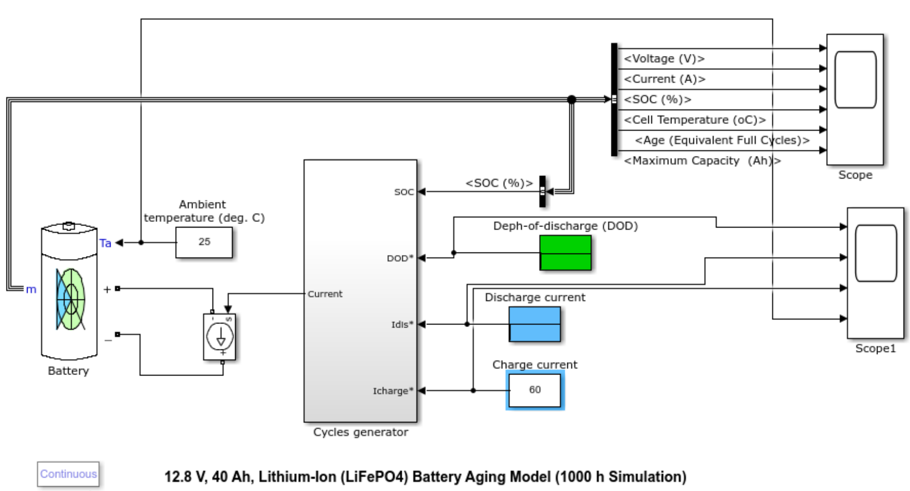


Figure 5 Simulink diagram (see online version for colours)



Case 1: High charging current and high temperature

In this case of analysis, the proposed battery ageing model is analysed with high charging current and high temperature. The battery SOC and DOD can be managed which enables the proper ageing model of the battery and enhance the lifetime of the battery in electric vehicle applications. To validate the proposed methodology, the ageing and capacity of the model, charging current and temperature, DOD and discharging current, SOC, and temperature and voltage with a current of the battery model are utilised.

In the battery ageing model, age and maximum capacity are given in Figure 6. The projected technique can be achieved in 800 cycles and 43 Ah. The charging current and temperature of the proposed model are given in Figure 7. The projected technique achieved a 60 A charging current and 250ºC temperature in the battery ageing model. The DOD and discharge current are given in Figure 8. The projected technique can be achieved 85 DOD and 40 A in the battery ageing model. The SOC and battery cell temperature are analysed and given in Figure 9. In the validation, the projected technique SOC is achieved at 80% and battery cell temperature is 650C respectively. After that, the battery current and battery voltage is given in Figure 10. In the validation, the projected technique is achieved at 12 V and 40 A. Based on the validation, the projected technique can be attained stable operation in the battery ageing model. The proposed method is utilised to manage the stable DOD and SOC in the battery for electric vehicle applications. So, the proposed model achieved efficient outcomes in terms of high temperature and high current applications.

Figure 6 Age and maximum capacity (see online version for colours)

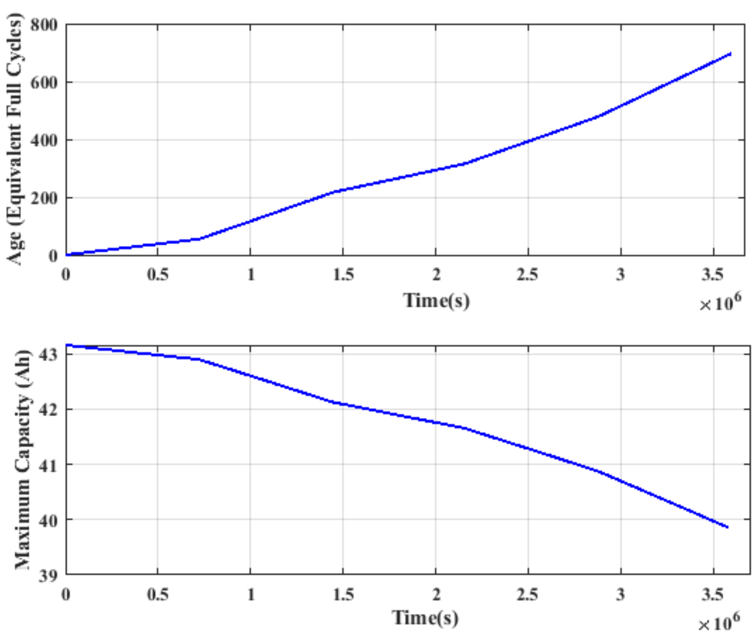


Figure 7 Charging current and temperature (see online version for colours)

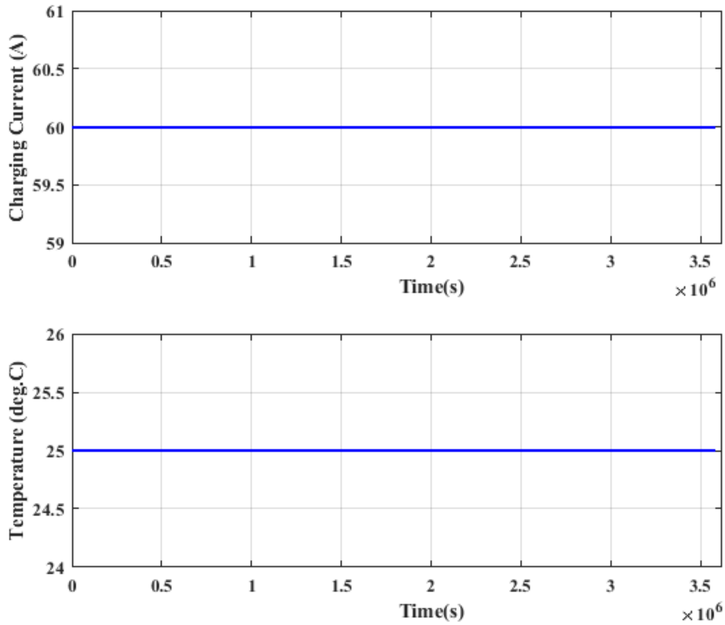


Figure 8 Depth of discharge and discharge current (see online version for colours)

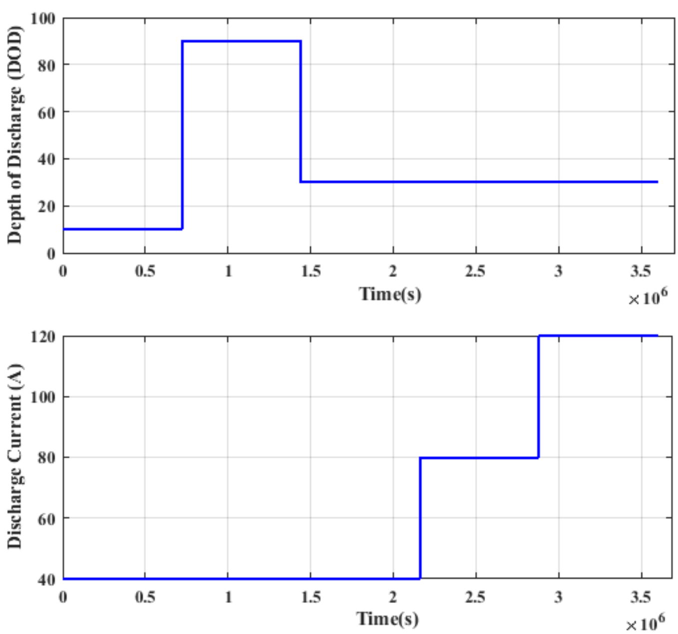


Figure 9 SOC and battery cell temperature (see online version for colours)

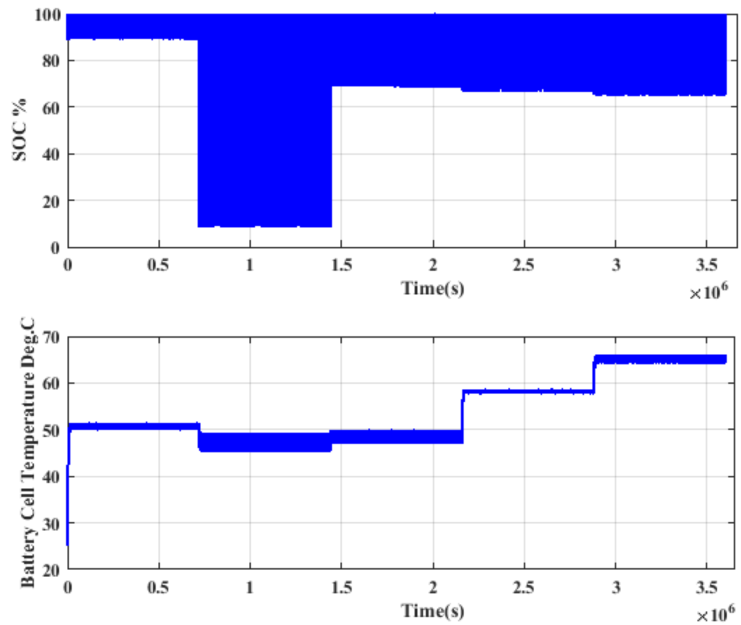
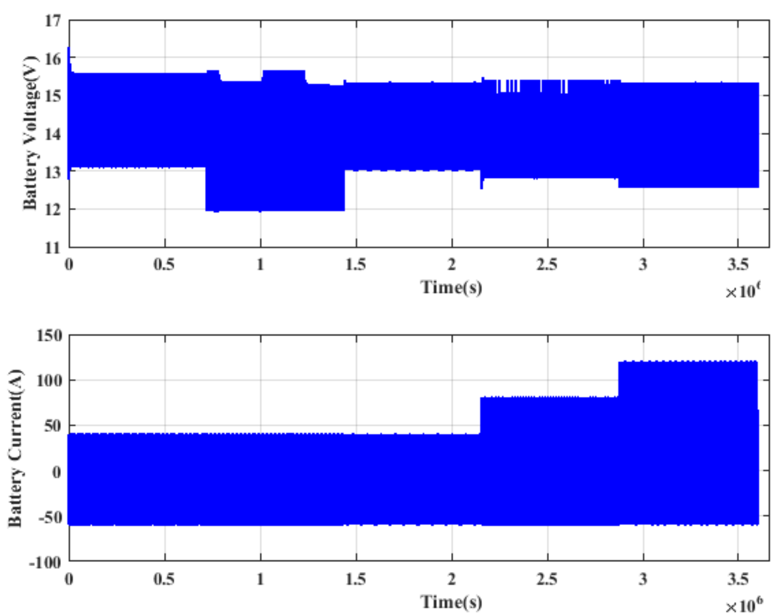


Figure 10 Battery voltage and battery current (see online version for colours)



Case 2: Low charging current and low temperature

In this case of analysis, the proposed battery ageing model is analysed with low charging current and low temperature. The battery SOC and DOD can be managed which enables the proper ageing model of the battery and enhance the lifetime of the battery in electric vehicle applications. To validate the proposed methodology, the ageing and capacity of the model, charging current and temperature, DOD and discharging current, SOC, and temperature and voltage with a current of the battery model are utilised.

In the battery ageing model, age and maximum capacity are given in Figure 11. The projected technique can be achieved in 300 cycles and 42 Ah. The charging current and temperature of the projected model are given in Figure 12. The projected technique can be achieved a 30 A charging current and 15ºC temperature in the battery ageing model. The DOD and discharge current are given in Figure 13. The projected technique achieved 50 DOD and 60 in the battery ageing model. The SOC and battery cell temperature are analysed and given in Figure 14. In the analysis, the proposed method SOC achieved 50% and battery cell temperature is 45ºC respectively. After that, the battery current and battery voltage is given in Figure 15. In the validation, the projected technique is attained at 15 V and 50 A. From the analysis, the proposed method achieved stable operation in the battery ageing model. The proposed method is utilised to manage the stable DOD and SOC in the battery for electric vehicle applications. So, the proposed model achieved efficient outcomes in terms of high temperature and high current applications.

Figure 11 Age and maximum capacity (see online version for colours)

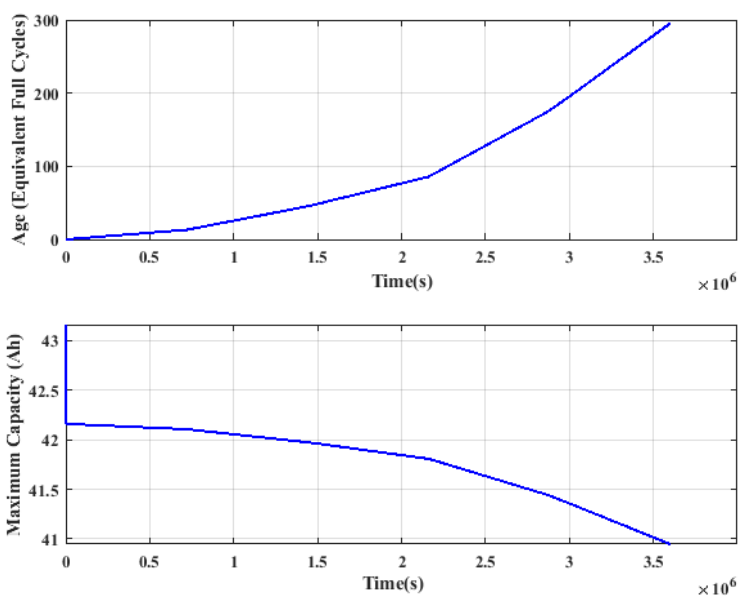


Figure 12 Charging current and temperature (see online version for colours)

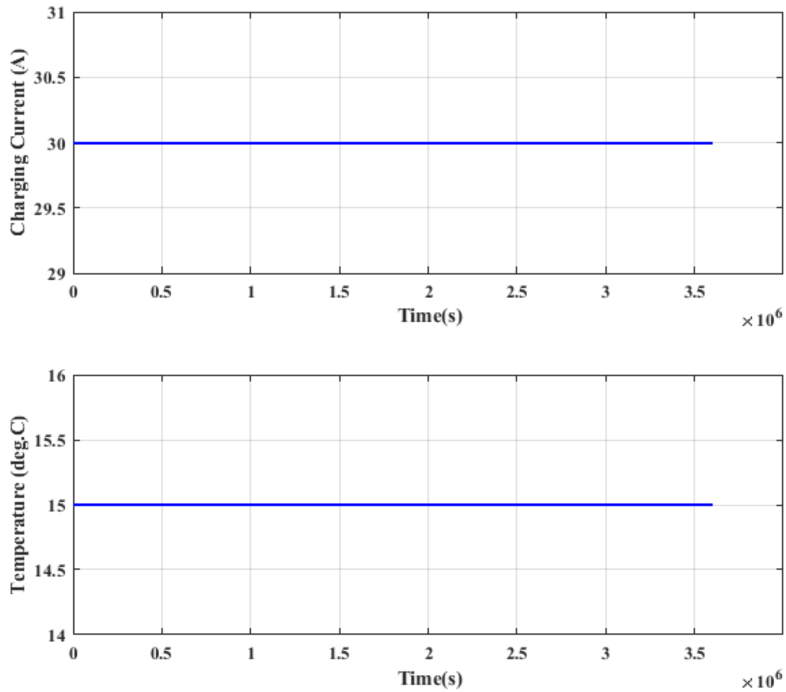


Figure 13 Depth of discharge and discharge current (see online version for colours)

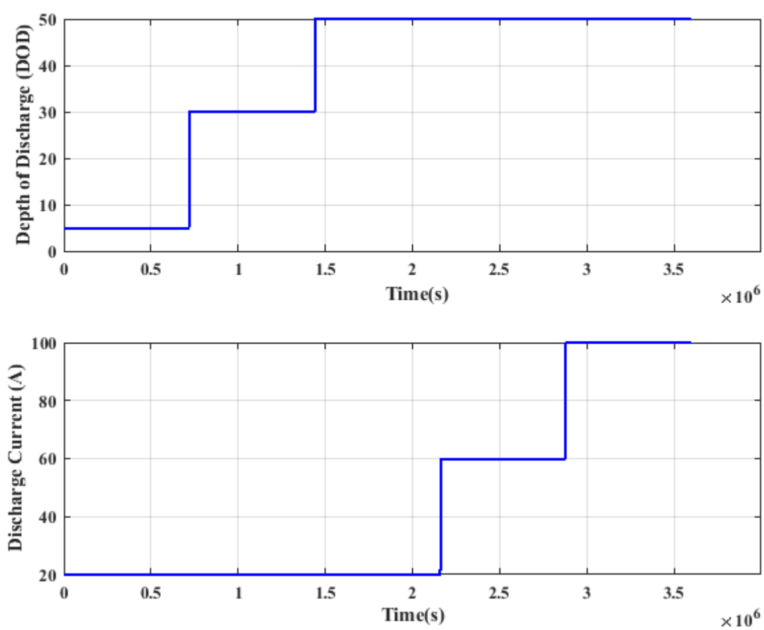


Figure 14 SOC and battery cell temperature (see online version for colours)

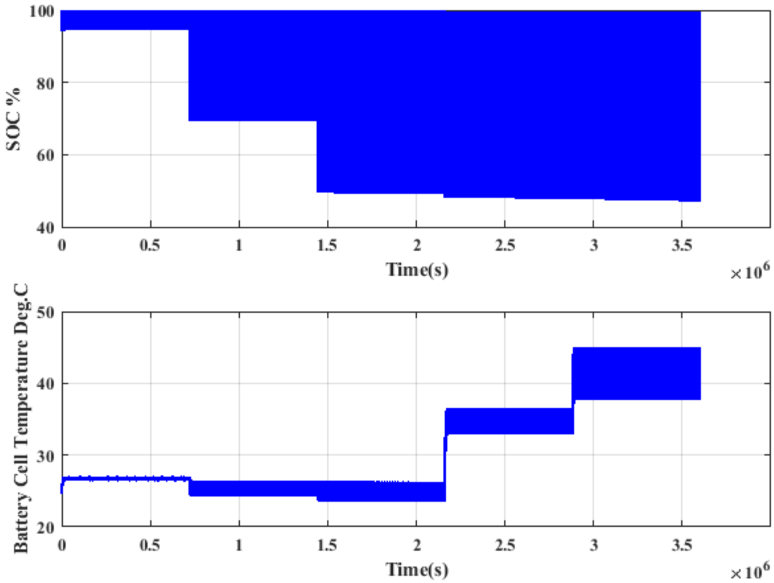
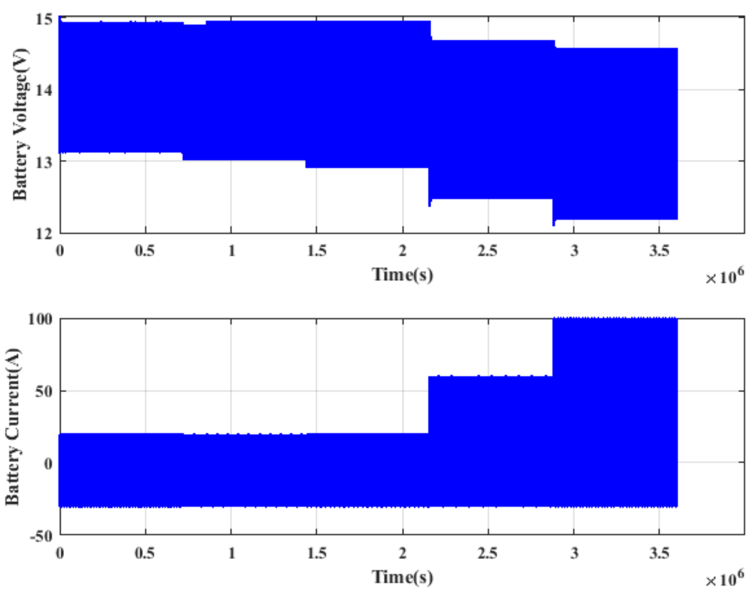


Figure 15 Battery voltage and battery current (see online version for colours)



5 Conclusion

This work has been developing a WOA-based battery ageing model for managing the battery capacity with the consideration of drivability, recharge time, and driving range. To achieve the battery ageing model, the DOD, SOC, and maximum battery current are considered. Additionally, the multi-objective function is considered to achieve a battery ageing model, which is solved by using WOA. Based on the electric load cycle, the battery control variables are upgraded with the consideration of weight updating in the battery model. The proposed technique can be implemented in MATLAB/Simulink in addition presentations can be examined with different parameters such as the ageing and capacity of the model, charging current and temperature, DOD and discharging current, SOC, and temperature and voltage with a current of the battery model. In the analysis, the proposed method achieved current and battery voltage of 15 V and 50 A. Based on the analysis, the projected technique can be attained stable operation in the battery ageing model. The proposed method is utilised to manage the stable DOD and SOC in the battery for EV applications. So, the projected model achieved efficient outcomes in terms of high temperature and high current applications. In future, we plan to present adaptive optimisation algorithm for developing efficient battery ageing model.

References

Anselma, P.G., Kollmeyer, P., Lempert, J., Zhao, Z., Belingardi, G. and Emadi, A. (2021) 'Battery state-of-health sensitive energy management of hybrid electric vehicles: lifetime prediction and ageing experimental validation', *Applied Energy*, Vol. 285, p.116440.

Ayyarao, T.S.L.V. and Kumar, P.P. (2022) 'Parameter estimation of solar PV models with a new proposed war strategy optimization algorithm', *International Journal of Energy Research*, Vol. 46, No. 6, pp.7215–7238.

Ayyarao, T.S.L.V., RamaKrishna, N.S.S., Elavarasan, R.M., Polumahanthi, N., Rambabu, M., Gaurav Saini, Baseem Khan, and Bilal Alatas (2022) 'War strategy optimization algorithm: a new effective metaheuristic algorithm for global optimization', *IEEE Access*, Vol. 10, pp.25073–25105.

Corno, M. and Pozzato, G. (2019) 'Active adaptive battery aging management for electric vehicles', *IEEE Transactions on Vehicular Technology*, Vol. 69, No. 1, pp.258–269.

Du, R., Hu, X., Lin Hu, S., Zhang, Z. and Lin, X. (2020) 'Battery aging-and temperature-aware predictive energy management for hybrid electric vehicles', *Journal of Power Sources*, Vol. 473, p.228568.

Han, L., Jiao, X. and Zhang, Z. (2020) 'Recurrent neural network-based adaptive energy management control strategy of plug-in hybrid electric vehicles considering battery aging', *Energies*, Vol. 13, No. 1, p.202.

Hussain, S., Ali, M.U., Park, G-S., Nengroo, S.H., Khan, M.A. and Kim, H-J. (2019) 'A real-time bi-adaptive controller-based energy management system for battery–supercapacitor hybrid electric vehicles', *Energies*, Vol. 12, No. 24, p.4662.

Karlsen, H., Dong, T., Yang, Z. and Carvalho, R. (2019) 'Temperature-dependence in battery management systems for electric vehicles: challenges, criteria, and solutions', *IEEE Access*, Vol. 7, pp.142203–142213.

Kuang, X., Li, K., Xie, Y., Wu, C., Wang, P., Wang, X. and Fu, C. (2020) 'Research on control strategy for a battery thermal management system for electric vehicles based on secondary loop cooling', *IEEE Access*, Vol. 8, pp.73475–73493.

Li, J., Wu, X., Xu, M. and Liu, Y. (2021) 'A real-time optimization energy management of range extended electric vehicles for battery lifetime and energy consumption', *Journal of Power Sources*, Vol. 498, p.229939.

Li, S., Zhao, P., Gu, C., Li, J., Cheng, S. and Xu, M. (2022) 'Battery protective electric vehicle charging management in renewable energy system', *IEEE Transactions on Industrial Informatics*, Vol. 19, No. 2, pp.1312–1321.

Lu, M., Zhang, X., Ji, J., Xu, X. and Zhang, Y. (2020) 'Research progress on power battery cooling technology for electric vehicles', *Journal of Energy Storage*, Vol. 27, p.101155.

Nguyen, B-H., German, R., Trovão, J.P.F. and Bouscayrol, A. (2018) 'Real-time energy management of battery/supercapacitor electric vehicles based on an adaptation of Pontryagin's minimum principle', *IEEE Transactions on Vehicular Technology*, Vol. 68, No. 1, pp.203–212.

Singh, A., Karandikar, P.B. and Kulkarni, N.R. (2021) 'Mitigation of sulfation in lead acid battery towards life time extension using ultra capacitor in hybrid electric vehicle', *Journal of Energy Storage*, Vol. 34, p.102219.

Xiong, R., Sun, W., Yu, Q. and Sun, F. (2020) 'Research progress, challenges and prospects of fault diagnosis on battery system of electric vehicles', *Applied Energy*, Vol. 279, p.115855.

Xiong, R., Zhang, Y., Wang, J., He, H., Peng, S. and Pecht, M. (2018) 'Lithium-ion battery health prognosis based on a real battery management system used in electric vehicles', *IEEE Transactions on Vehicular Technology*, Vol. 68, No. 5, pp.4110–4121.

Xu, B., Shi, J., Li, S., Li, H. and Wang, Z. (2021) 'Energy consumption and battery aging minimization using a Q-learning strategy for a battery/ultracapacitor electric vehicle', *Energy*, Vol. 229, p.120705.

Zhang, C., Kang, Y., Duan, B., Zhou, Z., Zhang, Q., Shang, Y. and Chen, A. (2021) 'An adaptive battery capacity estimation method suitable for random charging voltage range in electric vehicles', *IEEE Transactions on Industrial Electronics*, Vol. 69, No. 9, pp.9121–9132.

Zhou, B., Burl, J.B. and Rezaei, A. (2020) 'Equivalent consumption minimization strategy with consideration of battery aging for parallel hybrid electric vehicles', *IEEE Access*, Vol. 8, pp.204770–204781.