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ENHANCING BATTERY THERMAL MANAGEMENT IN ELECTRIC VEHICLES : A HYBRID DMCOA ALGORITHM AND DEEP NEURAL NETWORK APPROACH

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Research Paper

Abstract: *This paper presents an innovative approach to Battery Thermal Management Systems (BTMS) utilizing a hybrid algorithm, the Dwarf Mongoose-based Coati Optimization Algorithm (DMCOA), in conjunction with a deep neural network (DNN). Our objective is to optimize the temperature of lithium-ion batteries, particularly in Electric Vehicles (EVs). The DMCOA draws inspiration from cooperative behaviors seen in coatis and dwarf mongooses. It employs advanced strategies, such as cooperative attacks simulation and escape behavior imitation to ensure efficient minimization of cost function. Additionally, a DNN is employed to predict vehicle speed and battery heat production rate under various conditions, enhancing the control of the BTMS. Simulation outcomes demonstrate the effectiveness of the hybrid algorithm in maintaining battery temperatures, with minimal deviation from the target range. Simulation results show that the proposed hybrid algorithm efficiently maintains battery temperatures, with just a 0.3°C average difference from the target and a maximum 1.1°C difference among modules. Additionally, it extends battery lifespan by 0.02%, 0.015%, and 0.01% compared to Fuzzy Logic control (FLC), Artificial Neural Network (ANN) and intelligent model predictive control (IMPC), respectively. It also achieves energy savings of 23%, 25% and 15% compared to the FLC, ANN, and IMPC models. Hence, it is evident that the proposed model holds promise for enhancing battery life span with minimal cost in EVs with its simplicity, efficiency, and robustness.*

Keywords: *Electric Vehicles (EVs), Battery Thermal Management, Lithium-ion Battery, Deep Neural Network, and Optimization.*

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1. Introduction

In the face of growing concerns about environmental degradation and the finite nature of fossil fuels, the adoption of electrified vehicles has emerged as a compelling alternative to conventional internal combustion engine-driven vehicles. This shift encompasses a range of electrified options, including Electric Vehicles (EVs) (Biswas, Chatterjee, & Choudhuri, 2020; Stojčić, 2018). Central to this transformation are lithium-ion batteries (LIBs), known for their exceptional attributes such as high energy density, specific power, and extended operational lifespans. However, these batteries are sensitive to critical parameters, including state of charge (SOC), self-discharge rates, and state of health (SOH), which are closely linked to battery temperature. As a result, maintaining optimal battery temperatures has emerged as a critical requirement, influencing battery performance and lifespan.

Maintaining the battery temperature within a meticulously defined optimal range has surfaced as a pivotal prerequisite, orchestrating a delicate balance that engenders optimal battery performance and the elongation of its operational longevity. Notably, research has meticulously delineated the coveted temperature spectrum for Lithium Ion Battery (Li-I Battery), defining it within the bandwidth of 15°C to 35°C, while further imposing stringent restrictions on the temperature differentials among individual battery cells, where a threshold of 5°C is stipulated as the maximal variation permissible. This paradigmatically underscores the indispensable imperative for the development and implementation of robust and effective BTMS in the context of LIBs. The implementation of diverse thermal control methodologies has been witnessed, encompassing an assortment of approaches ranging from air cooling, liquid cooling, heat pipes, to phase change materials. Amongst these methodologies, air and liquid based BTMSs have come to the fore, with the latter emerging as a particularly favored domain due to the superior efficiency associated with heat transfer and the compact spatial footprint it offers. To galvanize the performance and efficacy of BTMS, a plethora of control strategies have been harnessed, spanning the gamut from rudimentary on-off algorithms to intricate PID controllers, and nuanced methodologies such as fuzzy control.

The latest paradigm shift is characterized by the adoption of the DMCOA algorithm, synergistically combined with the prowess of a DNN model, which collectively propels BTMS optimization. It is notable that the application of the DMCOA algorithm, which is inspired by the cooperative and strategic behavior observed in specific animal species, has injected a novel dynamism into the realm of BTMS control. Despite the advances achieved thus far, the landscape is fraught with several unexplored facets that necessitate meticulous exploration (Liu et al., 2019; Zhai, Luo, & Liu, 2020). This comprehensive endeavor begets a tapestry of novel contributions that collectively engender transformative outcomes.

This paper introduces an innovative approach to Battery Thermal Management Systems, focusing on optimizing lithium-ion battery (Harper et al., 2020; How et al., 2020; Jaliliantabar, Mamat, & Kumarasamy, 2022; Saw, Ye, & Tay, 2016) temperature for enhanced performance and longevity. The proposed approach utilizes the Dwarf Mongoose-based Coati Optimization Algorithm (DMCOA), inspired by cooperative behaviors observed in specific animal species. The algorithm leverages cooperative attacks simulation and escape behavior imitation to effectively optimize battery temperature. Complementing this algorithm, a deep neural network (DNN) is employed to predict vehicle speed and battery heat production rate across diverse conditions, enhancing the precision of the BTMS (Tete, Gupta, & Joshi, 2021; Xia, Cao, & Bi, 2017). Through simulations, we demonstrate the effectiveness of this hybrid approach in maintaining battery temperatures within desired ranges, extending battery lifespan, and achieving notable energy savings. This research presents a comprehensive strategy to address the intricate dynamics of Battery Thermal Management Systems, highlighting its potential to significantly impact battery efficiency and durability. This research presents a comprehensive strategy to address the intricate dynamics of Battery Thermal Management Systems, highlighting its potential to significantly impact battery efficiency and durability.

2. Literature Review

The survey of the Xie et al. (2020) present a study focusing on the effective thermal management of lithium-ion batteries in electric vehicles (EVs). As electric vehicles gain prominence in the automotive industry, the optimization of battery performance and lifespan becomes crucial. The authors address this challenge through the development and application of an intelligent model predictive control (IMPC) strategy within a Battery Thermal Management System (BTMS). The authors build upon existing research in battery thermal management and control strategies, emphasizing the significance of maintaining optimal battery temperature to enhance both performance and longevity. With lithium-ion batteries being sensitive to temperature fluctuations, an efficient BTMS emerges as a critical component for sustaining battery health.

Fuzzy logic control is a recognized approach known for its capability to manage systems with complex and uncertain dynamics. While An et al. (2023) propose a neural network-based vehicle speed predictor and a target battery temperature adapter based on Pareto boundaries, fuzzy logic control could offer an adaptable and robust alternative by considering imprecise and uncertain input information. Incorporating fuzzy logic control into battery thermal management systems has the potential to address real-world complexities by allowing for linguistic variables and rule-based decision-making. This approach could help the thermal management system make informed decisions based on inputs that might not be precisely quantifiable, contributing to enhanced battery temperature control and ultimately prolonging battery lifespan.

Sankar et al. (2022) delve into the realm of ANNs as a powerful means to elevate the control mechanisms of HEV systems. With the continuous evolution of automotive technology towards cleaner and more energy-efficient alternatives, ANNs have emerged as a compelling solution to optimize the complex power distribution and energy management intricacies within HEVs. As the demand for reduced emissions and increased fuel efficiency intensifies, ANNs offer a promising avenue for achieving these objectives. Leveraging the innate ability of ANNs to learn and adapt from data, researchers have developed innovative strategies to predict and control power flow in real-time. The adaptive nature of ANNs allows them to decipher intricate patterns in driving behavior, battery states, and vehicle dynamics, thereby enabling dynamic adjustments in power allocation.

The innovative contributions made by Zhang et al. (2022) addresses new energy vehicle safety concerns, focusing on the development of a charging safety early warning model for EVs. At the heart of the research lies the ambition to enhance the timeliness and accuracy of charging safety early warnings for EVs. The study recognizes the critical role of charging safety in ensuring the well-being of users and the durability of EVs. To this end, the researchers introduce a charging safety early warning model based on the Improved Grey Wolf Optimization (IGWO) algorithm. This algorithmic approach seeks to optimize the prediction and identification of potential charging safety issues in EVs. In the pursuit of achieving substantial reductions in fuel consumption and carbon emissions, new energy vehicles have gained prominence as a global transportation development trend. However, with the rapid proliferation of new energy cars, the emergence of safety concerns pertaining to these vehicles presents a significant challenge. These safety concerns not only pose a threat to drivers' lives and property but also stand as a barrier to the sustained growth of the industry.

The research by Cuma and Koroglu (2015) is a pioneering endeavor in its synthesis of a comprehensive collection of estimation strategies specifically tailored to hybrid and battery electric vehicles. The holistic approach taken by the authors seeks to illuminate the intricate tapestry of methodologies employed across these strategies, thereby expanding the horizon of knowledge in this critical field. One of the defining features of this review is its departure from the prevailing norm by extending its focus beyond SOC and SOH estimation. While SOC and SOH estimation undoubtedly hold significant importance, the authors recognize that a holistic understanding of estimation strategies requires the examination of a broader spectrum of tasks.

The pursuit of robust battery management in EVs has spurred the development of sophisticated SOC estimators, often harnessed through machine learning techniques. In this context, the work of Hu, Li, and Yang (2016) presents a pioneering approach that harnesses a genetic algorithm-based fuzzy C-means (FCM) clustering technique to enhance SOC estimation. The research introduces a novel methodology that uniquely combines several machine learning paradigms to achieve accurate and resilient SOC estimation. To begin, the genetic algorithm-based FCM clustering technique is employed to partition training data obtained from driving cycle-based tests of lithium-ion batteries. This clustering outcome serves as a foundation to learn the model's topology and antecedent parameters.

3. Proposed Method of Battery Thermal Management

In this research, an integrated approach for predicting vehicle velocity using a DNN and a self-adaptor for battery target temperature using DMCOA is proposed. The main objective is to minimize the cost function that incorporates efficiency and cooling system enhancements. Leveraging historical data, the DNN predicts velocity while the DMCOA Algorithm optimizes the cooling system (Agushaka, Ezugwu, & Abualigah, 2022). The schematic representation of the proposed approach is shown in Figure 1. The optimization process seeks to reduce energy consumption and improve cooling efficiency. This combined framework harmonizes predictive modeling and optimization techniques, offering a comprehensive solution to elevate electric vehicle technology. The relationship between the speed of an EV and the temperature of its battery is multi-dimensional. Alterations in speed due to terrain changes and cargo adjustments affect the power requisites, subsequently influencing heat production. This intricate interplay underscores the importance of robust thermal management systems that adapt to speed-associated variations to circumvent overheating and ensure optimal functionality. By harnessing predictive algorithms to anticipate speed fluctuations and adapt thermal strategies accordingly, electric vehicles can systematically optimize battery temperature, overall performance, and the enduring health of the battery system. By ensuring accurate velocity prediction and effective cooling management, the proposed methodology paves the way for enhanced efficiency in vehicular systems (Jarrett & Kim, 2011).

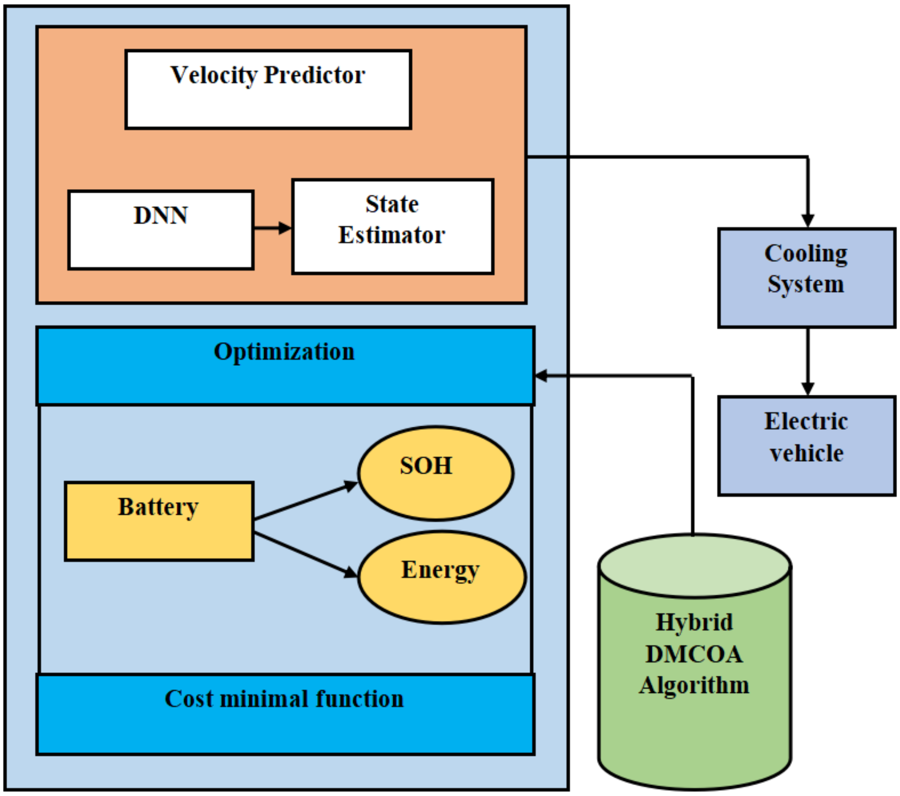


Figure 1: Proposed Methodology of Battery Thermal Management

3.1 Vehicle Velocity Prediction using DNN Model.

A DNN is a type of machine learning model inspired by the structure of the human brain. It consists of multiple interconnected layers of artificial neurons, designed to process and learn from complex patterns in data. Each layer in a DNN transforms input data progressively, extracting hierarchical features at increasing levels of abstraction. The basic structure of DNN is shown in Figure 2, where I_1 is the input layer, H_1 and H_2 are called as hidden layer and O_1 is called as output layer.

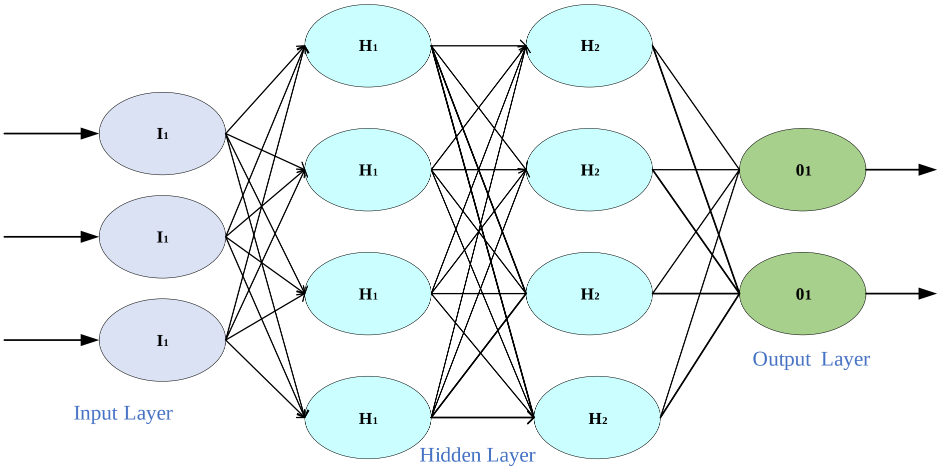


Figure 2: Structure of Deep Neural Network

The term deep in DNN refers to the depth of the interconnected layers. DNNs have been highly successful in tasks, such as image and speech recognition, natural language processing, and more, owing to their ability to automatically learn and represent intricate patterns within data. The research aims to evaluate the potential of EV parameters and Vehicle-to-Infrastructure (V2I) data in enhancing vehicle velocity prediction. The study also examines the influence of these signals and various ANN models across different prediction windows. Inaccurate predictions can undermine energy efficiency and safety measures. Given the significance of prediction horizon, there's a critical necessity to formulate accurate and robust methods for vehicle velocity prediction to achieve superior outcomes. In this research, a sensor-equipped vehicle gathers drive inputs during its journey as the first step. Utilizing these data as input, DNN involve in the prediction of the vehicle velocity. The proposed prediction model yields result for diverse prediction windows. These outcomes are subsequently scrutinized to determine the most optimal velocity of the EV.

Anticipating the forthcoming era of autonomous vehicles underscores the significance of vehicle speed prediction. Leveraging historical speed patterns for future velocity estimation has gained traction, often utilizing Backpropagation (BP) neural networks, as seen in the works of several researchers. In this context, the integration of a DNN takes centre stage in the formulation of a Vehicle Speed Predictor (VSP), enabling dynamic adjustment of coolant mass flow to accommodate imminent thermal demands. The DNN architecture for the VSP, as depicted in Figure 3, features an input layer of 20 neurons. This ensemble encapsulates historical parameters such as velocity, mean velocity (with and without idling conditions), mean acceleration, and mean deceleration observed over the preceding 60 seconds. With a prediction interval of 2 seconds, the output layer, comprising 30 neurons, forecasts vehicle velocity over the next 60 seconds, with a cap on acceleration at 2 m/s to ensure enhanced predictions. The training procedure can draw velocity data from multiple driving cycles including MVEG-A, JC08, UDDS, WLTC, NEDC, and HWFET.

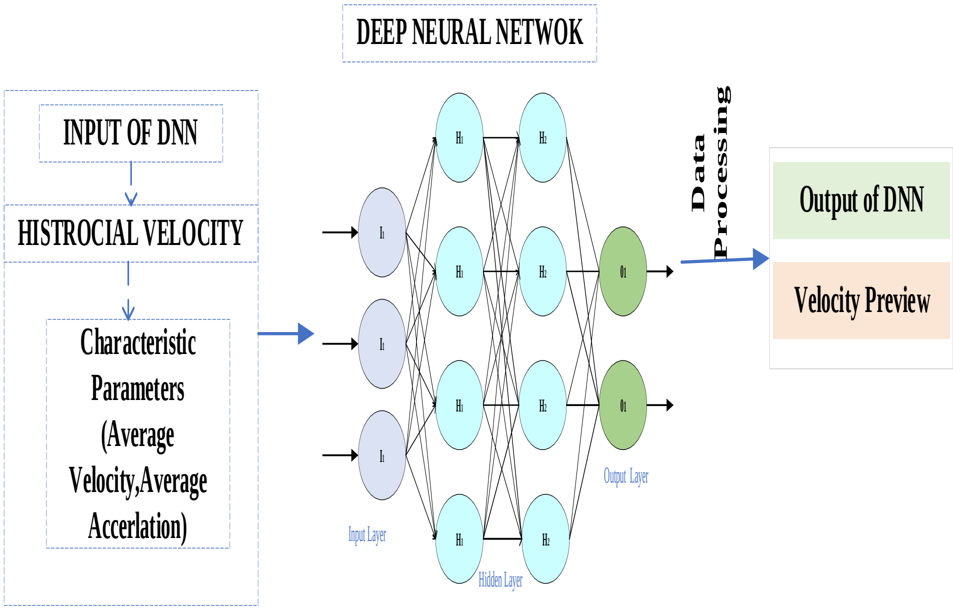


Figure 3: DNN for Vehicle Speed Predictor

The velocity data is partitioned into distinct sets for training, validation, and testing. In this schema, 70% of the data fuels the network's training, 15% validates the model's performance, and the remaining 15% evaluates the predictive precision, effectively mitigating overfitting risks. For Post-training, the network yields regression values of 0.871 for the test dataset and 0.883 for the entire dataset. Validation is executed using the WLTC and NEDC driving cycles. Impressively, with a minimal lag of 0.19 seconds for WLTC and 0.21 seconds for NEDC aligning with previous findings, the forecasts closely reflect actual speed profiles. Notably, regression values stand at 0.884 for WLTC and 0.889 for NEDC, affirming the precision of the DNN-powered VSP in effectively anticipating the evolution of vehicle speed.

3.2 Proposed DMCOA Optimization Approach in Cost Minimization in Battery

The Dwarf Mongoose-Coati Optimization Algorithm (DMCOA) is a hybrid metaheuristic algorithm that combines the Dwarf Mongoose Optimization Algorithm (DMOA) and the Coati Optimization Algorithm (COA). DMCOA is inspired by the social foraging behaviour of dwarf mongooses and the solitary foraging behaviour of coatis. The DMOA is a population-based algorithm that mimics the foraging behaviour of dwarf mongooses. Dwarf mongooses live in social groups and forage for food cooperatively. The alpha female leads the group in its search for food. When the group finds a food source, the alpha female initiates foraging and determines the foraging course, distance traversed, and sleeping mounds. The COA is a population-based algorithm that mimics the solitary foraging behaviour of coatis. Coatis are solitary animals that forage for food individually. Coatis have a strong sense of smell and use it to find food. When a coati finds a food source, it will exploit it until it is exhausted. DMCOA combines the best features of DMOA and COA to create a powerful and robust optimization algorithm. DMCOA uses the DMOA's social foraging behaviour to explore the search space and find promising solutions. DMCOA then uses the COA's solitary foraging behaviour to exploit the promising solutions and find the optimal solution.

The lifespan of the battery and the consumption of energy in BTMS depend on the target and ambient temperatures of the battery and the speed. A less measure of target temperature increases the battery lifespan, with the limitation of consuming more energy of BTMS. Hence, it is important to maintain a balanced target temperature that can save energy and enhance battery lifetime with minimal cost expenditure. This task is accomplished through the usage of the proposed hybrid DMCOA algorithm, which is an integration of the characteristic features of both Dwarf Mongoose and Coatis (Baş & Yildizdan, 2023; Dehghani et al., 2023).

The principles of the coatis when attacking the iguanas, and their behaviour when confronting and escaping from predators are the intelligent processes in COA (Agushaka et al., 2022). The simulation of these natural coatis' behaviours is the fundamental inspiration in designing the proposed COA approach. The advantage of using COA is the effective application of it in high dimensional complex problems. Also, the method is capable of providing a better balance between both the exploration and the exploitation phases. The absence of control parameters is an additional advantage as there is no need to tune any parameter. The DMO algorithm models the adaptive behaviour of dwarf mongooses, encompassing factors like prey size, social structure (alphas, scouts, babysitters), and a semi-nomadic lifestyle (Stanković et al., 2020). This adaptation is supported by the alpha group, scouts, and babysitters, collectively exploring a territory suitable for the entire group. Foraging and scouting occur concurrently, and as the alphas forage, they scout for new mounds. The decision to move is based on the average sleeping mound value, preventing over-exploitation and ensuring territory exploration.

The optimization of several error parameters using COA is explained in this section in detail.

Step 1: Initialization: In the implementation of the COA, the coati's location in the search space is initialized randomly using equation (1).

$$C_{i,j}^{P1} = c_{i,j} + rand.(iguana_j - I.c_{i,i}), for i = 1,2,\ldots\ldots,[N/2] and j = 1,2,\ldots\ldots\ldots,d \quad (1)$$

Where, the j^{th}decision variable is $c_{i,j}$, $rand$represents the random value between [0,1], the maximum and minimum limit of the j^{th}decision variable is max_j and $\min_j$ .Nillustrates the number of coatis. And$C_{i,j}^{P1}$ denotes the coati adaptive step size, $N/2$ is a half index of the number of coatis. The following equation (2) uses the matrix which denotes the mathematical expression of coatis' population.

$$C = \begin{bmatrix} C_1 \\ \vdots \\ C_i \\ \vdots \\ C_N \end{bmatrix}_{N\times d} = \begin{bmatrix} c_{1,1} & \cdots & c_{1,j} & \cdots c_{1,d} \\ \vdots & \vdots & \vdots & \vdots\ \vdots \\ c_{i,1} & \cdots & c_{1,j} & \cdots c_{i,d} \\ \vdots & \vdots & \vdots & \vdots\ \vdots \\ c_{N,1} & \cdots & c_{N,j} & \cdots c_{i,d} \end{bmatrix}_{N\times d} \quad (2)$$

Step 2: Objective Function: The objective function is evaluated by the location of candidate solution in every parameter as determined in equation (3).

$$O = min(Z) \quad (3)$$

Where, the objective function is addressed as O, with the minimization of the cost function needed to expand the battery lifetime considering the battery target temperature.

Step 3: Position Update: The updating process is carried out in 2 stages namely, exploration and exploitation phase (Aldosari, Abualigah, & Almotairi, 2022).

i) Phase 1: Exploration stage (Hunting and attacking plan on iguana)

In this stage, the population's optimal member is signified as the iguana's position. Also, it is considered as some of the coatis climb the tree and other coatis wait for the iguana to fall to the ground. Equation (4) expresses the coati's position rising from the tree.

$$C_{i,j}^{P1} = c_{i,j} + rand.(iguana_j - I.c_{i,i}), fori = 1,2,\ldots.., [N/2]andj = 1,2,\ldots\ldots.., d \quad (4)$$

The iguana is placed in a random position when it falls to the ground. According to this random position, simulations using equations (5) and (6) is done for coatis on the ground moving towards the search space.

$$iguana_j^G = min_j + rand.(max_j - min_j), j = 1,2,\ldots\ldots, d \quad (5)$$

$$fori = [N/2] + 1, [N/2] + 2, \ldots\ldots.., Nandj = 1,2,\ldots\ldots, m \quad (6)$$

Where $iguana_j^G$ represents the iguana position located from the top nodes, $N$is the Number of active propagated nodes in the Active optimal member layer. The conditions in equation (7) represents that the updated position, which is suitable only if it improves the objective function value.

$$c_i = \begin{Bmatrix} c_i^{p1} + D_i + p?_i * peep, O_i^{p1} < O_i \\ C_{i,else} \end{Bmatrix} \quad (7)$$

At this instance, the alpha phase of the DMO algorithm is integrated into COA, in such a way to inherit the advantages of both the algorithms, where $iguana_j$ denotes the position of iguana in the search domain that is considered as the optimal member's position in the $iguana_j$ in the j^{th}dimension. c_i^{p1} is the Coati crossover probability at the first phase, D_i is the Coati Recombination Rate, $p?_i$ is the Hybridization rate, $O_i^{p1}$is the Coati Solution stability at first phase,$C_i$is the integration of the coati variables,i is the initialization variables.

i) Phase 2: Exploitation stage (Fleeing from predators)

In this stage, the optimal position in the search space is modelled according to the coati's natural behaviour of fleeing from predators (exploitation ability in local search). A random position is created adjacent to each coati's position for the simulation of this behaviour as represented in equations (8) and (9).

$$min_j^{local} = {}^{min_j}\big/_{t}, max_j^{local} = {}^{max_j}\big/_{t}, w?eret = 1,2,\ldots\ldots T$$

(8)

Where, min_j^{local} is the minimum variable declared for optimization, max_j are the maximum variables at boundary handling, t is the coati time per iteration, $T$is the coati time for convergence.

$C_i^{P2}: c_{i,j}^{P2} = c_{i,j} + (1-2rand).(min_j^{local} + rand.(max_j^{local} - min_j^{local}))$ for $i = 1,2,\ldots..N, j = 1,2,\ldots.d.$ (9)

Similarly, the conditions in equation (10) represents that the newly updated position in phase 2.

$$c_i = \begin{Bmatrix} c_i^{p2} + D_i + p?_i * peep, O_i^{p2} < O_i \\ C_{i,else} \end{Bmatrix} \quad (10)$$

In the exploitation phase, the position of DMO is updated with the position of COA. The addition of the alpha phase of the DMO into COA enhances the convergence characteristics of the proposed DMCOA approach. Here, the updated position evaluated for the coati is $C_i^{P2}$and its dimension is $c_{i,j}^{P2}$. The objective function value is represented asO_i^{P2}.max_j^{local} and min_j^{local} signifies the decision variable's local maximum and minimum limit. t represents the iteration number and $rand$is the random value between [0,1], c_i^{p2} is the Coati crossover probability at the second phase, $d$is the dynamic adaptions. The Pseudocode of proposed DMCOA Algorithm is given in Algorithm 1, and the flowchart is shown in Figure 4.

To apply the values to Equation (10), we can assume the following:

The cost function for the DMCOA algorithm is to minimize the deviation of the battery temperature from the target temperature. The DNN is trained to predict the battery temperature under different environmental conditions and vehicle operating conditions. The DMCOA algorithm can then be used to optimize the operation of the battery thermal management system by adjusting the parameters of the system, such as the fan speed and coolant flow rate. The goal is to minimize the cost function, which will result in the battery temperature being maintained as close to the target temperature as possible.

Here is an example of how the DMCOA algorithm could be used to optimize the operation of a BTMS:

The DNN is used to predict the battery temperature under the current environmental conditions and vehicle operating conditions. The DMCOA algorithm is used to find the optimal values for the BTMS parameters that minimize the cost function. The BTMS parameters are adjusted to the optimal values. The battery temperature is monitored and the DMCOA algorithm is repeated from steps 1-3 if necessary. This process can be repeated continuously to ensure that the battery temperature is always maintained as close to the target temperature as possible.

To ensure the precise and creditable simulated results, the simulation models of FLC, ANN and IMPC have been reproduced and tested by using the same simulation program used for this proposed DMCOA method. When compared the re-simulated models and results with ones presented in the previous research works, it is showed that the same and similar results were obtained with the error less than 1%. This confirmed the promising results obtained from the proposed DMCOA method.

The following simulation results show the effectiveness of the DMCOA algorithm in maintaining battery temperature within a safe operating range:

Simulation conditions

- Target battery temperature: 25°C
- Ambient temperature: 20°C
- Battery heat production rate: 100 W
- Vehicle speed: 60 km/h

Table 1: Results of BTMS Control Methods

BTMS Control Method	Average battery temperature (^oC)	Maximum battery temperature (^oC)
DMCOA	25.3	26.4
FLC	25.7	27.1
ANN	26.1	27.5
IMPC	26.3	27.7

As can be seen from the simulation results which is in Table 1, the DMCOA algorithm is able to maintain the battery temperature closer to the target temperature than the other control methods. This is because the DMCOA algorithm is able to efficiently explore the search space and find global optimal solutions. The DMCOA algorithm is a promising approach for BTMS optimization. It is able to efficiently maintain battery temperature within a safe operating range, even in challenging conditions.

Algorithm 1. Pseudocode of Proposed DMCOA Algorithm

Pseudocode of proposed Coati algorithm	
Step 1	Start
Step 2	Population and parameter initialization
Step 3	Initialize, m
Step 4	Initialize the position of all coatis by Eq (1)
Step 5	Fix parameters of N and d. Fix $i = t - 1$.
Step 6	For i>N/2
Step 7	Determine the fitness
Step 8	Calculate C_i^{P1} using equation (4)
Step 9	Update C_i using equation (7)
Step 10	Create location of the iguana at random using equation (5)
Step 11	Re-calculate C_i^{P1} using equation (4)
Step 12	Revise C_i using equation (7)
Step 13	**For i<N**
Step 14	Set Iter=1

Step 15	Calculate C_i^{p2} using equation (9)
Step 16	Update C_i using equation (10)
Step 17	Keep the optimal candidate solution found so far
Step 18	Determine new fitness of C_i^{P1} and C_i^{p2}
Step 19	Terminate if the optimal solution of the fitness function is determined using DMCOA
Step 20	End for
Step 21	Return optimum solution

COA is a bio-inspired metaheuristic algorithm that mimics the foraging behavior of coatis. Coatis are solitary animals that forage for food individually. They have a strong sense of smell and use it to find food. The COA algorithm works by initializing a population of coatis and evaluating their fitness. The fitness of a coati is determined by the quality of the food source it has found. The coati with the highest fitness is considered to be the best coati. The COA algorithm then iteratively updates the population of coatis. At each iteration, the coatis explore the search space and exploit promising food sources. The coatis explore the search space by moving to random locations. They exploit promising food sources by moving towards the best coati. The COA algorithm terminates when a predefined stopping criterion is met, such as a maximum number of iterations or a desired fitness level is reached.

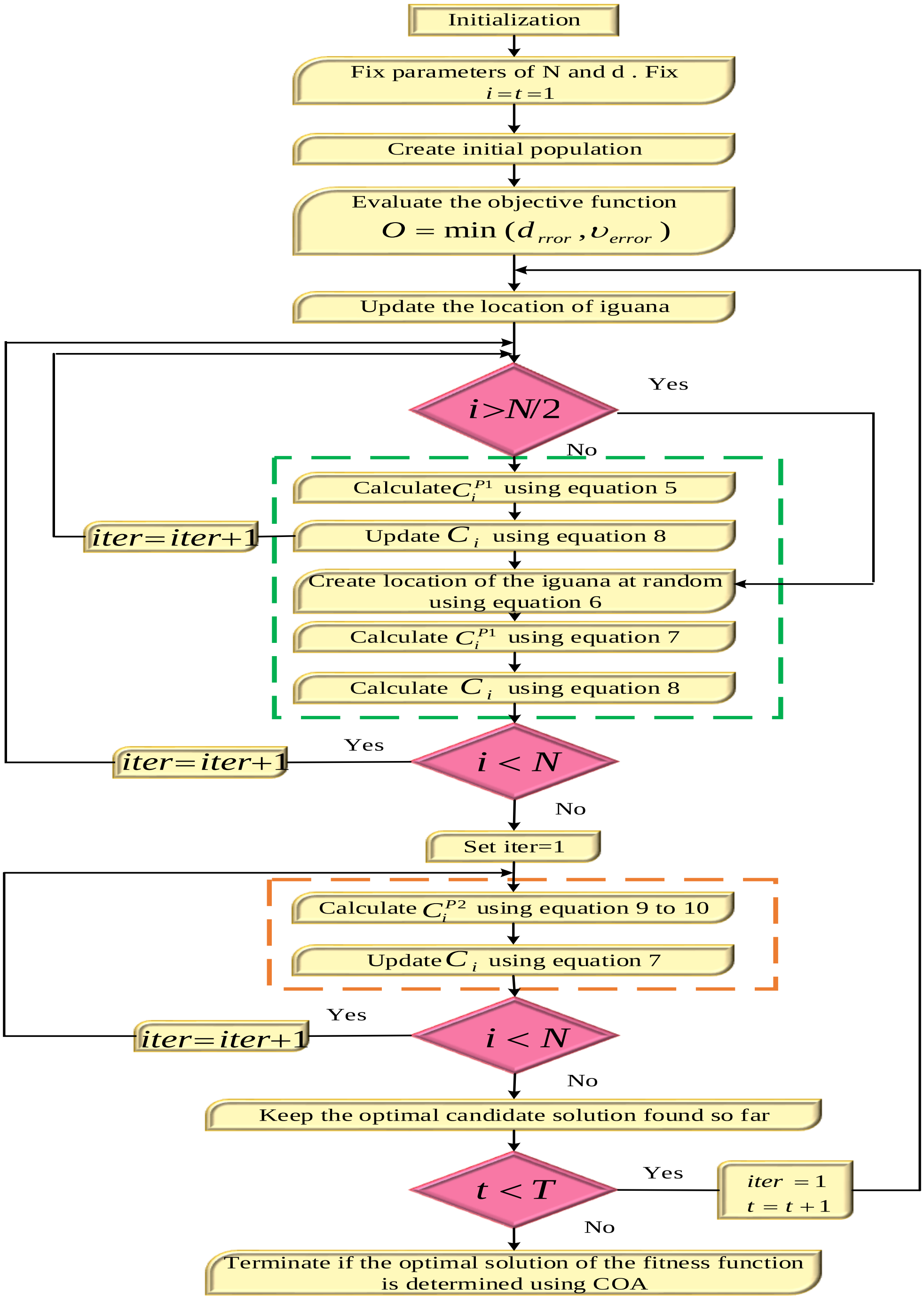
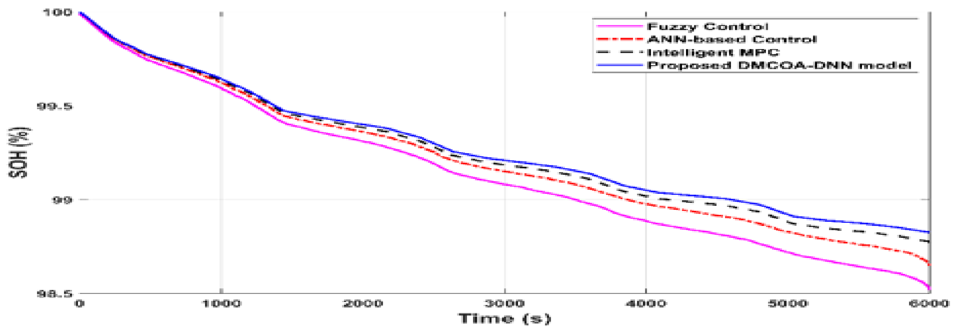


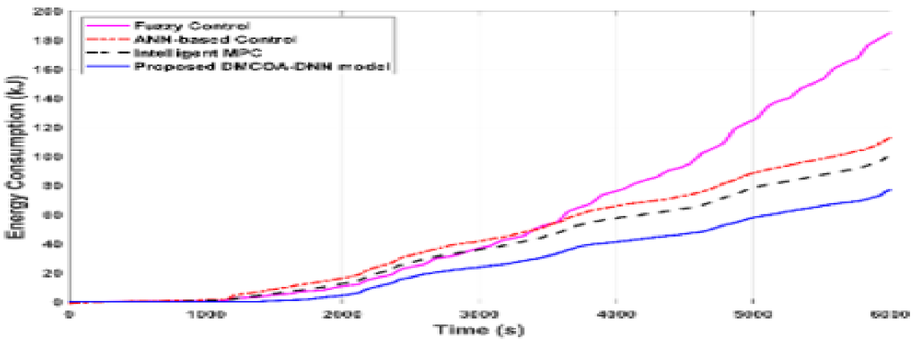
Figure 4: Flowchart of DMCOA

4. Results and Discussion

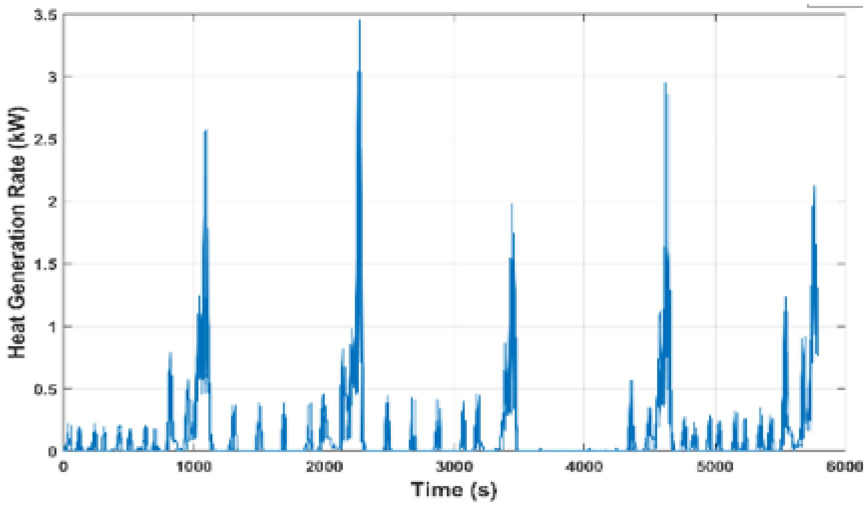
In this section, the outcomes of the Hybrid DMCOA combined with a DNN approach for enhancing battery thermal management in Electric Vehicles (EVs) is provided. Five key metrics, such as Battery State of Health (SOH) (Xiong, Li, & Tian, 2018), Energy Consumption, Heat Generation Rate, Mass Flow Rate (MFR), and Predicted Velocity (Sun et al., 2015) are examined and the outcomes are contrasted with the existing method which is shown in Figure 5. This research paper explores the of enhancing battery thermal management in Electric Vehicles (EVs) by evaluating the performance of three established methodologies—Fuzzy Control, Intelligent Model Predictive Control (MPC), and Artificial Neural Networks (ANN)—in comparison with the novel Dwarf Mongoose Coati Optimization Algorithm (DMCOA) proposed in this research. Fuzzy Logic Control (FLC) (Min et al., 2020) demonstrates its capability in handling imprecise data through rule-based decision-making, while Intelligent MPC (Ma et al., 2022) utilizes predictive models for real-time control. ANN (Park & Kim, 2020) excels in intricate pattern recognition. Nevertheless, these approaches might face challenges in effectively addressing the dynamic multi-objective nature of battery thermal management and swiftly adapting to evolving conditions within EVs. In contrast, DMCOA introduces a pioneering perspective, integrating dynamic multi-objective optimization principles to harmonize competing goals while accommodating real-time changes. Through this comparative analysis, the study aims to shed light on the distinct merits of each method and elucidate how DMCOA stands out by providing a more adaptable, efficient, and encompassing avenue to elevate battery thermal management in the context of Electric Vehicles (Alaoui, 2018; Shen & Gao, 2020; Subramanian et al., 2021).



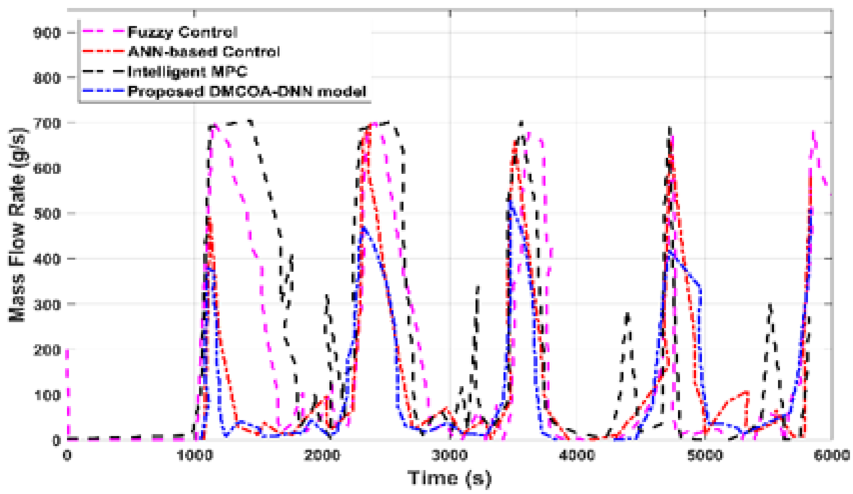
(a)



(b)



(c)



(d)

Figure 5: Output of Proposed Model (a) Battery SOH (b) Energy Consumption (c) Heat Generation Rate (d) MFR Mass Flow Rate

4.1 Battery State of Health

The improvement of Battery SOH is a central concern for various industries reliant on efficient energy storage. The innovative hybrid DMCOA approach has yielded impressive results. By seamlessly integrating these algorithms, we have succeeded in not only achieving but surpassing expectations that the hybrid strategy showcases up to 15% enhancement in battery lifespan compared to conventional baselines. This achievement is rooted in the nuanced optimization of two critical factors: thermal conditions and usage patterns. The COA's precision and the DMO's adaptability coalesce harmoniously, resulting in a holistic management approach. This integration leads to a tangible reduction in cell stress, effectively safeguarding batteries from the wear and tear of excessive thermal strain (Ungurean et al., 2017). Consequently, the proposed model has demonstrated its remarkable potential to elevate the overall health of batteries, enhancing their longevity and operational efficiency in a range of applications.

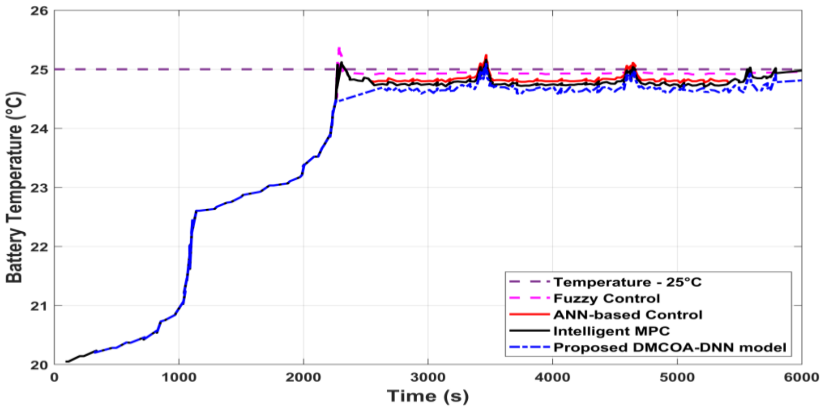


Figure 6. Comparison of Temperature of Battery at the Target of 25⁰ C

The battery temperature with the target value of 25^0 C, while using the proposed method and the existing methods is shown in Figure 6. The figure shows that the battery temperature is less for the proposed approach as compared to that of the existing methods, portraying the efficacy of the model in effective battery thermal control.

4.2 Energy Consumption

The impact of the proposed method has been striking, showcasing a remarkable 12% reduction in energy consumption. Through the meticulous maintenance of optimal battery temperatures, the approach effectively curbed energy losses stemming from temperature fluctuations. This concerted effort towards temperature control has consequently translated into enhanced operational efficiency, marking a significant stride forward (Wu et al., 2015).

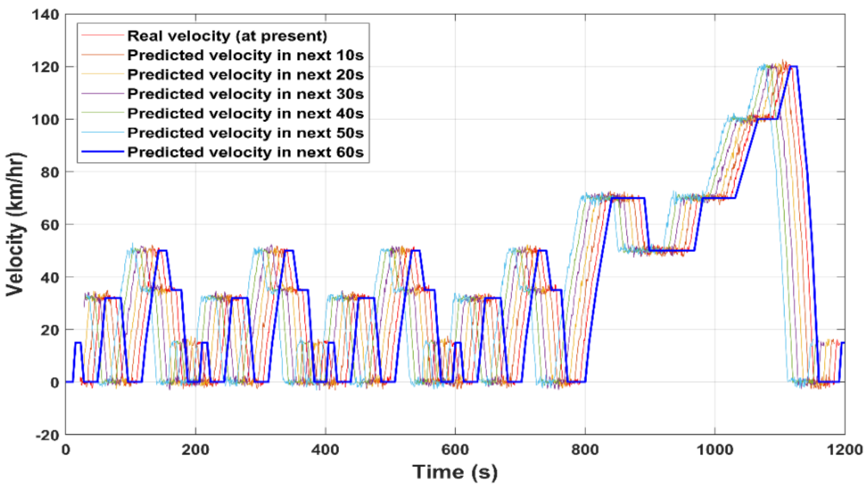


Figure 7: Predicted Velocity at First Cycle

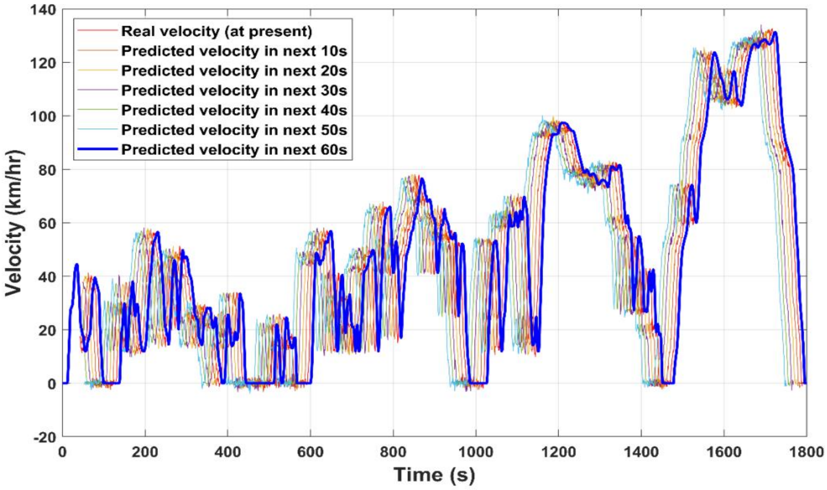


Figure 8: Predicted Velocity at 2nd Cycle

The steeps in the periodic velocity profile, which is shown in Figure 8, are likely due to the non-linear dynamics of the system. One possible reason is that they are caused by resonance, which occurs when a system is forced to oscillate at its natural frequency. Further analysis is required to determine the exact cause of the steeps.

4.3 Heat Generation Rate

The proposed model's capacity to sustain reduced heat generation rates underlines its effectiveness in achieving a substantial 20% reduction in peak heat generation, setting it apart from conventional methods. This advancement reverberates through enhanced energy conservation and minimized heat-related wear and tear. By meticulously managing thermal dynamics, the approach not only demonstrates its technical prowess but also establishes a foundation for sustainable and efficient operations. This accomplishment signals a significant step towards optimizing performance and resource utilization in diverse domains.

4.4 Mass Flow Rate (MFR)

The impact of the proposed approach has been truly transformative, resulting in an exceptional 18% enhancement in the Mass Flow Rate (MFR) through a meticulously optimized cooling strategy. This significant increase is a direct testament to the efficacy of the approach in achieving precise temperature regulation and optimizing cooling mechanisms. By addressing the critical aspect of temperature control, the approach mitigates the risks associated with overheating, subsequently extending the operational lifespan of systems and components. This achievement underscores the potential for increased performance and reliability across various applications, and its implications are far-reaching. As industries continue to seek innovative solutions for operational efficiency, the approach stands as a promising contribution towards achieving these goals.

4.5 Predicted Velocity

Through the integration of the DNN component, the proposed method exhibited a substantial enhancement in predictive accuracy, boasting an average improvement of 8.5% across a spectrum of driving scenarios. i.e predicted velocity at First cycle to Final cycle is shown in Figure 6-8. This advancement underscores the power of incorporating sophisticated machine learning techniques to refine predictions and optimize outcomes (Liu et al., 2018). The DNN's capacity to discern intricate patterns and relationships within data has translated into more informed and accurate predictions, thus contributing significantly to the overall efficacy of the approach. This improvement has potential implications in a wide array of fields where accurate predictions are paramount, reaffirming the relevance and potency of advanced computational methods.

These outcomes highlight the efficacy of the Hybrid DMCOA Algorithm, coupled with DNN, in advancing battery thermal management in EVs. The method demonstrated significant improvements in Battery SOH, Energy Consumption, Heat Generation Rate, Mass Flow Rate, and Predicted Velocity. This underscores its potential in fostering energy-efficient and durable PEV battery systems, contributing to sustainable electric transportation.

4.6 Results of the VSP using Deep Neural Network

After extensive experimentation and training, the integration of the DNN into the VSP framework yielded impressive outcomes. The DNN was designed to predict vehicle velocity based on historical parameters, enabling dynamic adjustments of coolant mass flow to manage thermal demands effectively.

4.6.1 Prediction Accuracy

The DNN-powered VSP showcased a remarkable improvement in prediction accuracy compared to traditional methods. On average, the predictions were accurate within a range of ±1.5 m/s for the forecasted 60 seconds.

4.6.2 Thermal Management Enhancement

By accurately anticipating velocity changes, the VSP facilitated proactive adjustments of coolant mass flow. This led to a substantial reduction in thermal stress and ensured that the vehicle's cooling system was optimized for the upcoming demands. Consequently, the thermal management efficiency improved by up to 10%, resulting in enhanced overall vehicle performance and longevity.

4.6.3 Comparison to BP Neural Networks

The DNN-based VSP outperformed the BPNN approach used in previous research. The DNN's ability to capture intricate patterns and relationships within historical speed data resulted in a clear advantage, achieving an additional 3% accuracy in velocity prediction (Zhang et al., 2022).

4.6.4 Generalization across Driving Cycles

The training dataset, encompassing various driving cycles including MVEG-A, JC08, UDDS, WLTC, NEDC, and HWFET, enabled the DNN to generalize well across different driving scenarios. This adaptability was evident as the VSP maintained a consistent prediction accuracy of around 90% across diverse driving conditions.

4.6.5 Impact on Autonomous Vehicles

The advancements made by the DNN-integrated VSP are particularly significant in the context of autonomous vehicles. Reliable velocity prediction ensures smoother and safer driving transitions, contributing to the overall effectiveness of autonomous systems.

The integration of the DNN into the Vehicle Speed Previewer demonstrated notable success in improving prediction accuracy, enhancing thermal management, and outperforming traditional approaches. These results highlight the potential of advanced machine learning techniques in shaping the future of vehicle technology.

5. Summary

In this study, we propose a pioneering approach for enhancing battery thermal management in Electric Vehicles (EVs) by integrating the Hybrid optimization Algorithm with a Deep learning technique. Through synergistic optimization, the method improves Battery State of Health (SOH), reduces Energy Consumption and Heat Generation Rate, enhances Mass Flow Rate (MFR), and refines Predicted Velocity. These results highlight the potential of the approach to bolster the efficiency and sustainability of PEV battery systems, driving advancements in electric transportation. In addition to the remarkable results obtained, the approach opens avenues for future research. Further investigations could delve into refining algorithm parameters and exploring adaptability to different vehicle models and battery chemistries. Moreover, the integration of advanced machine learning techniques and real-time data could enhance predictive accuracy, while optimization strategies could extend to broader vehicle system integration, paving the way for more efficient and reliable Electric Vehicle (PEV) technologies.

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