Optimal Scheduling of Electric Bus Fleets Using PSO-RNN for Enhanced Battery Life and Efficiency

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ABSTRACT

This paper presents an ideal strategy for electric bus fleets (EBFs) using a Particle Swarm Optimization-Recurrent Neural Network (PSO-RNN) approach, by a focus on enhancing battery life by considering battery capacity fade. The proposed method addresses the nonlinear nature of battery degradation and formulates the EBF scheduling problem as a multi-stage decision process. The PSO-RNN model is utilized to determine the optimal scheduling strategy that reduces the sum of battery alternates on the running life of the electrical vehicle (Buses). This research study is conducted using an urban public transit system as a case study, with scenarios considering five and seven different working loads. Results demonstrate that the optimal scheduling strategy significantly reduces battery capacity loss and the sum of alternates, leading to lower operational costs and extended battery life. The efficacy of the intended method is validated by comparing the battery capacity fading process and replacement frequency under both scheduled and unscheduled scenarios.

Keywords: Electric bus fleets (EBFs), Particle Swarm Optimization-Recurrent Neural Network (PSO-RNN), Optimal scheduling, battery capacity fade, Multi-stage decision process, Battery life extension, Operational cost reduction

1. INTRODUCTION

Electric vehicles (EVs) were acknowledged as a key solution for promoting sustainable economic development in urban areas. Today, three main types of EVs are widely utilized: plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), & hybrid electric vehicles (HEVs). EV buses in public transport were seen as an important first step toward wider EV adoption. BEVs represent a major category of EVs in public transportation. Lithium-ion batteries were primarily chosen as the energy storage system (ESS) for electric buses due to their best performance in balancing energy and power densities. Despite their advantages, the current battery-based ESS faces challenges such as limited battery lifespan and high replacement costs. Consequently, there is an urgent need to improve the management of energy of EVs to optimize in internal and external operations [1]. For internal operations, advancements in battery management systems (BMS's) that focus on the charging and discharging features of batteries be capable of increase battery life. Efficient BMS's monitor and manage the battery's state of charge, health, and temperature, thereby preventing overcharging and deep discharging, which are critical for prolonging battery lifespan and ensuring safety.

For external operations, balanced allotment of EVs formed on the qualities of their working loads can decrease the operational costs. This involves optimizing the routes and schedules of electric buses to match demand patterns, thus improving energy efficiency and minimizing idle time [2]. Additionally, the adding of smart grid technologies and real-time data analytics can further enhance the operational efficiency of EV fleets by enabling dynamic adjustments based on traffic conditions and energy availability. While EVs, particularly electric buses, offer a promising avenue for sustainable urban development, addressing the challenges associated with battery longevity and operational efficiency is essential. By improving BMSs and optimizing EV scheduling, it is possible to extend battery life, lower costs, and enhance the performance and Stability of electric public transit systems [3]. Transporting on electric buses involves setting up special charging facilities that need to be added to the existing infrastructure. There are various charging technologies available to adopt the effective operation of electric buses, each with its unique features and requirements. Slow plug-in mounts are typically connected at bus depots where buses are parked for extended periods, such as overnight. These chargers operate at a lower power level, allowing for a gradual and complete recharge of the bus batteries [4]. This method is cost-effective and minimizes the strain on the electrical grid, making it a practical solution for regular, scheduled charging cycles. Fast plug-in chargers or pantograph systems are designed for quick charging sessions, usually

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installed at bus terminals or along bus routes at designated stops. These chargers operate at higher power levels, enabling buses to receive a significant charge within a short time frame, typically during layovers or between trips. Pantograph chargers are mounted above the bus and automatically connect to the bus's charging system, providing a seamless and efficient charging process. Overhead contact lines and inductive chargers offer continuous or opportunistic charging while the bus is in operation. Overhead contact lines provide direct electrical contact with the bus via overhead wires, like traditional trolleybus systems. Inductive chargers, on the other hand, use wireless technology to transfer energy from embedded coils in the road to receiving coils on the bus [5]. This method allows buses to recharge their batteries without stopping, maintaining operational flexibility and reducing downtime. Battery swap is the process of exchanging a drained battery for a fully accused one at designated battery swap stations. This process can be done in a matter of minutes, significantly reducing the time buses spend out of service for recharging. Battery swapping stations require precise infrastructure and standardization of battery sizes and connections to ensure compatibility across different bus models. This method is particularly advantageous for maintaining high fleet availability and ensuring continuous operation without the need for lengthy charging sessions [6]. Each of these charging technologies plays a vital part in supporting the deployment and efficient use of electric buses. Integrating these facilities into the current infrastructure requires careful planning and investment, but the long-term benefits include reduced emissions, lower operational costs, and enhanced sustainability of public transportation systems [7].

Currently, the arranging of electric buses has emerged as a vibrant area of research due to the increasing adoption of electric vehicles in urban transit systems across the globe. In the domain of Battery Electric Bus (BEB) scheduling, recent research has expanded to include more realistic operating conditions. In [8], the focus was on lowering the operational costs of a BEB fleet by optimizing bus charging and running schedules, it also considering the costs related to battery scarcity. The problem was formulated as a set-splitting model, incorporating the exclusive properties of battery capacity degradation into the evaluating sub-problem. The researchers advanced their study by explicitly including a partial charging policy [9]. They used a mixed-integer nonlinear programming model to create a comprehensive basis to reach a global solution, by applying linearization and approximation techniques. Authors used a time-varying electricity scheme was fully integrated into the BEB scheduling optimization [10]. This approach ensured that BEBs were scheduled to control in off-peak times, leading to a cost-economical and grid-friendly BEB schedule. When scheduling BEBs, it's essential to consider unpredictable traffic conditions. In [11], this challenge was tackled by integrating the random variations in travelling duration of trip and energy utilization into the BEB scheduling framework. Their approach factored expected intervals in trip departure times into the cost function, improving the overall timely performance of the electric bus fleet.

An innovative scheduling approach was introduced for BEBs operating under fast charging conditions, considering unpredictable traffic scenarios. Their proposed strategy combined stable and active scheduling plans to effectively handle the unpredictability of traffic conditions [12]. Authors developed an integrated approach to address the electric bus planning problem, conceptualizing it as a bilevel model. In their framework, the lower-level model focuses on optimizing vehicle scheduling in accordance with predefined charging station designs [13]. This innovative approach aims to enhance the efficiency and efficacy of electric bus operations by integrating scheduling decisions with the physical infrastructure of charging stations. The temperature fluctuations in batteries are largely unavoidable due to environmental clauses and chemical effects that produce heat during charging and discharging methods [14]. Temperature changes greatly affect the running, lifespan, and protection of lithium-ion batteries [15]. So, it's important to consider how temperature impacts EV operations [16]. In [17], an analysis was performed on how varying battery prices and temperatures impact the optimisation of hybrid energy storage systems. This includes the capacity of supercapacitors and developing energy managing strategies specifically for EV functions. These studies highlight the need to examine how temperature affects the planning of EBFs.

Prolonging the battery lifespan in EBFs hinges on effectively managing energy in within board and externally during processes on the road, all while considering the features of battery capacity degradation over time. There has been no report thus far on extending battery lifespans through the integrated managing of internal and external aspects specific to electric buses [18]. This study proposes a comprehensive three-phase methodology for the efficient scheduling of Electric Bus Fleets (EBFs) by utilizing a hybrid optimization approach that combines Particle Swarm Optimization (PSO) with Recurrent Neural Networks (RNN). The core idea behind this methodology is to simultaneously account for both the operational demands placed on electric buses and the gradual degradation of battery capacity that occurs over time due to repeated charging and discharging cycles.

The approach is designed to achieve optimal synchronization between the internal battery management system (BMS) of electric buses and the external operational strategies, such as route assignment and charging schedules. By considering these factors together, the method ensures that the scheduling process not only supports daily transportation needs but also minimizes long-term costs associated with battery wear and replacements. The PSO component is used to explore various scheduling configurations to identify the most cost-effective solution, while the RNN—specifically employing long short-term memory (LSTM) cells—is trained to model and predict battery capacity fade under varying operational scenarios.

By aligning heavy-load routes with buses that experience lower battery degradation and refining schedules to extend battery lifespan, the hybrid PSO-RNN methodology presents a holistic solution. This strategy ultimately enhances the reliability, efficiency, and cost-effectiveness of electric bus fleet operations over their entire life cycle.

Conventional scheduling methods generally assume uniform or static battery behaviour. This work incorporates battery capacity degradation modelling into the optimization loop, allowing the system to schedule buses not just based on immediate cost or load balancing, but also on long-term battery lifespan, reducing replacement costs and enhancing sustainability.

A novel reverse-order matching strategy is proposed to align the fading battery capacity with route demands. This ensures high-load routes are allocated to buses with relatively healthier batteries. This nuanced matching delays battery replacements, minimizes degradation, and results in fewer disruptions.

2. DESCRIPTION OF THE PROBLEM

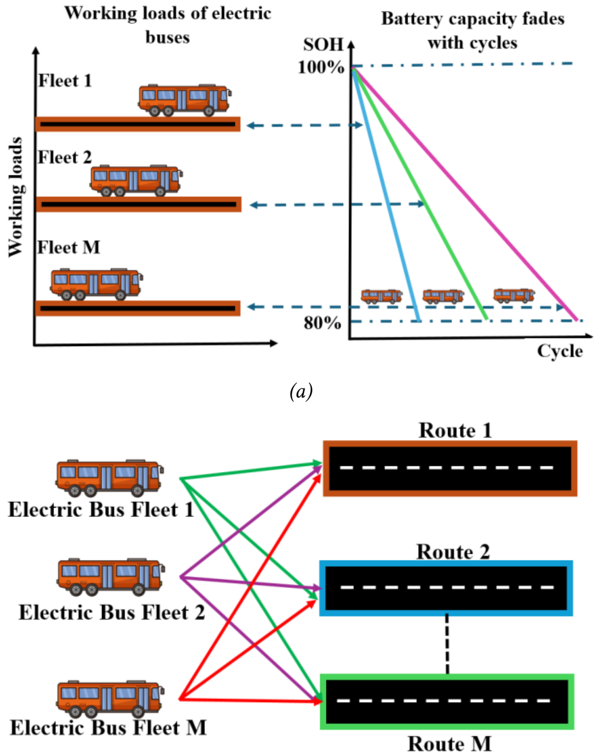
In a city's transit system, there are M fleets of electric buses, each assigned to a different route. Each fleet gets a specific number of electric buses. Due to the variability in daily operations across different routes, the electric buses experience varying working loads, leading to differential rates of battery capacity degradation, as depicted in Figure 1(a). To optimize battery lifespan and reduce replacement costs throughout the buses' operational life, scheduling of EBFs becomes crucial. This scheduling aims to align battery capacity losses with the buses' respective workloads, as shown in Figure 1(b).

In addressing, the known features include the effective loads of EBFs, and the activities combined with battery capacity degradation in electric buses., the primary objective is to schedule EBFs effectively on designated routes by sharing their effective loads constructed on battery capacity weakening patterns. This approach seeks to reduce the investment needed for battery alternates throughout the entire lifespan of the EV Buses.

For enhancing the resolution of these complex changes in allotment of EV Buses, the below mentioned assumptions are to be considered:

1. Electric buses are identical in terms of their specifications and operational capabilities.
2. Each fleet consists of an equal sum of electric buses.
3. Electric buses are charged in night time after ending their daily routes and go back to designated parking lots.
4. The functioning load for route remains continual throughout the scheduling period.

These assumptions were intentionally considered to simplify the modelling and scheduling process in the initial phase of the study, allowing us to focus on evaluating the core performance of the proposed algorithm under controlled conditions. However, authors fully acknowledge that in real-world operations, such assumptions may not always hold true due to unpredictable system uncertainties, varying route demands, dynamic charging behaviour, or differences in fleet composition. That being said, the current model serves as a foundational framework. It provides a benchmark for assessing algorithmic efficiency and system-level optimization under ideal conditions. While the assumptions in this study serve as a starting point for theoretical analysis and algorithm validation, we fully intend to expand the model to address uncertainties and enhance its realism in subsequent work. This will improve its practical relevance and applicability to real-time electric bus fleet scheduling in smart transit systems. These assumptions provide a foundational framework for developing an optimized scheduling strategy that accounts for both operational efficiency and battery longevity in electric bus fleets.



(b)

Fig. 1: Scheduling Approach for EBFs depending on Battery Capacity Degradation(a) Correlation Between Operating Hours and Battery Capacity Decline(b) Route Assignment Optimization.

3. METHODOLOGY FOR SCHEDULING OF BUS FLEET

In this paper, the hybrid Particle Swarm Optimization-Recurrent Neural Network (PSO-RNN) model is introduced to address the scheduling issues of electric bus fleets. An inverse order matching strategy is used to account for battery capacity fading and variations in working loads across different routes. In the next stage, detailed battery capacity degradation model is employed to quantify battery capacity loss and determine the required number of battery alternates. PSO-RNN creates a powerful hybrid algorithm, leveraging the strengths of both techniques. This hybrid approach is particularly useful for time-series prediction, sequence learning, and other tasks where RNNs excel but require optimization of their parameters for enhanced performance.

3.1 Particle Swarm Optimization (PSO)

The PSO method is a well-established population-based metaheuristic algorithm designed to tackle optimisation problems. Inspired by the social deeds of birds flocking towards a food source, PSO leverages the combination of both individual and collective experience to find optimal solutions. The inspiration for PSO comes from observing how birds within a flock move towards their target, such as a food source, by continuously varying their sets on their own experiences and the experiences of their peers. This dynamic regrouping and updating process allows the birds to efficiently converge on the target, forming an optimal pattern over time.

This behaviour led researchers, to create an optimization technique that copies this idea of social interaction. The result was the PSO algorithm, which was specifically designed to optimize continuous non-linear functions.

PSO is an iterative, nature-based swarm-intelligence algorithm that begins with a population of candidate solutions, referred to as particles. Every particle is a possible solution to the optimization problem. Key Components of the algorithm are population (Swarm), particle, position and velocity. Population is the collection of all particles. Particle means an individual candidate solution. Position is the current solution represented by an element. Velocity is the rate of change of the particle's position.

The algorithm starts by randomly placing particles in the solution space and giving them random speeds. Each particle's position is checked using a fitness function to see how good the solution is. The personal best (p_{best}) is the best position a particle has achieved so far based on its fitness evaluation. The global best (g_{best}) is the top position discovered by any particle in the entire swarm up to the current iteration.

In each iteration, the algorithm revises the velocity and position of all particle. The updates are influenced by two main factors. One is cognitive component (self-experience) which defines the particle's own (p_{best}) and second one is social component (social experience) which defines the best position got by the whole swarm. The position and velocity of all particle are got by the equations.

$$v_i(t+1) = w.v_i(t) + c_1.r_1(pbest_i - x_i(t)) + c_2.r_2(gbest - x_i(t)) \tag{1}$$

where $v_i(t+1)$ is the velocity of particle i at time $t+1$, w is the inertia weight that controls the effect of the earlier velocity, c_1 and c_2 are cognitive and social acceleration coefficients, r_1 and r_2 are random numbers in 0 and 1, $pbest_i$ is the best position initiate by particle i, $gbest$ is the best position found by the entire swarm.$x_i(t)$ is the current position of particle i.

Location of the particle can be updated by using

$$x_i\,(t+1) = x_i\,(t) + v_i\,(t+1) \tag{2}$$

where $x_i(t+1)$ is the updated position of particle i at time $t+1$.

3.2 Recurrent Neural Network (RNN)

The intelligence of humans and most animals heavily relies on the ability to remember past experiences. This memory can be short-term, or long-term. Recurrent Neural Networks (RNNs) emulate this memory function in neural networks. They introduce feedback mechanisms that use the outputs of earlier time steps while processing current inputs, effectively adding memory cells that mimic human slow and instant memory. RNNs enhance the traditional neural network model by incorporating recurrent layers. An RNN typically resides three layers: input, recurrent, and output. The input layers receive data from sensors and transfer to a vector gets the features of the input. This vector representation is crucial for the network to process the information accurately.

The recurrent layers provide the network with feedback by using the output from the previous time step. This feedback loop permits the network to maintain a memory of past information. In modern RNN models, these recurrent layers often include memory cells, which further enhance the network's facility to retain and utilize past data. Like traditional neural networks, RNNs conclude with Fully Connected (FC) layers and an output layer. The FC layers process the information from the recurrent layers and prepare it for the final output. The output layer, often a SoftMax layer, generates the final predictions or classifications. The inclusion of memory cells in RNNs is a significant advancement. These cells function similarly to human memory, storing information over time and allowing the network to recall past data when necessary. This capability is particularly useful for tasks involving sequential data, such as language modelling, where the network needs to understand and remember the context over multiple time steps.

Traditional RNNs often encounter the vanishing gradient problem, where the gradients used to train the network shrink dramatically as they are propagated backward through time. This makes it challenging for RNNs to learn and remember information over long sequences. LSTM overcomes this limitation by incorporating a unique architecture that enables the network to learn and propagate information over extended sequences. LSTM was developed to address a fundamental challenge in RNNs: capturing dependencies between

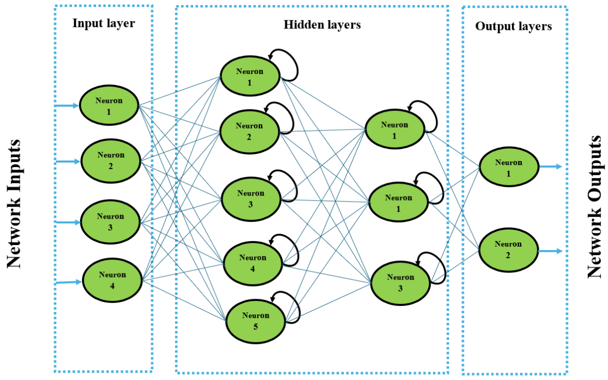


Fig. 2: *RNN structure.*

short-term and long-term information effectively. The structure of the RNN is presented in Figure 2.

The basic structure includes an input layer, one or more hidden layers with recurrent connections, and an output layer. RNNs can suffer from issues like vanishing gradients when dealing with long sequences, which is why variants like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are often used. RNNs are widely applied in tasks such as time-series forecasting, speech recognition, and natural language processing due to their ability to handle dynamic, time-dependent data.

The LSTM architecture includes several key components that work together to manage and retain information over time. These components are the cell state (c_t) and the hidden state (h_t). The cell state acts as a recall unit that carries information in altered time steps. It evolves relatively slowly throughout the computation process, allowing the LSTM to maintain long-term dependencies. The cell state is updated by various gates that control the movement of information. These gates include the input gate, forget gate, and output gate. The hidden state encapsulates the network's output at each time step and undergoes dynamic changes made on the input and previous hidden state. The hidden state generates the LSTM's output at each time step and is also passed into the next time step as part of the input. The functionality of LSTM is driven by three gates each controlling a different aspect of the information flow.

The forget gate is that which information from the cell state must be discarded. It takes the earlier hidden state (h_{t-1}) and the present input (x_t) and passes them through a sigmoid function to output a value among 0 and 1. This value is grown by the cell state (c_{t-1})to selectively forget information. The output of the forget gate f_t is given as

$$f_t = \sigma\left(W_f\left[h_{t-1},\ x_t\right] + b_f\right) \tag{3}$$

where W_f is the weight matrix, σ is the sigmoid function, b_f is the bias vector.

The input gate selects which new information to be added to the cell state. It takes h_{t-1} and x_t, processes them through a sigmoid function, and multiplies the result by a candidate value generated by passing h_{t-1} and x_t through a *tanh* function. This candidate value is the new data to be added to the cell state. The output if the input gate $i_t$is given as

$$i_t = \sigma\left(W_i\left[h_{t-1}, x_t\right] + b_i\right) \tag{4}$$

where W_i is the weight matrix, b_i is the bias vector.

The state computation in LSTM cells is a critical process responsible for updating the memory state, denoted as C_t. This computation ensures that the cell retains and updates information over time, enabling the network to handle dependencies in sequential data effectively.

Initially, the LSTM cell computes potential values for the new state. These potential values form the basis for updating the memory state. The new state vector C_t is determined by relating the earlier state vector $C_{t-1}$by the newly computed values. This combination is performed elementwise to ensure precise updates.

The previous state vector C_{t-1} is element-wise multiplied by the forget gate output vector f_t. The forget gate controls the earlier state is retained, allowing the cell to "forget" irrelevant information. The new state candidate vector $\check{C}_t$is computed and then element-wise multiplied by the input gate output vector i_t. The input gate forms how much of the new info is added to the state. Finally, the updated state vector C_t is computed by adding the contributions from the previous state and the new state candidate.

The equation for this combination is represented in (5),

$$C_t = \ f_t\ \odot C_{t-1} + i_t \odot \check{C}_t \tag{5}$$

Here, $\odot$ is element-wise multiplication. This operation ensures that the LSTM cell selectively updates its memory based on both past information and new inputs.

The output gate directs the report that is output from the cell state. It processes h_{t-1} and $x_t$through a sigmoid function, then multiplies the result by the *tanh* of the updated cell state (c_t) to make the hidden state (h_t).

$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right) \tag{6}$$

$$h_t = o_t \odot \tanh\left(C_t\right) \tag{7}$$

where W_o is the weight matrix, b_o is the bias vector.

In this study, the PSO-RNN algorithm is used to optimize the scheduling of electric bus fleets while considering long-term battery health. The overall computation process begins with the initialization of PSO, where each particle represents a potential schedule of electric buses to different routes over a specific period. Each particle contains a position and velocity, which are adjusted as the optimization progresses. The goal of PSO is to minimize total operational costs, which includes not just energy usage but also the effects of battery degradation and replacement costs.

The RNN, specifically designed using Long Short-Term Memory (LSTM) units, is trained beforehand using historical data. This data includes past battery usage patterns, charging cycles, route loads, and environmental factors. Once trained, the RNN can predict how the battery capacity will fade under different usage scenarios. These predictions are crucial because battery degradation impacts both vehicle performance and long-term operational costs.

As the PSO algorithm generates new scheduling solutions in each iteration, these solutions are passed through the RNN. The RNN predicts the corresponding battery capacity fade for each scheduling pattern. These predictions are then fed back into the PSO process during the fitness evaluation step. In this step, each particle's fitness is calculated by combining energy cost, route assignment efficiency, and battery degradation cost based on the RNN's prediction. This feedback loop ensures that the PSO does not just find the most energy-efficient schedule but also considers future battery health, making the solution more sustainable over time.

3.3 Optimal Scheduling

The primary objective of optimizing the schedule of EBFs by leveraging a hybrid approach that combines PSO with RNNs is to enhance the operational efficiency of EBFs while minimizing battery degradation and replacement costs over the vehicle's lifespan. Initially define the actual function to reduce the total operational cost, which contains energy consumption, battery degradation, and replacement costs. Incorporate constraints such as route schedules, battery capacity limits, charging infrastructure, and operational requirements.

The methodology for optimizing the scheduling of EBFs using a PSO-RNN approach with consideration for battery capacity fade involves several integrated steps to enhance operational efficiency and minimize battery degradation and replacement costs. The process begins with problem formulation, where the actual function is termed to reduce the total operational cost, encompassing energy use, battery degradation, and replacement costs. Constraints related to route schedules, battery capacity limits, charging infrastructure, and operational requirements are incorporated.

Data collection and pre-processing follow, ensuring accurate and consistent data on daily working loads, route characteristics, battery performance metrics, and environmental conditions. The PSO-RNN model is then developed, starting with PSO initialization. In this step, a swarm of particles is initialized, each denoting a potential solution to the scheduling problem. Particle positions and velocities are set within feasible bounds. Simultaneously, an RNN model, specifically using LSTM cells, is designed to predict battery capacity fade based on historical data. This model captures long-term dependencies and variability in battery performance and is trained using historical data on battery usage and degradation.

The hybrid optimization process involves PSO and RNN working together. PSO evaluates the fitness of every particle giving to the objective function, updating velocities and positions using p_{best} and g_{best} values. The RNN predictions adjust particle positions for better scheduling outcomes by predicting battery capacity fade for each scheduling scenario proposed by the PSO particles. These predictions are integrated into the PSO fitness evaluation to ensure battery degradation is considered.

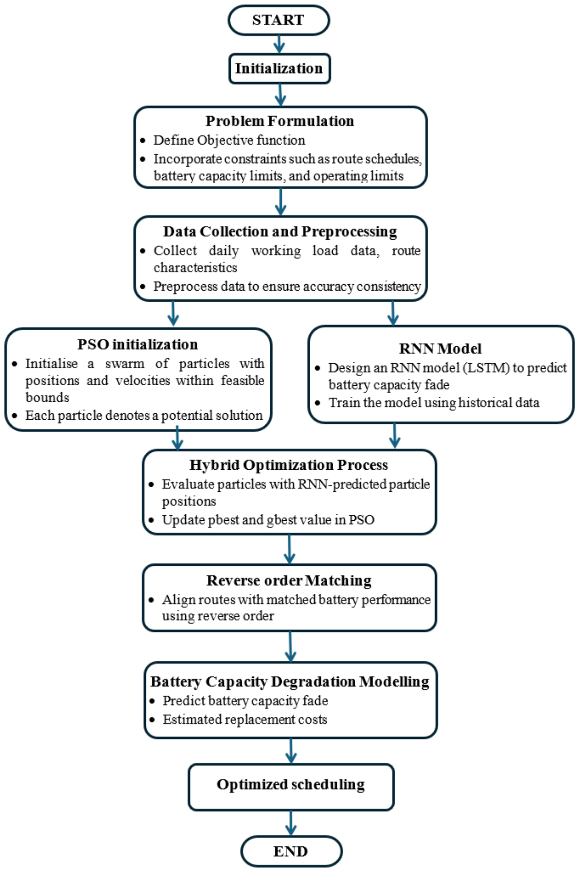


***Fig. 3**: Flow Chart for optimal scheduling of EBFs using hybrid PSO-RNN.*

A reverse order matching strategy is implemented to align differences in working loads with battery capacity fading processes, matching routes with higher working loads to buses with lower battery degradation. Additionally, a battery capacity degradation model estimates battery capacity loss and the sum of substitutes needed over the fleet's operational life. This model adjusts the scheduling to reduce battery replacement costs. Overall parameters of PSO-RNN hybrid algorithm are tabulated in Table 1. Overall flowchart of the proposed methodology is represented in Figure 3.

If the electric buses follow unscheduled operations, they will continue running on their initially assigned routes throughout the years. Mathematically the minimum and maximum battery capacities were represented by Eqs. (8) and (9).

$$0.2 \leq SOC\,(t) \leq 1 \tag{8}$$

$$SOC\,(t) \in \left[SOC_{min}, SOC_{max}\right] \tag{9}$$

where SOC_{min}= 0.2(20% of the total battery capacity)

***Table 1**: Parameters of the proposed hybrid PSO-RNN.*

Parameter	Value
Swarm Size	50
Inertia Weight	0.5
Cognitive Coefficient (C1)	1.5
Social Coefficient (C2)	1.5
Maximum iterations	100
Velocity Clamping	-1 to +1
Position Bounds	-100 to +100
Number of Hidden layers	1
Learning rate	0.001

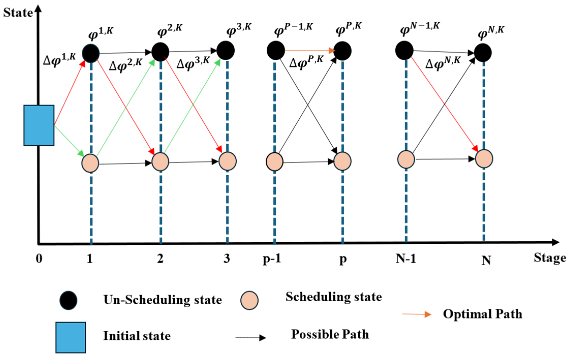


***Fig. 4**: Scheduling and unscheduled states.*

and SOC_{max}=1(100% of the total battery capacity).

4. OPTIMIZATION PROCESS

The EBFs future in this work is create on a PSO-RNN optimization approach. Given the nonlinear nature of the BCF method, the EBF allotment problem is made as a multi-stage decision problem. In this approach, PSO and RNN techniques are combined to handle the complexity of the scheduling task.

Figure 4 shows a basic diagram for EBFs. The x-axis represents different scheduling stages and y-axis shows the running positions of respective EBFs. The trips were allocated in stages that complete the total operating life of the EV buses, based on their lifetime and timetables. Each stage is stated as an interval $[p-1, \ p]$, where $p = 1, 2, \dots, N$. At the first stage, the loss in capacity of battery for each electric bus is nullified. This detachment allows for a structured approach to scheduling over the buses' operational period.

Each stage in the scheduling process can be in one of two states: the scheduled state or the unscheduled state. This shown as a black solid circle, indicates all electric buses continue to operate on the routes predetermined at an earlier stage. Conversely, the scheduled state, shown as an orange solid circle, means the electric buses are managing on routes firm by a specific matching strategy.

The diagram features paths connecting different states across stages. The black lines represent potential paths, while the red line highlights the select path. Although the diagram explicitly shows states at the end of all stage, there are K states at a given stage p, where $K = 2^p - 1$. Each state at stage $p$is denote by k (where $k = 1, 2, \dots, K$). Odd values of k indicate unscheduled states, whereas even values of k represent scheduled states.

This detailed enumeration of states and the division of scheduling stages form the basis of the PSO-RNN optimization method used to develop an optimal scheduling strategy for the EBFs, as the nonlinear feature of battery capacity fading and ensuring effective energy management and cost efficacy over the buses' service life.

In the state transfer diagram shown in Figure 4, $(\varphi_{p,k})$is the battery capacity loss at the kth position of the pth stage, and $(\Delta\varphi_{p,k})$is the related increase in capacity loss. The rise in capacity decrement for the whole system at the kth position of pth stage can be expressed using Eq. (10) :

$$\Delta\varphi_{p,k} = \varphi_{p,k} - \varphi_{p-1,\left[\frac{k-1}{2}\right]+1} \tag{10}$$

Here, $\varphi_{p,k}$ is the decision variable that varies depending on the same status of EBFs & their allocated ways.

For every fleet i, the increase in percentage of capability loss at the kth position of the pth stage can be defined by equation (??),

$$\Delta\varphi^i_{p,k} = \varphi^i_{p,k} - \varphi^i_{p-1,\left[\frac{k-1}{2}\right]+1} \tag{11}$$

In this equation, $\varphi^i_{p,k}$ represents the capacity loss percentage for fleet i at the kth state of the pth stage.

To capture the overall capacity loss of the system, the change losses of capacity for every fleet and the complete system modified and represented in the equation (??).

$$\Delta\varphi_{p,k} = \frac{1}{M}\sum_{i=1}^{M} \varphi^i_{p,k} - \varphi^i_{p-1,\left[\frac{k-1}{2}\right]+1} \tag{12}$$

This equation sums the differences in capacity loss percentages for all Mfleets and normalizes the value by dividing by M, providing a comprehensive measure of the system's overall capacity loss at each stage. By incorporating these state transfer equations, the scheduling strategy accounts for the battery capacity fading processes and adjusts the matching of routes to reduce the capacity loss and extend the service life of the EBFs.

As electric buses operate, the capacity of their battery's declines, necessitating replacement when the state of health (SOH) drops to 80%. Over the lifespan of electric buses, batteries will require multiple replacements. This frequent replacement, coupled with the inherent short lifespan of battery-based energy storage systems, leads to replacement costs, thereby raising the running expenses of electric buses. Consequently, this study aims to lower the number of battery alternates throughout the duration of the electric buses.

The fitness function, denoted as f_p, represents this objective. It focuses on reducing the no. of battery replacements, which can be mathematically expressed by Eq. (13),

$$f_p = \min\left(\sum_{p=1}^{N} R_p\right) \tag{13}$$

where N is the total number of stages (or time intervals) over the duration of the electric buses, and R_p denotes the No. of battery substitutes required at every stage p. The goal is to find the scheduling strategy that reduces the cumulative sum of R_p across all stages, thereby ensuring cost-effective operation by extending battery life and reducing replacement frequency.

Thus, the recurrence formula for the optimization problem can be as follows:

$$f_p^*\left(\varphi_{p,k}\right) = \min\left(R_p + f_{p+1}^*\left(\varphi_{p+1,k}\right)\right) \tag{14}$$

$$f_{N+1}\left(\varphi_{N+1,k}\right) = 0 \tag{15}$$

where $p = 1, 2, \ldots, N$; and $k = 1, 2, \ldots, K$.

In this model, the main goal is to minimize the total battery replacements in the EV buses' lifespan. The recurrence formula operates under the principle that for each state at each stage, the function $f_p^*\left(\varphi_{p,k}\right)$ calculates the minimum number of battery substitutes needed, taking into account the current number of replacements R_p and the future costs $f_{p+1}^*\left(\varphi_{p+1,k}\right)$. The boundary condition is set such that at the final stage, $f_{N+1}\left(\varphi_{N+1,k}\right) = 0$, indicating that no further replacements are needed beyond the last stage.

During scheduling, the sum of battery replacements, changes in the battery capacity fading rate, the matches in the fleets and the routes are chose for every position and stage. This information is then used to adjust the path for allocating the EBFs, aiming for reduction of operating cost for replacing with new batteries for the entire duration of the electric buses. By employing future PSO-RNN optimization approach, the best allocating strategy for all the electric bus fleets be derived by tracing the optimal way rearward from the last stage to the first. This ensures that the strategy chosen minimizes the number of battery replacements, thereby reducing overall operating costs and extending the battery life of the electric buses.

At each stage, there are many options for matching the EBFs to the routes, with both unscheduled and scheduled states. As shown in Figure 4, various matching methods to varying levels of battery capacity loss. In practice, the number of potential states in this method grows exponentially with the number of scheduling periods. Given this complexity, it's impractical to compute entire possible states to estimate battery capacity reduction and identify the optimal path. To address this challenge, the approach simplifies the problem by selecting only two states: The unscheduled and the scheduled state with the increase in capacity fading balanced to the unscheduled state. The unscheduled state represents a scenario where all the electric bus fleets continue operating on their predetermined routes without any reallocation. In contrast, the scheduled state represents a scenario where the fleets are reallocated to routes in a way that maximizes battery capacity fading.

To effectively identify the scheduled state, a reverse order matching strategy is employed. This strategy ensures that the evaluation focuses on the most significant changes in capacity fading, thereby streamlining the decision-making process. The implementation of this reverse order matching strategy involves several steps.

In the current study, passenger conditions are not considered as a constraint in the fleet selection and scheduling process. The focus of this work is primarily on optimizing the operational efficiency and minimizing battery degradation and replacement costs through the integration of PSO and RNN. Factors such as route loads, charging infrastructure, and battery capacity have been prioritized to establish a technically sound and cost-effective scheduling framework.

However, it is acknowledged that passenger-related conditions—such as passenger volume, comfort requirements, boarding and alighting patterns, or time-sensitive travel demands—can significantly influence real-world transit operations. These factors introduce additional complexity and can impact vehicle assignment and route planning decisions.

Therefore, incorporating passenger-related constraints is a valuable direction for future work. Enhancing the model to account for passenger demand patterns, peak-hour travel, or even adaptive scheduling based on real-time occupancy could improve the practicality and responsiveness of the system in real-world applications.

At the beginning of each stage, the current state of battery capacity loss is recorded. This initial state serves as a reference point for evaluating changes due to scheduling decisions. For each possible matching method, the increase in battery capacity loss is determined by comparing the battery capacity loss in the scheduled state with that in the unscheduled state. Among all evaluated states, the scheduled state with the increase in battery capacity fading assessed to the unscheduled state is chosen. This ensures that the most significant impact on battery capacity fading is considered. The opposite direction strategy is operated to trace back from the final stage to the initial stage, ensuring that the scheduling decisions at each stage are optimized to minimize the overall battery capacity fading.

By implementing the reverse order matching strategy, the proposed method efficiently narrows down the number of states to consider, focusing only on the most impactful changes in battery capacity fading. This approach balances the need for optimal scheduling with the practical constraints of computational complexity, providing a feasible solution for managing battery capacity loss in EVB's fleets.

4.1 Battery capacity fading

In battery capacity deprivation of electric bus i can be expressed by the Eq. (16):

$$\varphi_i = 0.0032\, e^{-\frac{15162-1516.C}{R.T}} .(Ah)^{0.824} \tag{16}$$

where φ_i is the ratio of battery capacity loss, R is the gas constant, T is absolute temperature in Kelvin (K), Ah is

Ampere-hour throughput, C is the discharge rate of the battery.

The Ampere-hour throughput, Ah is calculated using Eq. (17),

$$Ah = N_{cyc}.DOD.Q_B \tag{17}$$

where N_{cyc} is the cycle number of the battery, representing how many complete charge-discharge cycles the battery has undergone. DOD is the depth of discharge, indicating the fraction of the battery capacity that is used in each cycle. Q_B is the rated capacity of the battery, evaluated in Ampere-hours (Ah).

The battery capacity loss φ_i varies on the temperature, discharge rate, cycle number, depth of discharge, and the rated capacity. The equation (16) quantifies the ratio of battery capacity loss based on the Arrhenius-like behaviour of the degradation process, while the equation (17) calculates the total Ampere-hour throughput based on the usage pattern of the battery.

This detailed formulation allows for precise estimation of battery capacity degradation in electric buses under varying operational conditions. This method is effective in problems involving multi-stage decision-making under constraints and future state dependencies, as is the case in electric bus fleet scheduling with battery capacity degradation.

Each stage in the scheduling horizon corresponds to a specific time period or operational cycle. Decisions made at each stage (e.g., which bus is assigned to which route) directly influence not only the operational cost for that period but also the battery degradation trajectory and the number of battery replacements needed in the future. Therefore, to minimize the total cost across all stages, including long-term battery maintenance and replacement, it becomes essential to consider the implications of current decisions on future states.

By starting from the last stage and tracing backward, the algorithm evaluates the optimal cost-to-go from each future state. This ensures that each current decision is informed by its impact on future costs and system performance. A forward-tracing approach may lead to locally optimal but globally suboptimal decisions, as it lacks the foresight into how early-stage choices affect long-term battery health and replacements.

This backward tracing allows for efficient handling of the state explosion problem—as described, the number of possible state combinations increases exponentially. By limiting the evaluation to key representative states (i.e., scheduled and unscheduled), and optimizing from the end goal backwards, the method ensures computational tractability while still arriving at a near-optimal or optimal solution.

5. RESULTS AND DISCUSSION

In this section, using an urban public transit system equipped by EBFs as a case study, demonstrated the application of the intended method. This paper search into the key characteristics and implementation details of the optimal scheduling strategy tailored for EBFs. Parameters of hybrid PSO-RNN are presented in Table 1.

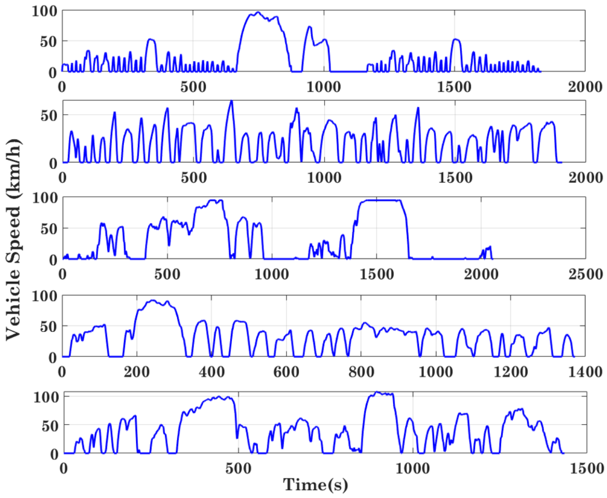


***Fig. 5**: Working Loads of five fleets and five routes.*

***Table 2**: The operating loads and key parameters of the loads.*

Route	Average Velocity (km/hr)	Battery Power (kW)	Current (A)	Discharge Rate	DOD
1	17.97	8.65	22.56	0.0645	0.387
2	19.84	10.4	27.13	0.0775	0.465
3	31.43	18.65	48.68	0.1391	0.756
4	34.11	20.78	54.24	0.1550	0.819
5	39.58	26.34	68.78	0.1965	0.862

5.1 Case 1:

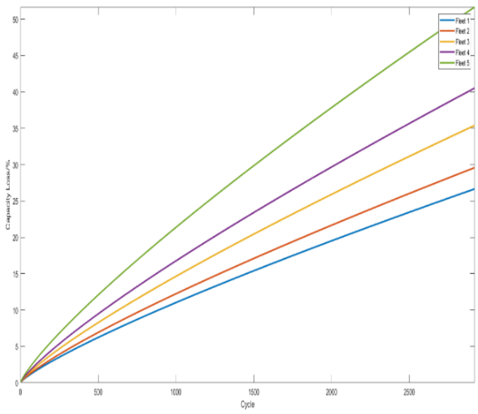
In the bus transportation system under consideration, there are five EBFs, denoted as $i = 1, 2, 3, 4, 5$ each operating on one of five distinct routes $j = 1, 2, 3, 4, 5$. Each fleet comprises ten buses. The operational loads [19] of these electric buses across the five ways are depicted over time in Figure 5.

The power battery has capacity of 350 A. Battery capacity degradation mainly depends on the average operational load rather than short peak loads. Increased internal resistance is primarily begun by average currents and deepness of discharge, not by momentary peak loads. So, the battery's power output can be based on the average operational load. Meanwhile, the discharge rate and depth of discharge can be determined by the output power and discharge current.

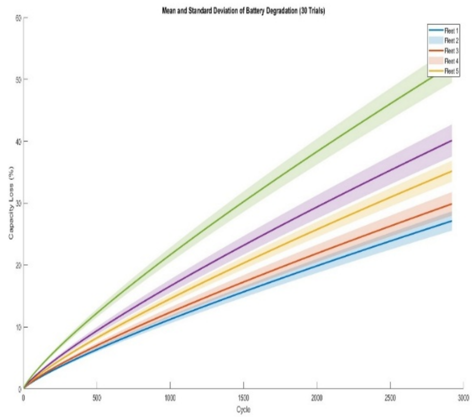
For clarity, operating loads and key factors derived from these loads are in Table 2.

The operational lifespan of the electric bus is defined as ten years, equivalent to 3650 days. The state of charge (SOC) limits is set with $SOCmin$ at 20% of the valued capacity, i.e. $SOCmin = 0.2$, and for full charge it is considered $SOCmax = 1$

Table 4 shows the battery cycle life and the number of replacements needed for the electric buses. It projects a



(a)



(b)

***Fig. 6**: (a) Fading process of battery capacity of five fleets with one trial (b) Fading process of battery capacity of five fleets with thirty trials.*

***Table 3**: Mean and standard deviation for 30 trials.*

S.no	Mean ± standard deviation for each fleet and year		
	Fleet	**Year 4 Loss (%)**	**Year 8 Loss (%)**
1	Fleet 1	15.42 ± 1.06	27.30 ± 1.87
2	Fleet 2	17.29 ± 1.04	30.61 ± 1.85
3	Fleet 3	20.49 ± 1.07	36.27 ± 1.90
4	Fleet 4	23.26 ± 1.22	41.18 ± 2.16
5	Fleet 5	29.73 ± 2.02	52.64 ± 3.58

total of 120 battery replacements over 10 years. Figure 6 illustrates how battery capacity gradually decreases over time. This base case serves as a benchmark for comparing the outcomes achieved through scheduling optimizations of the electric buses, both in terms of cycle life extension and reduction in battery replacement frequency.

The Fading process of battery capacity of five fleets for one trial and 30 trials are shown in Figure 6.a and 6.b respectively. It's observed that as the number of trials is increasing battery life span is increasing as losses are decreasing. Mean and standard deviation is calculated for

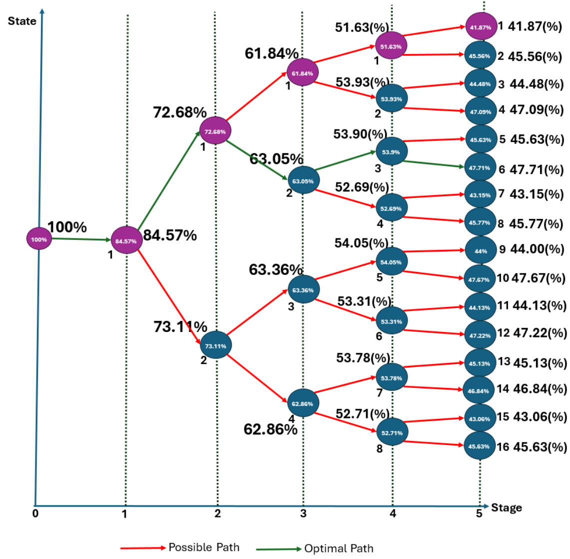


***Fig. 7**: Optimal path determined by PSO-RNN optimization.*

***Table 4**: The cycle life and corresponding sum of battery replacements for the EV buses.*

Fleet	Cycle Number	Number of replacements	Daily mileage/km
1	1782	10	107.82
2	1471	10	119.04
3	863	30	188.58
4	787	30	204.66
5	726	40	237.48

30 trials and values are represented in Table 3.

In ten-year service life of the EV buses, the forecast process is split into 5 stages, with each stage covering 730 days of scheduled periods. This division enables a systematic assessment of battery capacity fading and the sum of necessary battery replacements across different states within each stage. For each state in every stage, the raise in battery energy loss and the addition of corresponding battery replacements can be meticulously determined. This approach enables a comprehensive assessment of how different scheduling strategies impact the longevity of battery life and active costs throughout the electric buses' service duration. In this stage, the EV buses are scheduled on their original routes, leading to a recorded battery energy loss from 100% to 84.57%, as shown in Figure 7. From the second stage onward, every stage presents 2 possible outcomes: not operating state or operating state, decided by the inverse order matching strategy. When scheduling happens, the EV buses start operating on new routes, initiating an extra battery energy loss of 11.16%. This directs to state 2 with a total energy loss of 26.89%. Alternatively, the entire system can stay in state 1 with a total energy loss of 27.32%. This process continues as each state and its associated weights are decided. By applying the proposed optimization, the optimal path of state transitions for the EBFs is identified, as depicted in Figure 7.

Table 5: *The number of battery replacements required for each state within each stage.*

State	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
1	0	10	20	30	20
2	0	0	30	40	20
3	0	0	40	40	30
4	0	0	40	10	30
5	0	0	0	10	40
6	0	0	0	0	0
7	0	0	0	0	30
8	0	0	0	0	20
9	0	0	0	0	10
10	0	0	0	0	40
11	0	0	0	0	50
12	0	0	0	0	20
13	0	0	0	0	30
14	0	0	0	0	50
15	0	0	0	0	40
16	0	0	0	0	50

Here, the numbers on the arrows represent the weights, while the numbers within the circles denote the states. Different scheduling paths result in varying battery capacity fading and required battery replacements. From Figure 7, in the 2^{nd} stage, 2^{nd} state is a not operating state with an 11.46% rise in battery capacity reduction, while state 1 is an operating state with an 11.89% rise in battery energy loss. Table 4 shows the number of battery replacements required for each state at each stage. For example, in state 1 of the second stage, 10 battery replacements are required, while state 2 needs none. This observation suggests that using the reverse order matching strategy lowers battery energy loss and delays the need for battery replacements.

Dividing of entire 8-year working life of the EV buses in 5 distinct stages enables the construction of 16 potential paths. Using PSO-RNN optimization, the optimal path that minimizes the sum of battery replacements is identified. As depicted in table 5, the least number of battery replacements appear in the 6^{th}stage, underscoring the strategic advantages of the proposed scheduling approach in optimizing battery longevity and operational efficiency for electric bus fleets.

The OSP, known as the 6^{th} route, sets a standard by minimizing the sum of scheduling periods. By effectively managing total working loads and fully utilizing battery capacity, this path reduces the number of battery replacements by a factor of 20 compared to other paths. In the sixth path, the scheduling of electric bus fleets occurs twice over the course of eight years.

By using the finest scheduling strategy, the battery capability declining of the EBFs can be assessed. This work applies the remaining capacity from preceding conditions to place the battery capacity on the fading curve for new operational conditions. This approach accepts the deprivation from new running conditions is not depends on the path taken for added capacity fading.

The impact of electric bus routes on battery capacity fade is significant and underscores the need for optimal scheduling strategies. This study also adds inner battery management with outer bus scheduling to enhance battery lifespan and reduce operational costs for EBFs. By strategically scheduling the buses, the battery capacity fading process can be influenced, thereby minimizing the need for battery replacements. The approach employs PSO-RNN to enumerate battery capacity losses and replacement counts at each stage, facilitating the derivation of an optimal scheduling path. This path contrasts with an unscheduled approach, highlighting the ability of the intended method in reducing battery replacements.

Table 6: *The working loads and key parameters of the seven loads.*

Route	Average Velocity (km/hr)	Battery Power (kW)	Current (A)	Discharge Rate	DOD
1	17.97	8.95	23.34	0.0667	0.4
2	22.53	12.4	32.35	0.0924	0.55
3	22.69	13.1	34.18	0.0977	0.58
4	31.43	18.75	48.94	0.1398	0.83
5	34.11	21.64	56.49	0.1614	0.85
6	39.58	28.04	73.23	0.2092	0.88
7	64.14	42.15	110.19	0.3148	0.92

The implementation involves a detailed analysis of PSO-RNN combined with a reverse order matching plan. This methodical approach is illustrated through a base case scenario, where the results demonstrate substantial reductions in battery replacements achieved through optimal scheduling for electric buses. The comparative assessment between scheduled and unscheduled paths underscores the effectiveness of the proposed methodology in optimizing battery utilization and operational efficiency for EBFs.

Each state in the table represents a unique scheduling and fleet allocation configuration, which directly affects the battery usage pattern and consequently the battery degradation and replacement frequency. State 6 shows zero battery replacements in all five stages. This outcome suggests that this particular allocation strategy is highly optimal or conservative in terms of battery usage. It allocated by less demanding route to fleet with better-matching workloads with batteries that have experienced less fade, leading to no replacements over the observed period. State 6 is the direct result of reverse order matching, where early-stage decisions are made with full awareness of their long-term effects (as ensured by backward tracing from the last stage).

5.2 Case 2

Seven electric bus fleets are considered in this case, denoted as $i = 1, 2, 3, 4, 5, 6, 7$ each operating on one of five distinct routes $j = 1, 2, 3, 4, 5,6,7$. Each fleet comprises ten buses. Figure 8 shows the operational loads of these electric buses across the seven routes over time.

Table 7 presents the key parameters of seven fleets and seven loads. Figure 9 presents the battery capacity fading process of seven fleets. Table 6 shows the cycle

***Table 7**: Cycle life and the corresponding No. of battery replacements for the EV buses.*

Fleet	Cycle Number	No. of replacements	Daily mileage/km
1	1720	20	107.82
2	1228	20	135.18
3	1160	30	136.14
4	786	40	188.58
5	755	40	204.66
6	704	50	237.48
7	623	50	384.84

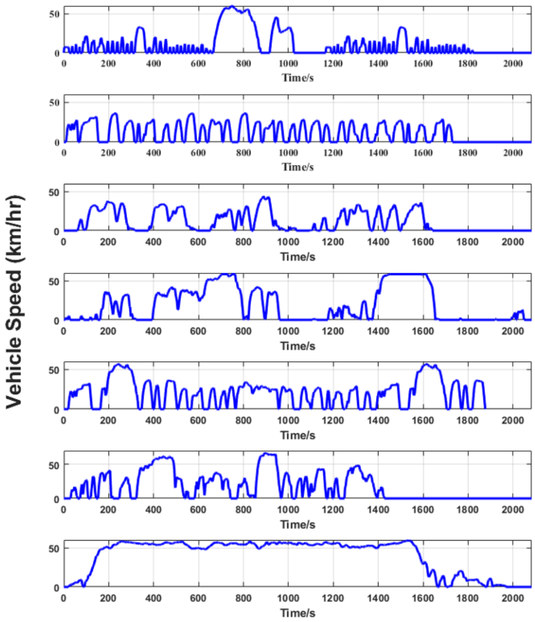


***Fig. 8**: Working Loads of seven fleets and seven routes.*

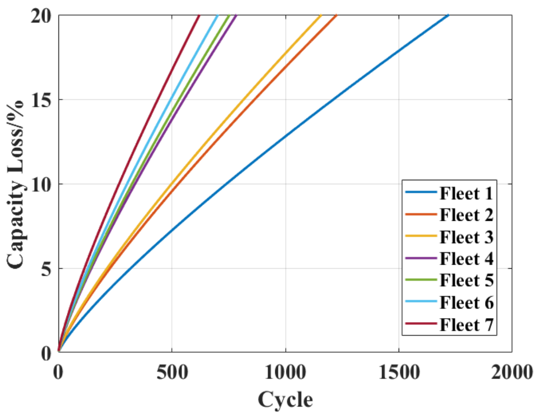


***Fig. 9**: Fading process of battery capacity of seven fleets.*

life and the sum of total replacements of the battery needed for the electric buses. Table 8 presents the optimal scheduling path by PSO-RNN optimization for seven fleets and seven routes. Figure 10 presents the battery fading process of five stages.

In the current study, the PSO-RNN hybrid model was proposed to optimize the scheduling of EBFs with a specific focus on battery degradation and replacement cost

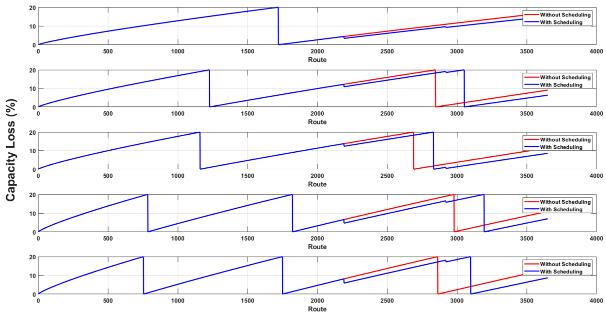


***Fig. 10**: The battery capacity loss processes.*

***Table 8**: Cycle life and the corresponding No. of battery replacements for the EV buses.*

<table>
<tr><th rowspan="2">State</th><th colspan="6">Stage</th></tr>
<tr><th>0</th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th></tr>
<tr><td>1</td><td rowspan="16">100%</td><td rowspan="16">85.75%</td><td rowspan="8">74.43%</td><td rowspan="4">64.18%</td><td rowspan="2">56.62%</td><td>49.67%</td></tr>
<tr><td>2</td><td>49.61%</td></tr>
<tr><td>3</td><td rowspan="2">56.83%</td><td>50.03%</td></tr>
<tr><td>4</td><td>50.06%</td></tr>
<tr><td>5</td><td rowspan="4">64.47%</td><td rowspan="2">56.45%</td><td>49.48%</td></tr>
<tr><td>6</td><td>50.22%</td></tr>
<tr><td>7</td><td rowspan="2">56.53%</td><td>49.38%</td></tr>
<tr><td>8</td><td>50.24%</td></tr>
<tr><td>9</td><td rowspan="8">74.21%</td><td rowspan="4">64.35%</td><td rowspan="2">57.25%</td><td>50.61%</td></tr>
<tr><td>10</td><td>50.32%</td></tr>
<tr><td>11</td><td rowspan="2">57.40%</td><td>50.60%</td></tr>
<tr><td>12</td><td>49.66%</td></tr>
<tr><td>13</td><td rowspan="4">64.10%</td><td rowspan="2">56.25%</td><td>49.92%</td></tr>
<tr><td>14</td><td>50.17%</td></tr>
<tr><td>15</td><td rowspan="2">57.86%</td><td>50.91%</td></tr>
<tr><td>16</td><td>50.83%</td></tr>
</table>

minimization. This model leverages the strengths of PSO for global search capability and RNN–specifically LSTM cells—for accurately predicting battery capacity fade based on historical and usage data. The hybridization allows for dynamic adaptation of scheduling decisions based on both operational and degradation parameters, making it suitable for long-term fleet planning under realistic operational constraints.

Authors agree that comparing the proposed PSO-RNN with other optimization approaches would provide a stronger validation of the performance gains achieved. These comparisons would help to establish the relative advantages of the proposed model in terms of convergence speed, solution optimality, robustness, and computational efficiency. While this comparative analysis was beyond the scope of the current study, we intend to incorporate it as part of future work. A detailed benchmarking with multiple optimization techniques and real-world datasets will offer a clearer picture of the efficacy and scalability of the proposed PSO-RNN in diverse operational environments. This will also help refine the hybrid model and potentially inspire further enhancements through hybridization with other AI-driven forecasting or control strategies.

Conventional scheduling methods generally assume uniform or static battery behaviour. This work incorporates battery capacity degradation modelling into the optimization loop, allowing the system to schedule buses not just based on immediate cost or load balancing, but also on long-term battery lifespan, reducing replacement costs and enhancing sustainability.

A novel reverse-order matching strategy is proposed to align the fading battery capacity with route demands. This ensures high-load routes are allocated to buses with relatively healthier batteries. This nuanced matching delays battery replacements, minimizes degradation, and results in fewer disruptions.

6. CONCLUSION

The study presents a comprehensive analysis of the effectiveness of the PSO-RNN approach for optimizing the scheduling of EV bus fleets (EBFs) while considering the battery capacity fade. By setting up the scheduling problem as a multistage decision-making process, the proposed technique aims to lower the number of battery replacements and extend the batteries' overall service life. The method's robustness is proven through a detailed case study involving scenarios with five and seven different working loads. The outcome from the case study focuses the significant benefits of implementing the PSO-RNN approach. Specifically, the optimal scheduling strategy achieved through this method leads to substantial reductions in battery capacity loss over time. This not only extends the lifespan of the batteries but also translates to lower operational costs due to fewer battery replacements. The scenarios analysed in the study show a clear comparison between the outcomes of scheduled and unscheduled states, illustrating the marked improvements in battery life and cost-efficiency when the PSO-RNN model is applied. Furthermore, the approach's adaptability to different working loads showcases its versatility and effectiveness across various operational conditions. The study features the ability of the PSO-RNN method to enhance the sustainability of urban public transit systems by optimizing the use of electric buses. By ensuring that the batteries are utilized more efficiently and replaced less frequently, this method offers a viable solution for reducing the environmental impact and operational expenses associated with electric bus fleets. Overall, the findings affirm that the PSO-RNN approach is a powerful tool for improving the organizing and managing of electric bus fleets. It provides a strategic pathway to achieving more sustainable and cost-effective public transportation systems, addressing both the economic and environmental challenges posed by battery capacity fade.

Future extensions of this work will include a more comprehensive set of variables to account for uncertainties such as heterogeneous bus specifications, varying fleet sizes, dynamic energy pricing, unpredictable traffic patterns, real-time energy availability, and on-route or opportunity charging. By gradually relaxing the assumptions and integrating these real-world dynamics, the model can be made more robust and applicable to practical transit operations.

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