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RHO–LSTM-based optimal scheduling at the motorcycle battery swapping station under battery heterogeneity

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Abstract

This research proposes a mechanism that enables the battery swapping station (BSS) to provide battery swap services for multiple types of batteries, termed battery heterogeneity, utilized in electric motorcycles. The number of batteries for each type is established. The battery charging cost is calculated in real time, and the station's profit is maximized by optimizing battery swap scheduling. The issues are modeled as a mixed-integer non-linear problem (MINLP), then linearized as a mixed-integer linear problem (MILP), using the grid electricity price from the real-time pricing mechanism to calculate the battery's charging/discharging cost. Swap scheduling is optimized using the rolling horizon optimization (RHO) approach, which takes into account a variety of constraints. These constraints include battery type, battery SoC, arrival time of the electric motorcycle, grid electricity pricing at time t, and battery power utilization. The long-short term memory (LSTM) predicts the electric motorcycles' arrival time at *t+1* based on prior data. The results show that optimization scheduling generates a higher overall profit per day than unscheduled operation. Profit by the RHO-LSTM method is 23.77 % greater than by the RHO-Polynomial method and 0.26 % greater than by unscheduled operation. Furthermore, the number of batteries provided by the RHO-LSTM method is 40 % greater than by the RHO-polynomial method.

Keywords: battery heterogeneity; electric motorcycle; mixed-integer linear problem; long-short term memory; rolling horizon optimization.

I. Introduction

The adoption of electric motorcycles in Indonesia has been accelerating, influenced by environmental sustainability goals [1]. Nevertheless, this upward trend presents significant challenges, including prolonged battery charging durations, congestion at charging facilities, and spatial constraints for infrastructure development. Battery swapping stations (BSS) offer a viable alternative by enabling rapid battery exchange, thereby minimizing user wait times and reducing spatial requirements. Furthermore, implementing optimized battery charging schedules during periods of low electricity demand can enhance operational efficiency and reduce energy costs for BSS operators.

Currently, BSS remain limited in number and are typically designed to support only a single battery type or brand-specific configurations. This limitation

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underscores the need for a BSS capable of accommodating heterogeneous battery types. Although extensive research has been conducted on BSS, few studies have addressed the design and operation of multi-brand battery compatibility. For instance, one study introduced a BSS model that supports heterogeneous batteries and implemented a dynamic charging schedule to enhance revenue generation [2]. Another investigation optimized battery charging schedules and swapping services through a reservation-based system; however, this was limited to four-wheeled electric vehicles [3]. The majority of BSS-related research has focused on homogeneous battery systems for electric cars [4]. In contrast, battery-swapping solutions for electric motorcycles are gaining prominence, with 369 BSS units reported across Indonesia as of 2022 [5]. In that study, an internet of things (IoT)-based BSS was developed for electric motorcycles, enabling real-time monitoring of battery parameters such as state of charge (SoC), state of health (SoH), temperature, current, and charging cycles. Additionally, [6] proposed an optimization model for electric motorcycle BSS using genetic algorithms (GA), demonstrating improvements in operational efficiency by optimizing battery scheduling and minimizing total operating costs while addressing both technical and economic considerations.

Numerous studies have examined a wide range of forecasting techniques for predicting time series. For a variety of scenarios, machine learning and traditional models like autoregressive integrated moving average (ARIMA), autoregressive integrated moving average with exogenous variables (ARIMAX), and seasonal autoregressive integrated moving average with exogenous variables (SARIMAX) are used. Machine learning and deep learning are used to forecast the grid's demand response (DR) in order to determine more effective techniques [7][8]. The grid's electric load is predicted by comparing machine learning techniques, including k-Nearest Neighbors (kNN), Random Forest, Gradient Boosting, and neural network with long short-term memory (LSTM). To pick the best feature and determine the ideal time lags, respectively, the LSTM is paired with feature selection and GA [9]. The conventional model delineates optimal performance in time-series data. In comparison to traditional models, machine learning and deep learning models yield superior results in managing uncertainty and dynamic conditions. Convolutional neural networks (CNNs) are employed for semi-supervised time-series forecasting and classification through self-supervised learning [10], where the results using the CNN model outperform other approaches, such as ConvLSTM and AttConvLSTM. The study employed a dataset characterized by short time periods, which aligns well with the temporal feature extraction capabilities of CNN-based architectures. Predicting the demand for electric vehicle charging is another application of machine learning, with a revolutionary deep long-short term memory (DLSTM) model that yields superior predictions due to a minimized mean square error [11]. The utilization of the LSTM methodology for forecasting battery-swapped demand and vehicle arrivals at BSS was discussed in a referenced work, whereby LSTM surpassed other applied methods [12]. Moreover, utilizing time-series data to forecast electric motorcycle arrival times, supervised machine learning, and deep learning models may be optimal selections.

When optimization is used to solve the suggested model, the best outcome can be achieved. To determine the best distribution networks for several distributed generations (DGs), optimization approaches such as GA, particle swarm optimization (PSO), and hybrid optimization BF-PSO (butterfly-particle swarm optimization) are used [13]. The proximal policy optimization (PPO) method is another optimizer used to optimize the performance of every device in the energy replenishment station (ERS), which may be used for electric vehicle charging and battery swapping [14].

An optimizer known as rolling horizon optimization (RHO) repeatedly maximizes choices made within a certain time frame. This method solves the problem by using the predicted data at $t+1$. Additionally, it uses the prior iteration's optimization outcomes as input for the subsequent iteration. In order to improve the schedule of battery changing in a single day, RHO determines the best short-term solution, which is referred to as the horizon. When the input data in this system varies over time, issues are resolved using RHO that operates on time intervals in the resilience of active distribution networks (ADNs) [15], hinterland intermodal transportation [16], cogeneration energy systems of the grid [17], and energy supply and demand planning in microgrids [18]. These models employ RHO to optimize outcomes, and the results demonstrate that RHO can enhance the models to attain the optimal objective.

This research presents the development of a BSS intended for electric motorcycles in response to the increasing prevalence of motorcycle usage in Indonesia. The station is architected to accommodate multiple battery types and operates without requiring prior reservations. An optimal battery scheduling mechanism is implemented to fulfill user swapping requests while maximizing station profitability, as determined through computational simulations. To support real-time decision-making, the system forecasts electric motorcycle arrivals at time step *t+1* based on time-series data derived from recent historical arrival patterns.

This research aims to develop an effective design and implement an efficient system for battery swapping stations (BSS) serving electric motorcycles by optimizing battery scheduling through an RHO-LSTM-based approach under conditions of battery.

II. Materials and Methods

Charging stations for electric vehicles face a number of challenges, including queuing because the charging procedure is lengthy, and vehicle users must adhere to a time limit. Battery swap services are provided in an effort to shorten the recharging time of electric vehicles. This invention is the outcome of the long battery charging process. An innovative system for charging batteries at the swapping station is required.

A. Battery heterogeneity at battery swapping stations

The public electric vehicle battery swapping station (BSS) is classified into four types: single BSS, multiple BSS, combination of single BSS-BCS, and combination of multiple BSS - BCS [4]. In general, the battery swap station is exclusively intended for one type of battery from a certain electric vehicle, such as the Gogoro or Gesits electric motorcycles, with each BSS tailored especially to the motorcycle given by the manufacturer. The BSS to be designed is specified as being capable of battery swapping for more than one electric motorcycle manufacturer and/or battery type. As a result, the consumer base will expand.

The decision-making scenarios in BSS are divided into five categories: charging schedule, service policy, construction and planning, dispatching and routing, and power management. In this study, the best charging schedule for the station will be studied further. Many studies have been undertaken to develop an optimal charging scheduling mechanism [4]. The population-based heuristic technique is employed for optimization [19], the RHO method for optimization [2], the genetic algorithm (GA) [6], and the hybrid algorithm, JAYA-BBA, to solve the bilevel optimal scheduling issue model [20]. The optimal operation schedule is intended for BSS and microgrids. The scheduling system employs a bilevel problem model with the alternative direction method of multipliers (ADMM) [21]. A charging schedule mechanism that takes into account the quality of service (QoS) of various BSSs has been developed [3]. The first and second studies discussed in this publication use more than one type of battery, which is uncommon in BSS research [2][3]. The presented bilevel model includes an upper-level problem that determines optimal charging and discharging schedules for aggregated BSSs. Meanwhile, the low level determines the reserve capacity pricing for each BSS. The bilevel model is developed as a mixed-integer linear problem (MILP) model in order to develop the best operating model for aggregated BSSs [22]. Modeling a fluid-based optimization framework improves battery charging and purchase procedures for BSS [23]. Pricing issues in BSS are also addressed by a three-tiered BSS pricing mechanism that takes into account the electric vehicle demand market clearing. To optimize BSS pricing, the three-level model considers the interaction of the distribution system operator (DSO), BSS, and electric vehicles (EVs) [24]. In Beijing, a BSS configuration and operating model with three charging points improves BSS profitability [25]. The optimal operating model of BSS with photovoltaics includes the BSS operation mechanism, the BSS load model, and the price mechanism, all of which strive to maximize the number of charged batteries [26]. These studies concentrate on four-wheeled electric vehicles.

In this study, an optimal charging scheduling mechanism for two-wheeled electric vehicles is developed at a station with diverse batteries. Table 1

Table 1.
Comparison of characteristics in this study with previous ones.

Features	Operation model of BSS in previous research						BSS in this research
	[2]	[3]	[6]	[19]	[20]	[21]	
Battery heterogeneity	v	v	x	x	x	x	v
Battery charging characteristic	v	x	v	v	x	x	v
Battery degradation	v	x	v	x	x	v	x
Swap/charge scheduling	v	v	v	v	v	x	v
Multi BSS	x	v	x	x	x	x	x
Single BSS	v	x	v	v	v	v	v
Electric motorcycle	x	x	v	x	x	x	v
Semi-universal charger	v	x	x	x	x	x	v

compares the features of the station to be designed to past studies.

B. Battery swapping station model

BSS with heterogeneous batteries is a battery swap station that supports many battery types and electric motorcycle brands. The batteries utilized will be the LiFePO4-constructed battery {60 V, 6 Ah} and the Gesits electric motorcycle {72 V, 20 Ah}.

Each battery will utilize the same charger, even if the sockets are different. The Gesits battery will be charged using the manufacturer's charger socket, which will then be linked to a variable charger. The battery swap operation is carried out dynamically, which means that electric motorcycle riders will come immediately to the station to swap batteries. Batteries can be replaced with those that are completely charged or below 100% but not above the threshold. Empty batteries swapped by prior electric bikers will be charged to meet the next battery swap request. The RHO approach includes scheduled battery swapping.

Battery swap scheduling is determined by the battery's charging characteristics. If the battery reaches a state of charge (SoC) of 70 % (ω), the charging current decreases, affecting the charging power for each battery. This charging characteristic is applicable to lithium-ion batteries. Figure 1 depicts the results of battery charging measurements with a variable charger. This charging method is sometimes referred to as the constant-current/constant-voltage charging strategy. The flat shape of the discharge curve in lithium-ion batteries implies that the voltage remains constant during the discharge process. The power used for battery charging will vary depending on the number of battery swap requests and the availability of fully charged batteries at the BSS. Each battery will be charged using the same charger. The batteries are charged using a variable charger.

The profit earned by BSS will be maximized and balanced against the number of riders provided. Thus, BSS operational procedures will permit the sale of power to the grid. Aside from the proceeds of the battery swap, there will be additional BSS revenue. At the same time, the cost of charging the batteries will be reduced. The number of electric motorcycles served and the number of batteries switched at time t reflect the highest profit and minimal charging cost, respectively, when the electricity price is low and high.

The BSS system model contains five assumptions, which include 1) Riders can apply for several battery swaps. 2) The battery is owned by BSS. 3) The battery cannot be swapped while it is charging or discharging. 4) Batteries can be swapped if their state of charge is at least a certain level. 5) If the rider requests multiple battery swaps, the swapped batteries will have the same capacity. Figure 2 shows the BSS system structure. The number of battery slots is determined based on the historical data of electric motorcycle arrivals.

C. Optimization model

The battery swap operation is carried out dynamically, which means that electric motorcycle riders will come immediately to the station to swap batteries. Empty batteries swapped from the previous electric motorcycle will be charged to meet the upcoming battery swap request. The battery swap is scheduled using the RHO method. RHO optimization begins with identifying the period length parameter of the defined horizon; the optimization issue is then solved at time $T=1$, and the solution value is saved at time T. The optimization problem is then solved iteratively at the following T until T exceeds the previous T in the period [27]. RHO consists of three horizons: the current horizon, the forecasting horizon (u), and the scheduling horizon (T). In this system with a time slot t, the arrival of the electric motorcycle to the control horizon is taken into account, as is the prediction of the electric motorcycle' arrival at $t+u$. Figure 3 shows the schematic of RHO. The scheduling horizon is defined as the scheduling period T, which is

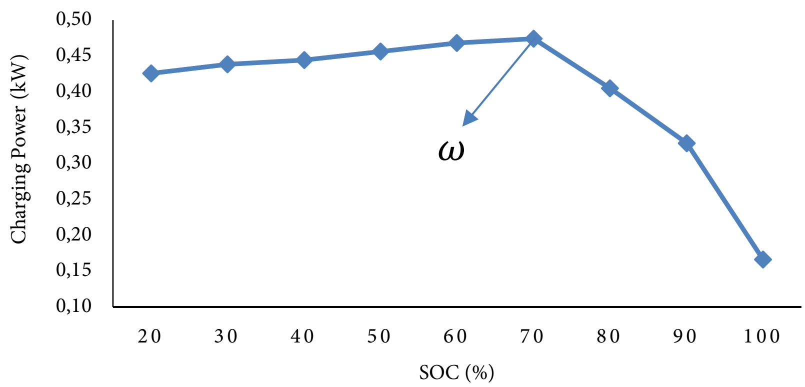

Figure 1. Li-Ion battery charging curve by experiment.

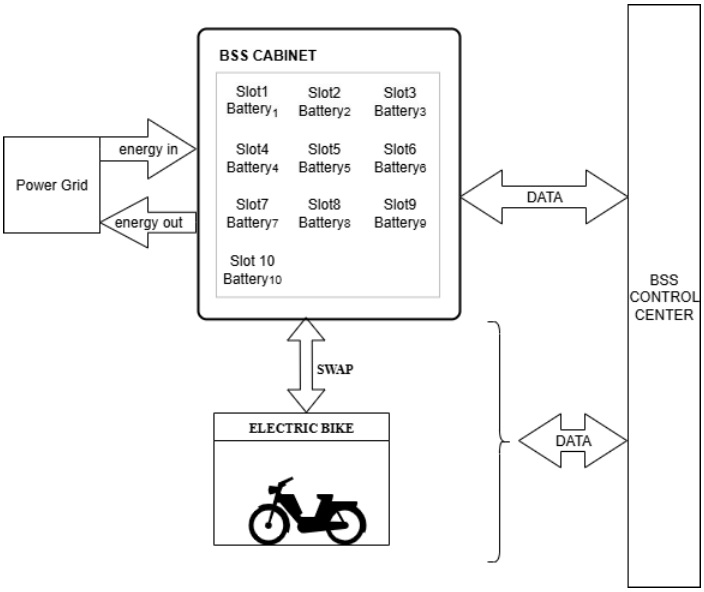

Figure 2. BSS system structure.

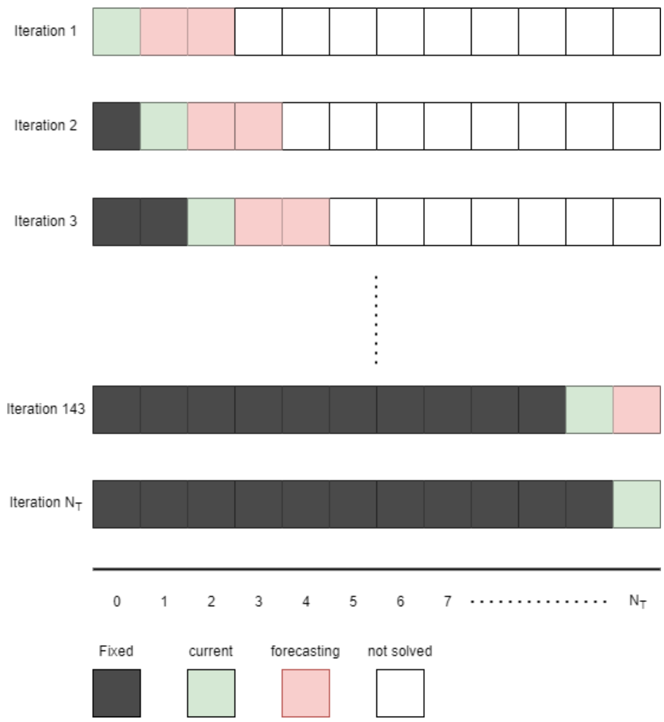

Figure 3. Schematic of rolling horizon optimization.

made up of multiple time slots. A solution is found for each battery in the station.

The forecasting horizon employs the LSTM for data prediction. LSTM is a deep learning neural network architecture based on the recurrent neural network (RNN) that models and predicts sequential data. LSTM can handle data with long-term relationships, which are frequently encountered as an issue in RNN. It has memory blocks called cells and three gates for managing memory contents. The gates in this approach are logistic functions with multiple weights. The three gates are the forget gate, the input gate, and the output gate. These gates are an extension of the RNN method designed to solve data problems with long-term dependencies. Each gate contains a sigmoid function that determines which data will be removed in each cell. The input gate determines which new inputs enter the cell state. The forget gate determines which value of the former output is forgotten and which is retained. The current input and prior output are used to determine the forgotten and remaining values. The output gate determines the value to be executed by using the state vector from the previous step [28]. Figure 4 shows a flowchart of the system.

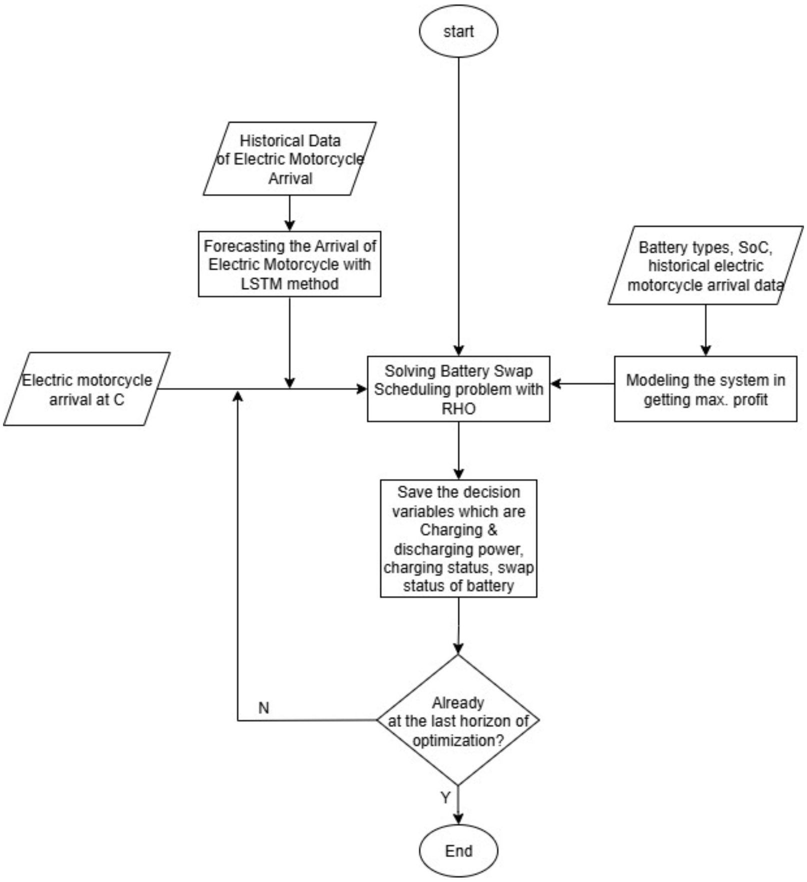

Figure 4. Flowchart of the system at the station.

The dynamic problem can be represented as a mixed-integer nonlinear problem (MINLP) and then linearized into a mixed-integer linear problem (MILP). The station's system optimizes profit as the objective component of MILP modeling. MILP is used to model the restrictions on the station's components. The limitations include battery type, battery SoC, battery swap status, battery charging state at time t, electric motorcycle arrival time, grid electricity pricing at time t, and each battery's power usage.

The intended modelling will be solved inside the RHO's current horizon (C) in order to acquire optimal constraint values. The battery swap scheduling system uses the battery swap status and battery charging state at time *t* when the power price is low as decision variables.

D. Real-time pricing mechanism

The real-time pricing mechanism in BSS is dependent on the overall system load. The real-time pricing mechanism is defined as the sum of the grid load level (P_t^{LL}) and the traded electricity quantity (P_t^{LL}) between BSS and the grid multiplied by the grid charging reference price (P_t^{LL}) and divided by the average of load level (P_{avg}^{LL}). The mathematical model is stated in equation (1). $K_{BSS,t}$ is obtained by summing the charging ($P_{t,b}^{c}$) and discharging power ($P_{t,b}^{d}$) during charging-discharging schemes.

$$cost_t^{rt} = \frac{P_t^{LL} \times \Delta t + K_{BSS,t}}{P_{avg}^{LL} \times \Delta t} \times cost_t^{rf} \tag{1}$$

E. Mathematical model of MILP

The mathematical model for a four-wheeled vehicle is constructed using MILP [2]. Conversely, a mathematical model is modified to account for the vehicle type, specifically an electric motorcycle, and the battery swap scheduling system, which consists of two dimensions: the set of times T and the set of batteries B, as it is explicitly designed for electric motorcycle Battery Swap Systems (BSS). The set of times T and the set of batteries B are known. The set T contains time slots t and the set B contains batteries with two battery types b, where $b = \{1, 2, 3, \ldots, 10\}$. The set of battery types is represented by U_I as a subset of B, where $i=\{1,2\}$. The charger used for each battery type is represented by g_j as a subset of B, where $j=\{1,2\}$. Charger g_1 and Charger g_2 are both variable chargers that are grouped based on the maximum charging power of each battery type. This mathematical modeling for battery swap scheduling aims to maximize the profit received by BSS in equation (2).

Profit is obtained from the revenue of battery swap activities and power sales to the grid by reducing the cost of charging batteries from the grid and the cost of battery degradation. Battery swap revenue has two price parameters, namely the battery swap price and the price of the difference between the SoC of the battery from the rider and the one being swapped. In the prior study, battery discharging income was calculated by multiplying the discharged power by the time-of-use electricity price [2]; in this research, the electricity price is derived using the real-time pricing mechanism in equation (1). The equations to get the value of the four variables can be seen in equation (3) to equation (6). Battery degradation cost is the reduction of battery capacity after a day has passed (N_T = 480) multiplied by the battery degradation cost. The battery capacity decline model is created by observing how temperature, cycle, discharging rate, and DoD affect battery capacity reduction when discharging lithium-ion batteries [29]. Where R represents the gas constant and Temp denotes the absolute temperature. The degradation cost is calculated by multiplying the battery capacity loss by the battery degradation price indicated in equation (6). This MILP-based model's decision variables are the charging/discharging power and charging and swap state of each battery at time t, DV = $[P^c_{t,b}, P^d_{t,b}, c_{t,b}, s_{t,b}]$.

Objective :

$$F = \max(Rev^s + Rev^d - Cost^c - Cost^{deg}) \quad (2)$$

$$Rev^s = \left(\begin{array}{c} \sum_{t \in T} \sum_{b \in B} s_{t,b} \times cost^s_b + \\ \sum_{t \in T} \sum_{b \in B} \frac{Q^{max}_b}{100} \times \Delta SoC^s_{t,b} \times cost^{kWh} \end{array} \right) \quad (3)$$

$$Rev^d = \left(\sum_{t \in T} \sum_{b \in B} (\eta^d \times P^d_{t,b}) \times \Delta t \times cost^{rt}_t\right) \quad (4)$$

$$Cost^c = \left(\sum_{t \in T} \sum_{b \in B} \left(\frac{P^c_{t,b}}{\eta^c}\right) \times \Delta t \times cost^{rt}_t\right) \quad (5)$$

$$Cost^{deg} = \sum_{b \in B} k.\exp\left(\frac{\ell}{R \times Temp}\right) \times (\mu_{num} \times \mathrm{DoD}_{max} \times 2)^{0.552} \times cost^{deg}_b \quad (6)$$

Constraints for objective F are described in equation (7) to equation (21). Equation (7) is to find the change value of SoC when an empty battery is swapped by the rider with a battery from BSS at the initial time slot (*t = 1*). Meanwhile, equation (8) is the change in SoC value due to battery swap at *t+1*. Equation (12) to equation (14) state the swap and charging status of each battery at t. Both variables are binary variables where the value 1 is being charged or can be swapped, and the value 0 is the opposite. The swap status will equal 0 if there is no battery swap request by the driver at $T^{arrival'}_j$ and $T^{arrival'}_j \cup T^{arrival} = T$). Equation (12) to equation (16) define and quantify the SoC of each battery at time slot t, and identify which batteries meet the criteria to be swapped with the rider's battery. Only batteries with an SoC exceeding the 90 % threshold are permitted for swapping.

Subject to :

$$\Delta SoC^s_{t,b} = \left(SoC_{0,b} - SoC^{em}_t\right) \times s_{t,b}, \forall (t-1) \in T, \forall b \in B \quad (7)$$

$$\Delta SoC^s_{t,b} = (SoC_{t-1,b} - SoC^{em}_t) \times s_{t,b}, \forall (t \neq 1) \in T, \forall b \in B \quad (8)$$

$$c_{t,b} + s_{t,b} \leq 1, \forall t \in T, \forall b \in B \quad (9)$$

$$\sum_{b \in B} s_{t,b} = N^{units}_t, \forall t \in T^{arrival} \quad (10)$$

$$s_{t,b} = 0, \forall t \in T^{arrival'}_j, \forall b \in B \quad (11)$$

$$SoC_{t,b} = SoC_{0,b} + \frac{(P^c_{t,b} - P^d_{t,b}) \times \Delta t}{Q^{max}_b} \times 100\% - \Delta SoC^s_{t,b}, \forall b \in B \quad (12)$$

$$SoC_{t,b} = SoC_{t-1,b} + \frac{(P^c_{t,b} - P^d_{t,b}) \times \Delta t}{Q^{max}_b} \times 100\% - \Delta SoC^s_{t,b}, \forall b \in B \quad (13)$$

$$SoC_{0,b} \geq \zeta \times s_{t,b}, \forall b \in B \quad (14)$$

The amount of charging/discharging power is written in equation (17) to equation (19). Equation (17) represents the battery charging characteristics, where at SoC above 70 % the charging current will decrease, which affects the charging power. The charging power decreases exponentially due to the constant decrease in current and voltage at SoC above 70 %. Equation. (18) to equation (19) allows the charging and discharging power values not to exceed the maximum charging/discharging power of each battery type. The total of electric motorcycles served, and batteries swapped is represented in equation (20) and equation (21), respectively. Equation (22) allows the charger to be used at the same time. However, the total number of chargers must not exceed the number of chargers of each type.

$$SoC_{t-1,b} \geq \zeta \times s_{t,b}, \forall b \in B \quad (15)$$

$$(SoC^{max}_b - DoD^{max}) \leq SoC_{t,b} \leq SoC^{max}_b, \forall t \in T, \forall b \in B \quad (16)$$

$$0 \leq P^c_{t,b} \leq (P^{MAXch}_{cg} \times \exp(\frac{\omega - SoC_{t,b}}{P^{MAXc}_{cg}}) \times c_{t,b} \quad \forall t \in T, \forall b \in U_i, \forall cg \in g_j, \forall (i=j) \in U \quad (17)$$

$$0 \leq P^c_{t,b} \leq P^{MAXch}_{cg} \times c_{t,b} \quad \forall t \in T, \forall b \in U_i, \forall cg \in g_j, \forall (i=j) \in U \quad (18)$$

$$0 \leq P^d_{t,b} \leq P^{MAXd}_{cg} \times c_{t,b} \quad \forall t \in T, \forall b \in U_i, \forall cg \in g_j, \forall (i=j) \in U \quad (19)$$

$$N^{served} = \sum_{t \in T} \frac{\sum_{b \in B} s_{t,b}}{N^{units}_t}, \forall N^{units}_t \neq 0 \quad (20)$$

$$N^{swapped} = \sum_{t \in T} s_{t,b} \quad (21)$$

$$\sum_{b \in U_i} c_{t,b} \leq G_j^c \; \forall \, t \in T \; \forall (i = j) \in U \tag{22}$$

The big difference between the SoC of the battery at BSS and the battery owned by the rider is represented in equation (8), where the multiplication between the variables $soc_{t-1,b} \times \omega_{t,b}$ is the non-linear component, which is then linearized in equation (23) to equation (26). It is known that $x_{t,b}$ is a positive variable. If the battery swap status is 1, then $x_{t,b}$ will be equal to $soc_{t-1,b}$ and will be equal to 0 otherwise. Equation (17) also needs to be linearized because the battery charging power will decrease exponentially, which makes this equation non-linear. The linearization is expressed in equation (27), where the charging power ($P_{t,b}^c$) is generated by performing linear regression fitting. The parameter α represents the slope, and β denotes the intercept of the linear regression model.

$$\Delta SoC_{t,b}^s = (x_{t,b} - SoC_t^{em}) \times s_{t,b} \,, \forall (t \neq 1) \in T \,, \forall b \in B \tag{23}$$

$$x_{t,b} \leq s_{t,b} \times SoC_b^{max} \,, \forall t \in T^{arrival} , \forall b \in B \tag{24}$$

$$x_{t,b} \geq SoC_{t-1,b} - (1 - s_{t,b}) \,, \forall t \in T^{arrival} , \forall b \in B \tag{25}$$

$$x_{t,b} \leq SoC_{t-1,b} \,, \forall t \in T^{arrival} , \forall b \in B \tag{26}$$

$$P_{t,b}^c \leq -\alpha \, SoC_{t,b} + \beta \,, \forall t \in T \,, \forall b \in B \tag{27}$$

F. Computer program: Case studies

All the simulations from each case are implemented in Python and solved by the Gurobi optimization 10.0.2. Table 2 shows the values of parameters used for simulation. This section provides a collection of case studies illustrating the efficacy of the introduced scheduling system. This work essentially examines three cases: the BSS unscheduled operation, battery swapping scheduling utilizing RHO-LSTM, and battery swapping scheduling utilizing RHO-Polynomial regression. The simulation is implemented on BSS across all instances, accommodating two types of batteries with capacities of 60 V, 6 Ah and 72 V, 20 Ah. The parameter values applied in the three scenarios are presented in Table 2. The second battery type is preferred by customers due to its higher demand [6].

The BSS unscheduled operation entails the exchange of batteries without a scheduling mechanism. In this procedure, the battery's SoC constraint mirrors the scheduling method with RHO, allowing for battery swap if the SoC reaches or exceeds its threshold. The SoC threshold is 90 %, with the maximum SoC attaining 100 %. The BSS is capable of managing numerous battery swapping requests simultaneously. If a battery swap request is not received at time *t*, the BSS will refrain from executing the battery change service.

Table 2.
Values of the parameters used.

Parameters	Value
Q_b^{max}	1,44 kWh $\forall b \in \psi_1$ 0,36 kWh $\forall b \in \psi_2$
Δt	1/6
$cost_t^{rf}$	1036 IDR
$cost_b^s$	2000 IDR $\forall b \in \psi_1$ 4000 IDR $\forall b \in \psi_1$
η^d	0.95
η^{ch}	0.95
SoC_b^{max}	100 %
DoD^{max}	80 %
R	8,31
$Temp$	-273,15
$cost^{kWh}$	1036 IDR
P_{cg}^{MAXd}	0,72 kW $\forall b \in \psi_1$ 0,36 kW $\forall b \in \psi_1$
P^{MAX-PT}	144 kW
P_{cg}^{MAXc}	0,57 kW $\forall b \in \psi_1$ 0,12 kW $\forall b \in \psi_2$
ℓ	-31500
k	30330
C_{rate}	0,5
b ∈ ψ_1 b ∈ ψ_2	b = [1-4] b = [5-10]
ζ	90 %
$SoC_{0,b}$	100 %
ω	70 %

Upon receiving a depleted battery, the BSS immediately initiates fast-charging at constant power until the end of the time interval *t*, without discharging to the grid. The swap procedure is emulated without scheduling, distributed over 24 hours consisting of 480 time intervals, each with a duration of 3 minutes. It is not assumed that each battery within the BSS is fully charged at the beginning of each day.

RHO is an optimization technique that enhances the objective of a model within a certain time frame. This optimization is performed iteratively to determine the optimal short-term decisions while accounting for their long-term implications. This approach is employed under varying temporal conditions. The RHO in this system establishes three horizons: the current horizon, the forecasting horizon (*u*), and the scheduling horizon (*T*). The comprehensive schematic of the RHO utilized in this simulation is depicted in Figure 3. LSTM and polynomial regression are employed to execute the forecasting horizon. The outcomes of each hybrid approach are evaluated to assess the effectiveness of the RHO-LSTM method. Furthermore, the simulation is conducted to represent a full day of BSS operation across 480 time slots. The goal is to optimize the profit as specified in equation (2). Each iteration generates income from swapping, discharging, and the expense of charging the battery. The final iteration incorporates the cost of degradation. The simulation outcomes are analyzed across various machine learning techniques.

III. Results and Discussions

Simulations are conducted using an electric motorcycle arrival history dataset derived from the battery-swapping activities of an online transportation rider in Bandung, Indonesia. Qualitative data were collected to determine the frequency of battery swaps among electric motorcycle users, as well as the proportion of battery capacity typically consumed during each swapping event. The dataset contains the arrival time of electric motors along with the number of batteries requested per 3 minutes. Battery swapping demand and arrival times are generated randomly, informed by values from previous time intervals and qualitative data. Data generation is limited to working days to minimize uncertainty associated with transportation activity during weekends.

A. Forecasting simulation

The data used is time-variant, which has an increasing trend at the end of the time slot. As a result, the data is not stationary. To solve forecasting problems using time series data, one must use a stationary dataset. Therefore, data shifting is necessary to eliminate the non-stationary nature.

The dataset is divided into training and testing sets, with the training data emphasizing the arrival patterns of electric motorcycles and the corresponding battery quantities. The test data lags behind the arrival of electric motors and numerous batteries. In polynomial regression, the training data includes information on the arrival of electric motorcycles and the number of batteries requested from Monday to Thursday. Test data is motorcycle-arriving data on Friday that has been shifted by one time slot. The model is constructed to accommodate multiple inputs, specifically through the application of multivariate polynomial regression.

The LSTM method modifies the data to have only one input. The electric motorcycle arrival history data from Monday to Friday is consolidated into a single column. In this method, data shifting is also carried out to avoid non-stationary data properties. Data on the arrival history of electric motors at t represents x, while data on the arrival history of electric motors at *t+1* represents y. Training data and test data are divided by a ratio of 80:20, where previously data normalization has been carried out first. The training data are subsequently divided into two subsets: validation data and training data.

Figure 5 and Figure 6 display the prediction results using polynomial and LSTM methods, respectively. Prediction results using the LSTM method are more accurate than those using polynomial regression. The large root mean square error (RMSE) of each method demonstrates this. Predicting the arrival of electric motors with LSTM produces an RMSE of 0.002, while using polynomial regression is 0.484.

Although these two methods can process non-linear data, it can be seen that the RMSE generated by them is very different. This is likely due to the poor correlation value between the day variables and arrival time. The correlation result can be seen in Table 3. The LSTM

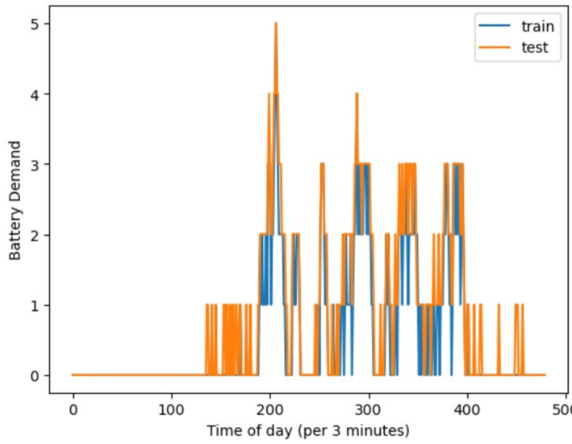

Figure 5. Prediction results using polynomial regression.

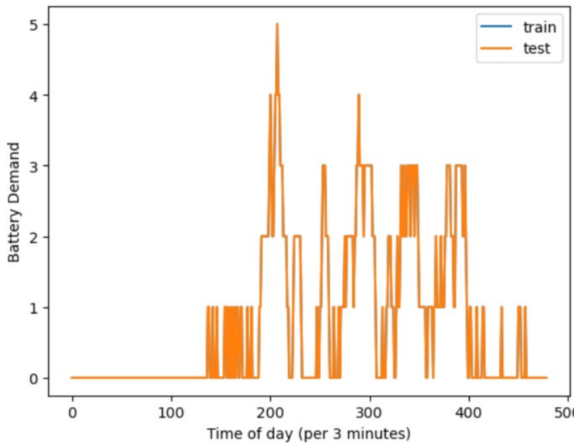

Figure 6. Prediction results using LSTM after denormalization.

Table 3.
Correlation values days vs time.

Days	Time
Monday	0.12604
Tuesday	0.133365
Wednesday	0.215388
Thursday	0.22695
Friday	0.266208

method, with its cells and layers, may also contribute to the more intricate computational process of data training. The inclusion of forget cells in the LSTM method facilitates a more advanced data training process. LSTM is able to identify long-term patterns and long-range dependencies in the data.

B. RHO and polynomial regression simulations

The preceding subsection examined the forecasting horizon process employing LSTM and polynomial regression techniques. The predicted outcome is utilized as the input for time step *t+1*. This subsection presents an analysis of the simulated results obtained through the RHO and polynomial regression prediction techniques. In the RHO approach, the initialization of the optimization process is recognized as a critical step. Accordingly, the initial value is first determined. This value, along with the decision variable, is subsequently employed as the primary input for the optimization process at time *t+1*. In the last iteration, the aggregate degradation cost of all batteries diminishes the total value of the objective functions.

Figure 7 and Figure 8 illustrate the battery demand and the frequency of battery swaps per hour, respectively. Polynomial regression predicts the emergence of electric motorcycles, considering the SoC of the battery. The efficacy of RHO-polynomial regression scheduling is inadequate for enabling battery changes. During peak hours, BSS can supply 50 % of battery type 2 while surpassing the demand for battery type 1 by 14.28 %. This approach generally fails to satisfy the demand for type 2 batteries. There is a significant demand for type 2 batteries.

The results of the polynomial regression forecasts influence the battery-swapping outcome. This also aids in establishing charging-discharging protocols using real-time pricing mechanisms.

C. RHO and LSTM simulations

This subsection discusses how LSTM handles the simulation forecasting horizon in RHO. The RHO-LSTM method performs better than RHO-Polynomial. Figure 8 and Figure 9 present the total battery swaps for each method. During peak hours, this method performs well, providing up to 75 % of the battery type 2 and more than 50 % of battery type 1. Generally, the RHO-LSTM method provides a total battery of each type that closely matches the battery swap demand.

This occurs because the process of predicting data on the arrival of the desired electric motorcycle and battery outperforms polynomial regression. Real-time pricing also contributes to the scheduling of power charging-discharging schemes. Figure 10 shows a graph of the relationship between real-time pricing and the charging-discharging scheme. Figure 11 presents a graph depicting the correlation between real-time

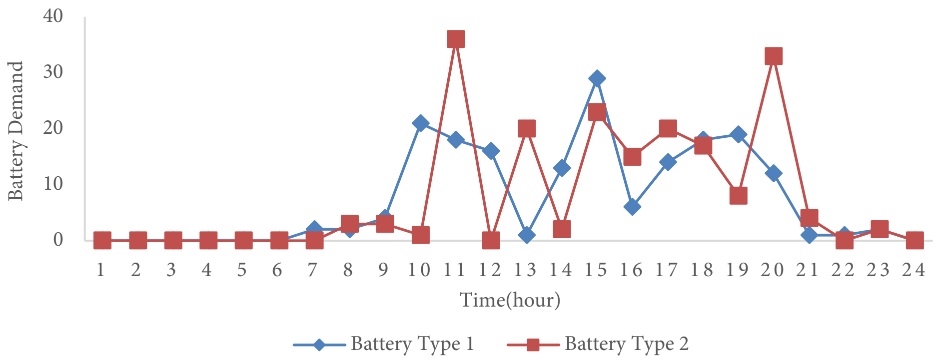

Figure 7. The battery demand at the end of workdays.

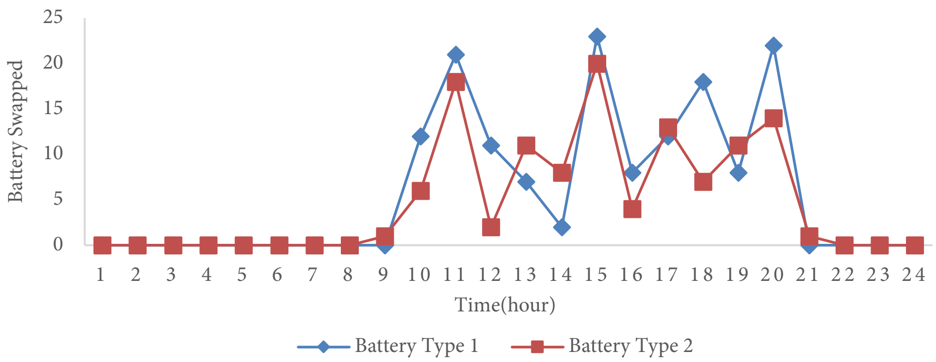

Figure 8. The battery swapped by RHO-polynomial regression method.

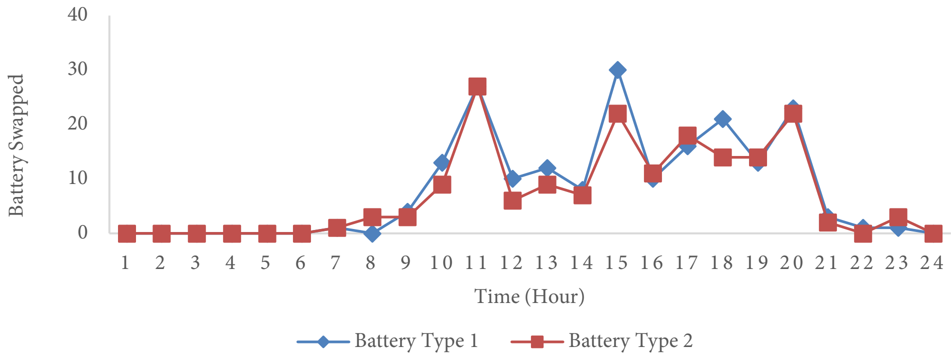

Figure 9. The battery swapped by RHO-LSTM method

pricing and the charging-discharging strategy. At grid peak prices, the total power at the BSS decreases.

D. Unscheduled operation simulation

An unscheduled BSS operation is a battery swap that happens without the use of a scheduling system. This procedure aligns the battery's SoC limitation with the RHO scheduling process, allowing for battery swap if the SoC exceeds the threshold. The threshold SoC is 90 %, while the maximum SoC is 100 %. The BSS may have the capability to accommodate many battery-changing requests concurrently. The BSS will not perform the battery swap service if there is no request at the specified time. This operation does not execute a discharge scheme. A fast-charging system, which utilizes constant charging power, immediately charges the battery upon replacement and does not utilize a real-time pricing mechanism. The BSS will operate with normal pricing, which uses a set grid price.

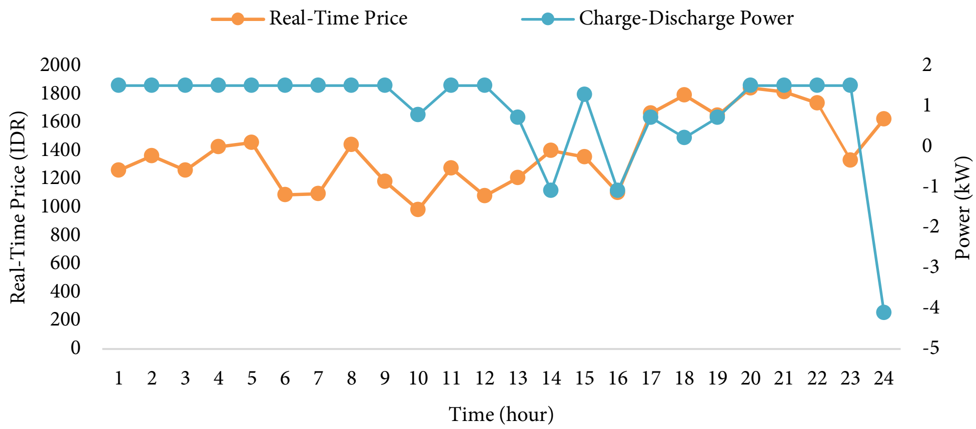

Figure 10. The BSS power curves vs real time price with RHO-LSTM.

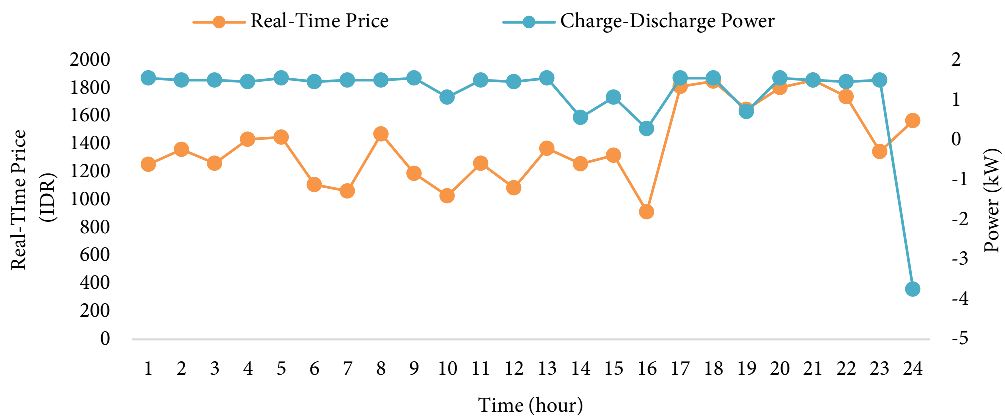

Figure 11. The BSS power curves vs real time price with RHO-polynomial regression.

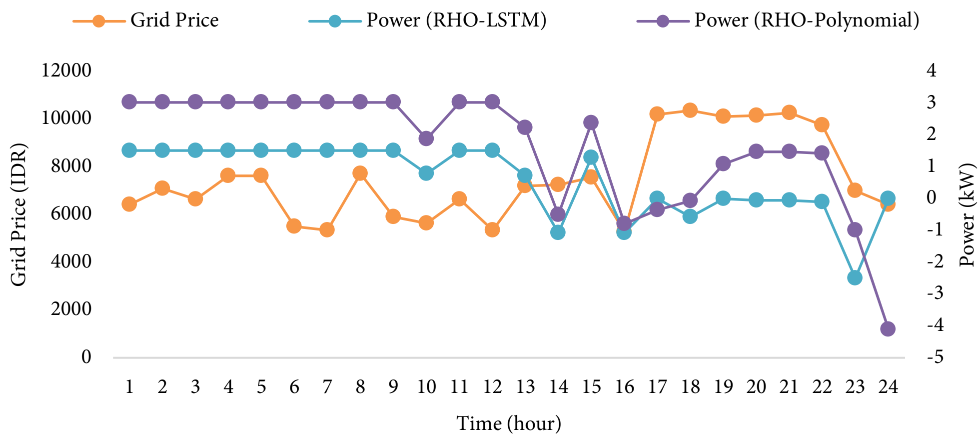

Figure 12. The BSS power curves vs grid price with RHO-LSTM and RHO-polynomial regression.

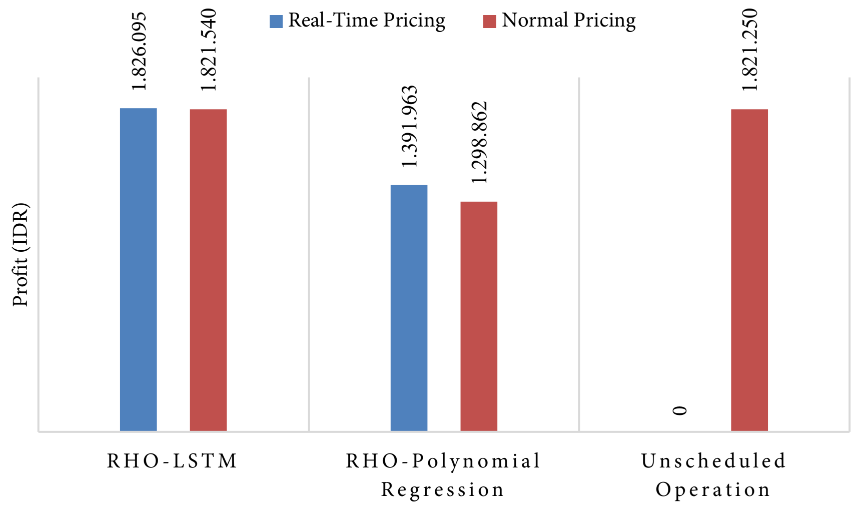

Figure 13. The BSS profit.

This unscheduled operation approach, which lacks integration with real-time system variables, results in a charging rate that remains constant across all time intervals t, regardless of fluctuations in grid electricity pricing, as illustrated in Figure 12. This static charging scheme significantly contributes to the observed performance disparities among the other methods. The profit outcome associated with the unscheduled operation, presented in Figure 13, further reflects the impact of these operational limitations. The addition of a real-time pricing mechanism affects BSS profits compared to using normal grid prices. The profit from BSS utilizing the RHO-LSTM technique surpasses that of the RHO-polynomial approach, as the electricity price incurred by BSS at grid peak pricing is lower than the price derived from the RHO-polynomial method and the established grid price, as illustrated in Figure 12. Figure 13 illustrates the BSS earnings achieved in each scenario.

IV. Conclusion

Battery swapping stations (BSS) are generally configured to support a single battery type corresponding to a specific electric motorcycle model. In this study, the BSS capable of accommodating multiple battery types is classified under the concept of battery heterogeneity. To ensure operational efficiency, a swapping schedule is optimized through the application of a rolling horizon optimization (RHO) framework, while long short-term memory (LSTM) networks are employed to forecast both battery demand and vehicle arrival patterns. Charging and discharging costs are determined based on real-time electricity pricing. The designed scheduling model is empirically evaluated and benchmarked against alternative methods, including polynomial regression and unscheduled operations. The proposed system enables the BSS to accommodate two types of batteries while demonstrating superior efficiency in battery allocation compared to other cases, thereby enhancing the overall performance of BSS operations. Among the evaluated methods, the RHO-LSTM approach yields the highest profit, primarily due to the integration of real-time electricity pricing and an optimized charge-discharge power management scheme. The implementation of the real-time pricing mechanism significantly improves BSS profitability when compared to the use of static grid pricing. Specifically, the profit achieved by the RHO-LSTM method exceeds that of the RHO-polynomial method and the unscheduled operation. This improvement is attributed to the lower energy procurement costs during peak grid pricing periods, which are more effectively managed under the RHO-LSTM framework. Quantitatively, the RHO-LSTM approach results in a 23.77 % higher profit than the RHO-polynomial method and a 0.26 % increase compared to the unscheduled operation. Furthermore, the number of batteries supplied under the RHO-LSTM method is 40 % greater than that of the RHO-polynomial method, indicating a substantial improvement in battery availability and system responsiveness.

Declarations

Author contribution

All authors contributed equally as primary contributors to this paper. Each author has reviewed and approved the final version of the manuscript.

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Competing interest

The authors declare that they have no known competing financial interests, nor any personal or professional relationships, that could have been perceived as influencing the work reported in this paper.

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