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Developing a Multipurpose Battery Swapping Station to Energize Mobile and Stationary Loads

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ABSTRACT

The increasing importance of electric vehicles lies in their lower emissions compared to fossil fuel vehicles. However, challenges like long charging times and range anxiety hinder their widespread adoption. Battery swapping stations offer a practical solution to expedite EV refueling, reducing wait times and range concerns. This research proposes a battery-swapping architecture that provides battery-swapping services to electric vehicles while exploring additional revenue sources and cost reductions. The model uses batteries of the battery swapping station as a battery energy storage system, supplying power to mobile or stationary loads during grid or renewable energy source downtime. By offering cost-effective electricity during peak hours or non-availability, the model demonstrates up to a 35% reduction in consumer electricity costs during peak hours and an 8.8% reduction in overall costs during 24-hour operation. The implementation combines linear programming with machine learning to forecast renewable energy output and electric vehicle energy demand, considering flexible battery charging and discharging controls and degradation processes. These optimization results show the potential of the proposed model to boost battery swapping station income and cut costs, contributing significantly to the electric vehicle market's growth.

Keywords: battery swapping station, electric vehicles, battery energy storage system, energy arbitrage, energy food and transportation nexus, optimization.

NONMENCLATURE

Abbreviations	
EV	Electric Vehicles
BSS	Battery Swapping Station
BESS	Battery Energy Storage System
SOH	State of Health
SOC	State of Charge
DB	Depleted Battery
FCB	Fully Charged Battery
Symbols	
T	Period

1. INTRODUCTION

The rise of electric vehicles (EVs) has significantly reduced greenhouse gas (GHG) emissions compared to traditional fossil fuel vehicles, resulting in a lower carbon footprint [1]. Due to these reduced emissions and competitive advantages, EVs have the potential to replace conventional vehicles in advanced EV markets. Additionally, the United Nations Climate Change (UNCC) has established climate targets, aiming to limit global temperature increases to 1.5°C and reduce GHG emissions by 43% by 2023 [2]. Achieving these emission reductions necessitates clean energy adoption and the integration of emission-free vehicles into the energy and transportation sectors. As a result, addressing the challenges associated with widespread EV adoption in the transportation sector through advanced charging methods, swapping stations, or hybrid models is imperative.

While EVs have the potential to cut challenges like range anxiety and long charging times impede their adoption. Battery Charging Stations (BCS) offer fast chargers to address prolonged charging; however, these are not widely available and can accelerate battery degradation, reducing battery life [3]. EV batteries typically range from 70-100 kWh, with charging times of 20+ hours for Level-1 (L1) slow chargers, 5+ hours for Level-2 (L-2) medium chargers, and approximately 45-60 minutes for Level-3 (L3) fast chargers. Despite L3

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chargers' quick charging, they can hasten battery degradation and reduce efficiency [28].

Proposing battery swapping stations (BSS) to address EV challenges by exchanging discharged batteries with charged ones, extending EV range [4]. BSS ensures rapid refueling with readily available charged batteries while optimizing the charging of incoming discharged batteries. However, this architecture incurs extra capital and operational costs, hindering global adoption and leading to high swapping service fees, limiting widespread use. Additionally, monitoring and controlling battery stock, quality, state-of-health (SOH), state-of-charge (SOC), life cycles, and degradation mechanisms are crucial for optimal BSS operation.

In a typical BSS setup, a fully charged battery (FCB) is provided to an EV in exchange for a depleted battery (DB), with the DB scheduled for charging based on a designated scheme. Integration of the BSS with a solar energy generation plant, such as a PV panel, enables DB charging using clean, cost-effective solar energy. A time-series probabilistic machine learning (ML) algorithm forecasts EV arrival times, energy demands, and solar energy output for a specified period, often planned for the next 24 hours, to optimize charging operations.

With precise knowledge of EV arrival times, energy supply, and demand, BSS optimizes energy operations to minimize grid electricity costs, particularly during peak hours, fostering energy and transportation synergy. A key challenge lies in additional operational costs, which can be mitigated by diversifying income streams—providing services to the grid utility, participating in electricity markets, or supplying electricity to external mobile or stationary loads. These supplementary income avenues boost BSS profitability by, enhancing resource utilization and promoting broader adoption of the BSS architecture.

This paper describes an innovative way of using a portable battery-based storage system in multiple use cases. We introduce a novel BSS-based strategy that leverages grid availability data, solar energy generation forecasts, EV arrivals, and energy demand predictions to minimize purchased electricity costs for external loads like cold storage or electric ovens. Its key contributions include balancing supply and demand using idle BSS batteries as a backup energy source (BES), reducing upfront battery costs, and enhancing storage services. It also introduces flexibility in battery charging and discharging rates for smooth system operation, incorporates battery degradation via the State of Health (SOH), and integrates both energy and transportation sectors, creating an Energy Transportation Nexus (ETN) to address multifaceted challenges. This strategy aims to optimize BSS efficiency while promoting sustainable and cost-effective energy management and transportation solutions.

The rest of the paper is arranged as follows: The literature review in Section 2 presents the state-of-the-art research in the area while highlighting the gap and potential for improvement. Section 3 defines the problem statement and key aspects of the study. Section 4 highlights the proposed methodology of the underlying architecture. Section 5 describes the mathematical formulation of the proposed model. Section 6 demonstrates the simulation output of the model and discusses the results and implications. Section 7 provides the conclusion of the study.

2. LITERATURE REVIEW

Solar energy, integrated with existing transmission and distribution infrastructure, is the fastest-growing renewable energy source, pointing to a renewable energy-driven future for the energy sector [6]. The non-dispatchable nature of renewable energy leads to supply-demand mismatches, causing fluctuations. These fluctuations are managed by utilizing BSS in a B2G model, where the BSS not only offers swapping services to EVs but also contributes services to the grid [5].

Multi-objective BSS optimization orchestrates battery charging schedules to minimize grid load fluctuations and maximize revenue, capitalizing on diverse renewable energy sources like wind and solar [7], while diminishing load fluctuations, and enhancing economic parameters. A smart grid minimizes supply-demand gaps by deploying demand response techniques such as soft load shedding or brownout and supply-side strategies to ensure cost-effective electricity [8].

The BSS technology review underscores its potential integration with grid-related functions, encompassing B2G, grid-to-battery (G2B), and battery-to-battery (B2B) operations [9], realizing operational flexibility based on charging schedule. Battery optimization is carried out by the battery management system (BMS) which oversees voltage, current, and temperature control rendering it indispensable for optimizing BSS operations [10].

The study delves into the combined effects of a PV-based distributed generation system, using the battery-to-X operational model to facilitate flexible B2G, G2B, B2B, PV2G, and PV2B transactions while adhering to quality of service (QOS) and battery SOH constraints. This research provides a valuable business model and insights, with potential extensions to consider various battery capacities, price stochasticity, and PV production [29].

In BSS architecture, aggregators maximize profits by balancing energy demand and supply. While Battery Charging Stations (BCS) are cost-effective compared to BSS, the centralized charging approach [11]. Although PV-integrated BSS reduces battery charging costs, it can introduce negative impacts on electricity markets and system fluctuations which can be addressed by the BSS [12]. A dynamic model empowers BSS to participate in the electricity retail market. This strategy responds to price signals, allowing BSS to sell surplus energy to the market during high-price periods [31].

To reduce cost and increase profit within the BSS, linear programming is employed for charging expenses, battery depreciation costs, and Operation and maintenance (O&M) expenses, and factors affecting both are indicated by sensitivity analysis [13]. Net present value (NPV) analysis assists in selecting the site and size of the BSS required for electric buses on specific routes. It's observed that the BSS size correlates directly with electricity sold [14]. Moreover, the application of the BSS architecture for private EVs has also proven beneficial and holds potential for widespread adoption.

To maximize profits, BSS explores diverse income sources, including the novel use of idle batteries for frequency regulation services in the electricity market [15]. Optimizations in these scenarios focus on scheduling battery charging during PV availability, reducing electricity costs [16]. Furthermore, a day-ahead business model emphasizes optimal charging and bidding strategies, factoring in market dynamics, customer behavior, EV characteristics, and swapping fees, all aimed at maximizing BSS profits while managing inflows and outflows effectively [30,31,32,33].

A chance-constraint programming method is utilized to address uncertainties in PV generation and EV demand at the BSS, aiming to minimize grid electricity purchase costs while allowing for a controlled probability of constraint failure [17]. Additionally, a bi-level optimization approach, employing the Alternative Method of Multiplier (ADMM), is proposed for both the microgrid (MG) and BSS. This method targets cost reduction and congestion avoidance while considering battery degradation modeled in terms of depth of discharge (DOD) [18]. In alignment with the MG concept, a cyber-physical model integrates the nanogrid (NG) with the EV-BSS architecture, enhancing energy supply, reliability, resilience, and profitability using mixed-integer linear programming (MILP). Effectively utilizing BSS storage capacity minimizes the investment cost of planned PV and energy storage system (ESS) capacity [23].

To mitigate congestion in EV taxis, a ranking system based on vehicle occupancy status is employed, translating into efficient scheduling plans [19]. Within the BCS architecture, battery charging scheduling (BCSS) optimizes Fast Charging Battery (FCB) demand while minimizing electricity cost [22]. BSS outperforms BCS in terms of flexibility and cost reduction potential, offering a broader array of services.

While many BSS studies assume battery homogeneity, real-world scenarios often involve battery heterogeneity [20]. In contrast, another study employs a stochastic model to forecast electric bus (EB) load demand, accounting for unknown EB swap demands without reservations [21].

The review assesses the technical, economic, and environmental aspects of EV charging stations powered by hybrid generation sources, incorporating PV/Wind Turbine (WT)/Diesel Generator (DG)/Battery configurations, with battery types including lead-acid, flow-zinc-bromine, and lithium-ion based on NPV [24]. In another analysis of a typical BSS with installed solar generation, Markov Decision Problem (MDP) techniques are employed to minimize the weighted sum of charging costs [25].

A dynamic BSS optimization model, utilizing Long Short-Term Memory (LSTM) and Rolling Horizon Optimization (RHO), accommodates BSS heterogeneity. This model facilitates energy sales to the grid during peak load hours, offering B2G, G2B, B2B, and ancillary services, with model performance assessed via Root Mean Squared Error (RMSE) [26]. In a preliminary analysis, the BSS supplies electricity to an external load on a remote farmland, primarily serving a crop storage facility. Results reveal a reduction in the cost of electricity supplied to the grid [27].

Extensive research has explored BSS's technical, economic, and business dimensions, utilizing advanced ML algorithms and mathematical models to boost profitability, and cut costs. Yet, harnessing BSS energy storage for external loads remains underexplored. Prior studies often neglect battery charging, discharging, and degradation. This study introduces an innovative approach, integrating BSS-PV architecture and EVs to leverage BES capabilities, bolstering BSS income while lowering electricity costs. BES also has potential as a backup power source, addressing challenges in energy

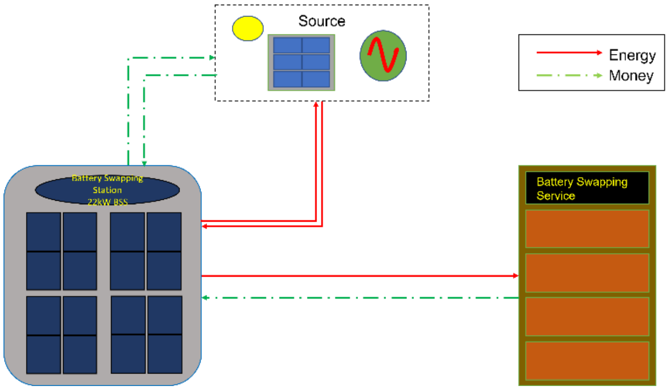

Fig. 1. A Typical BSS Architecture

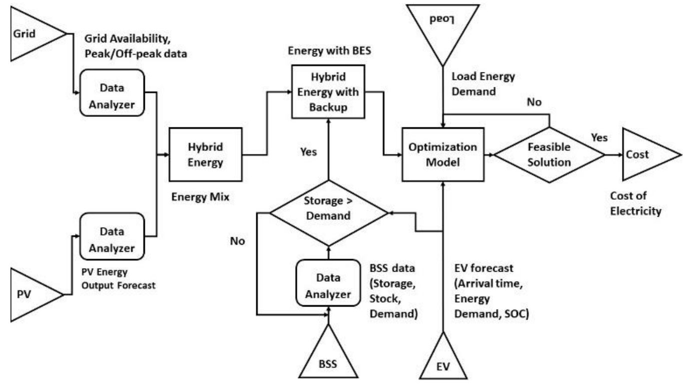

Fig. 2. A Flow Diagram of Proposed Model

and transportation. The next section outlines the problem and dataset.

3. PROBLEM DESCRIPTION

The problem description comprises problem statement Section 3.1 defining the underlying problem, and data description Section 3.2 which identifies the type of data, data resolution/granularity, and processing.

3.1 Problem Statement

The research problem caters to minimizing the cost of electricity purchased by an external load interconnected with a solar energy generation plant, or grid utility while considering the energy storage component of a battery swapping station as a backup source of electricity.

3.2 Data Description

The obtained data is processed and provided to the proposed architecture which is bound to real-world constraints including the demand and supply balance, and battery limitations at the BSS to reduce the cost for optimal operation of the integrated system.

Incoming EV arrivals follow a random pattern, typically represented by a probability density function (PDF) of a random variable. This randomness introduces uncertainty into the energy demand forecast, which is vital for the BSS battery charging schedule. The BSS relies on this forecast to determine the number of depleted batteries (DB) that should be fully charged (FCB) before an EV arrives. Accurate forecasting and proper scheduling lead to efficient BSS operations, reducing EV refueling time, range anxiety, and unexpected stress on the charging infrastructure. The randomness in EV arrivals is reflected in the BSS's energy demand, making it suitable for exploring BSS as a dual-purpose source of operation.

Energy from renewable sources, such as solar, exhibits inherent intermittency, contributing uncertainty to the system model. To address this, an accurate prediction model is employed, forecasting solar irradiance for the upcoming period. This irradiance data guides a Maximum Power Point Tracking (MPPT) model to estimate energy output from the PV module. Precise predictions and effective MPPT result in improved scheduling and BSS optimization. This uncertainty and prediction impact the energy profile of solar PV data. Meanwhile, the grid availability dataset reveals load-shedding periods throughout the day, pinpointing off-peak and peak demand times. Data processing and analysis focus on the following aspects:

- Identify the high/low price, availability/non-availability periods of electricity from the grid and the solar energy generation plant.
- Identify the period of the next EV arrival, along with the energy requirement.
- Interlink the devised periods and share the outcome with the simulation model.

4. PROPOSED METHODOLOGY

The battery swapping station (BSS) operates in two modes: one for swapping EVs' depleted batteries (DB) with fully charged ones (FCB), and the other for managing and charging incoming DBs for future use. A typical BSS architecture includes the BSS control center, chargers in multiple bays, an inventory with FCB called the fully charged battery inventory (FCBI), a charging infrastructure connected to the grid and solar PV module, and a battery management system (BMS). The system is powered by both the grid and solar energy from PV panels. The energy and financial flows are depicted, emphasizing the system's income stream. Solar energy, a renewable and clean resource, can lead to cost

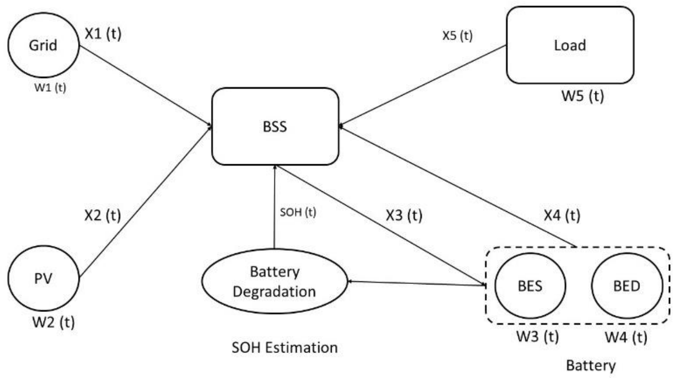

Fig. 3. Optimization Model

savings compared to grid electricity, which varies in cost between peak and off-peak periods, with peak rates being 50% higher, making grid electricity more expensive for the system.

Efficient battery operation and health monitoring are ensured by the battery management system (BMS), which acts as the central control unit of the BSS. The BMS monitors cell temperature, voltage, and current, and estimates state of charge (SOC) and state of health (SOH) to ensure battery safety and longevity. A typical BSS has a maximum capacity of 22kW, composed of sixteen individual batteries with 1.375kW capacity each, organized in sets of four batteries for each swapping demand, providing 5.5kW energy capacity to arriving EVs. This swapping service represents the BSS's sole income source and optimizing its operation or increasing its profit potential could drive wider adoption of this infrastructure. Fig. 2 shows an overview of the proposed methodology.

The widespread adoption of the BSS architecture is hindered due to the inherent cost of electricity which results in expensive charging producing expensive swapping service fees. Most recent methodologies use the available solar energy to maximum by proposing various charging schemes where the batteries are scheduled to charge maximally during the solar availability period, while the grid station is kept as a last resort. To cater to this optimal utilization smart switches are installed which switch the energy resource based on the demand criticality, available energy, and system cost. The main objective of the smart switch includes the maximum utilization of solar energy, minimum system cost, and meeting the defined minimum energy demand criteria of DB charging.

The approach aims to efficiently utilize the available energy stored in the batteries of BSS while considering EV energy demand, available PV energy generation, and battery life. With accurate EV arrival forecast data and energy information, the model utilizes idle batteries as a backup source of energy during periods when solar generation and the grid are unavailable. Additionally, the high cost of grid electricity, especially during peak hours, makes the use of grid electricity the last resort. During peak load periods, energy demand is fulfilled by the batteries at the BSS, which are then recharged either by solar generation or the grid during off-peak periods. The model incorporates flexibility in controlling the charging and discharging of the batteries at the BSS. It has been observed that battery charging and discharging rates can sometimes be undesirable given the energy demand and generation profile.

To avoid undesirable scenarios, the model manages and controls both the allowed charging rate and the allowed discharging rate based on demand and supply. Moreover, the model includes a battery degradation process based on the battery State of Health (SOH). The BSS estimates the incoming battery SOH, which is then used to determine the effects of battery degradation. This is incorporated in the model as the energy component that could have been provided by the battery but is unavailable due to degradation. The primary goal of the model is to minimize the cost of electricity. The model is simulated for four different scenarios highlighted in Table 1. The "Low" attribute in the table indicates that the system is either unable to achieve the desired output or is completely unavailable. Similarly, "High" indicates that the system is available to provide the desired energy output. These scenarios are based on grid and solar availability, which define the reliability of supply coming from these sources. The next section describes the mathematical formulation of the proposed model.

5. MATHEMATICAL FORMULATION

The proposed architecture comprises a BSS which acts as a control center where the optimization process takes place. The goal of this control center is to minimize the cost of electricity offered to the connected secondary load which can either be a mobile or a stationary load. For simplicity, it is assumed that the secondary load is stationary in the form of cold storage for crops installed on the farmland.

Fig. 3 outlines the optimization structure and key components of our model, including the BSS control center, the grid utility providing electricity categorized as peak and off-peak, and solar energy generation. Solar power availability depends on local solar irradiance. The BSS serves as an energy hub, storing and selling energy

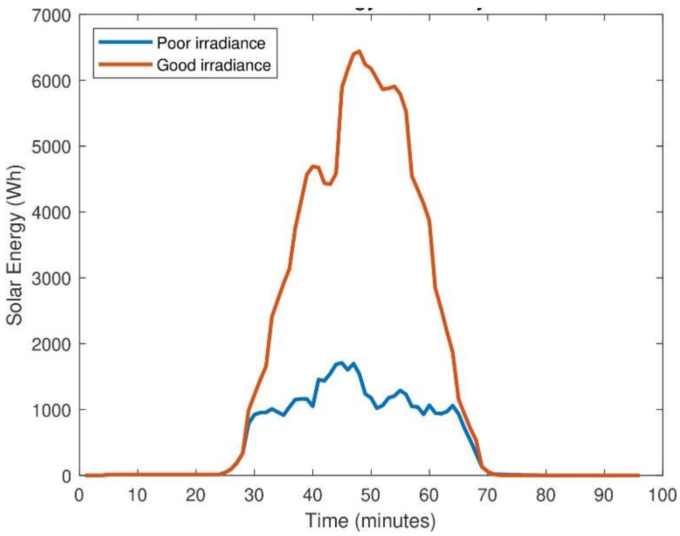

Fig. 4. Solar Energy Availability

to the load as needed, primarily through battery charging.

Table 1. Model Simulation Scenario

Scenario No.	Grid Reliability	Solar Reliability
1	Low	High
2	Low	Low
3	High	Low
4	High	High

Tool: The model is implemented and simulated using MATLAB, including the creation of the model, incorporating the constraints, data pre-processing, and deduction of statistical and graphical output for meaningful results. The model is formulated as the linear programming (LP) problem having the objective function of minimizing the cost of electricity as follows:

Objective function:

$$min \sum_{t=1}^{24} \sum_{i=1}^{3} x_i(t) * w_i(t) \tag{1}$$

Subject to:

$$x_1(t) + x_2(t) + x_3(t) = x_4(t) + x_5(t) \quad \forall t = \{1,2, \dots, T\} \tag{2}$$

$$x_1(t) \leq G_{max} \tag{3}$$

$$x_2(t) \leq PV_{max} \tag{4}$$

$$x_3(t) \leq BES_{max} \tag{5}$$

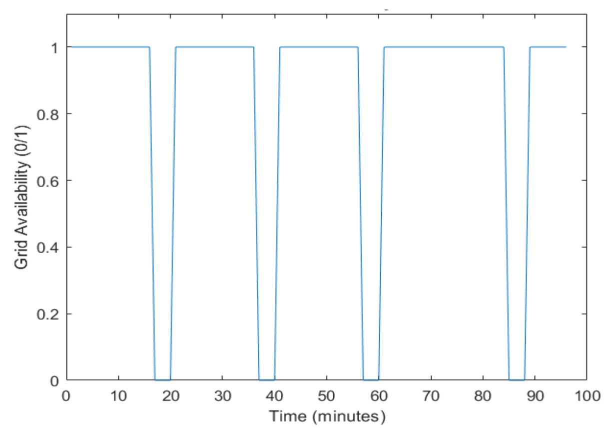

Fig. 5. Grid Energy Availability

$$x_3(t) \leq ABD \tag{6}$$

$$x_3(t) \leq BES - C_{threshold} \tag{7}$$

$$x_i(t) \geq 0 \quad \forall\, t = \{1,2, \dots, T\}, i = \{1,2,3,4,5\} \tag{8}$$

In the above formulation $x_1(t)$ represents the number of units of electricity sold by the grid utility during the period t. $x_2(t)$ represents the number of electricity units sold/produced by the solar generation, i.e., PV, during the period t. $x_3(t)$ represents the number of units of electricity sold by the battery energy storage system (BESS) to the stationary load during the period t. $x_4(t)$ and $x_5(t)$ refers to the number of electricity units consumed by the battery and load for the period t.

The period is defined over the next 24 hours where each slot is kept variable based on the desired data granularity. For analysis, a 15-minute time slot is used, therefore, 96 periods are defined in the dataset, i.e., T=96. The weight component of the objective function $w_1(t)$ is the cost of electricity offered by the grid during the period t. $w_2(t)$ is the cost of electricity offered by the PV generation for the period t. $w_3(t)$ is the cost of electricity offered by the BESS during the period t. $w_4(t)$ and $w_5(t)$ are the cost system constraints associated with both battery and stationary load respectively set to unity for the period t

The objective function (1) tries to minimize the cost of electricity purchased by the stationary load. The first constraint in (2) is the demand fulfillment criteria to balance the demand and supply of the system while ensuring stability. The battery degradation process is included in the model which is defined using the rated capacity of the battery C_{rated} , battery's running capacity $C(t)$ and battery's state-of-health $SOH(t)$ which is estimated during the period t. The maximum energy offered by the grid utility is limited by the capacity of the grid denoted by G_{max} in (3). Similarly, the maximum energy offered by the PV and the battery are limited by their maximum capacity denoted by PV_{max} and BES_{max} shown in (4) and (5) respectively.

Moreover, the amount of energy that can be drawn from the BESS at the BSS is limited by the Allowed Battery Discharge (ABD) as in (6) which is a flexible parameter defining the battery discharge rate. It is observed that if the batteries are allowed to discharge without any control or flexibility they tend to discharge at a high rate. Therefore, ABD is essential to incorporate the battery discharge process providing flexibility and control over the BESS operation. Furthermore, the amount of energy that can be drawn from the BESS is also limited by a threshold value as in (7) beyond which the BESS cannot provide energy. This threshold in capacity is denoted by $C_{threshold}$ whose value is computed using (9) where SOC_{max} is the maximum SOC allowed while charging, SOC is the flexible minimum allowed SOC beyond which BESS is prohibited from providing energy and C_{rated} is the rated battery capacity.

$$C_{threshold} = \frac{SOC_{max}}{SOC} * C_{rated} \tag{9}$$

The cost of electricity offered by the BES at the BSS is subjected to multiple constraints and given the fulfillment of these constraints, the BES at the BSS offers the electricity at a price that is the weighted average of the electricity purchased by the grid and solar energy generation plant to charge DB at the BSS given by (10).

$$BES_{pu} = \frac{\left(PV_{pu} * t_{PV}\right) * \left(grid_{pu} * t_{gPV}\right)}{T} \tag{10}$$

The term BES_{pu} refers to the per unit cost of electricity offered by the BES at the BSS. PV_{pu}denotes the per unit cost of electricity offered by the PV while t_{PV} represents the subset of the period where the solar energy is available, $grid_{pu}$represents the per unit cost of electricity offered by the grid while t_{gPV} refers to the subset of the periods where the grid is available except for the solar availability and T is the number of periods. The next section highlights and discusses the optimization outcome along with the implications of the model.

6. RESULTS AND DISCUSSION

Fig. 4 displays the solar energy available in kilowatt-hours at the proposed site. The time is denoted in minutes over the next 24 hours, and the solar energy is obtained from the site's available solar irradiance passing through the inverters after conversion and maximum power point tracking (MPPT). For the case study, two separate days are selected: one with ample solar irradiance, while the other has the least energy available due to poor solar irradiance spread over 24 hours. As solar energy is the least expensive source of energy, it is best to maximize its utilization to reduce the cost of electricity. During periods of non-availability, the battery energy storage system (BESS) at the BSS can be used to provide energy to the load more cost-effectively than the grid utility. Moreover, grid availability also varies, and two separate cases are considered: one where the grid is always available, and the second where the grid may not be accessible due to load shedding, making it unreliable. The grid availability forecast is shared daily, and for simplicity, the output is presented in binary form as shown in Fig. 5.

The model output generates a cost comparison of the two cases under discussion. The first setup implements the model without battery energy storage (BES), where the primary sources of energy are the grid utility and solar generation through PV panels. From the per unit cost of electricity dataset, it is evident that solar energy is prioritized over grid electricity in both peak and off-peak periods due to its lower cost. Therefore, whenever solar energy is available, the model maximizes its utilization by offering cheap electricity to the load, resulting in reduced consumption costs.

The cost can be further reduced if the model incorporates batteries installed with the given solar PV panels to offer electricity during other periods as well. However, the high upfront cost of the batteries increases the overall expenses of the solar generation system and reduces the benefits. Given the problem of the high-cost requirement of the batteries, the second case considers the use of batteries at the BSS to complement solar energy during periods when solar energy is unavailable. This scheme not only eliminates the need for purchasing batteries for the solar generation system but also effectively utilizes the available solar generation energy, which can be used at a later stage. In the second case, the cost of electricity offered by the BES of the BSS is obtained using the weighted average cost of both grid and solar energy per unit, as expressed in (10).

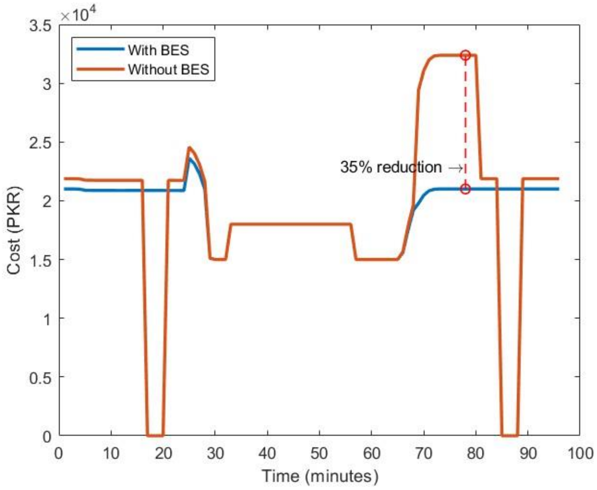

Fig. 6. Cost Comparison of Scenario-1

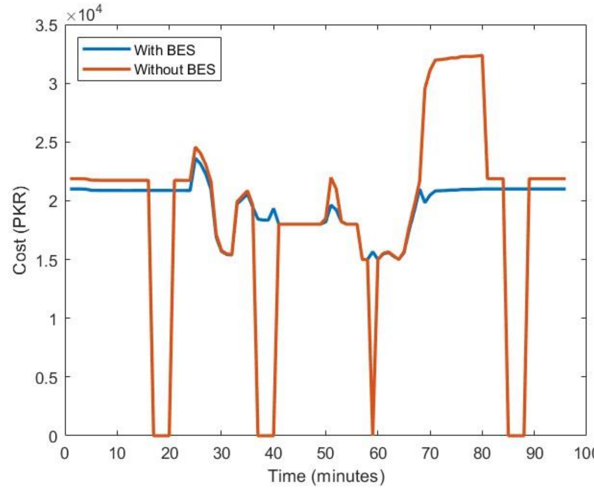

Fig. 7. Cost Comparison of Scenario-2

Fig. 6 displays the model output for the first scenario, where we have a good solar energy output but an unreliable grid with load shedding incorporated. The simulation is performed with and without involving BES. From the output, it is observed that due to the non-availability of solar energy and grid utility, the system is unable to provide energy to the load, resulting in load shedding. At the start of the day, the model predicts load shedding in the first case due to the non-availability of both solar and grid electricity. In the second case, the BES at the BSS fulfills the same energy needs during these periods. Moreover, the cost of electricity is lower for the BES case compared to the case without BES.

During the solar availability period, it is observed that solar energy is maximally utilized, and both cases have the same output as they prefer to use available solar energy for cost reduction. As the solar irradiance decreases towards the end of the day, a peak period emerges where the available grid energy is more expensive than during the off-peak period. In the first case, the cost of electricity increases to the maximum value, while in the second case, the idle batteries of the BSS provide energy as a BES at a consistent price. During this period, a maximum reduction in the cost of electricity is observed, with a 35% decrease occurring if the batteries of the BES at the BSS are used. Finally, towards the end of the day, there is again a period of solar and grid non-availability. This remains unfulfilled in the first case, but the demand is met by the BES at the BSS in the second case.

The second scenario is simulated, where the grid availability is low, i.e., the grid is unreliable, along with low solar irradiance, i.e., solar energy is not available. Therefore, there are periods of grid and solar energy non-availability, and as a result, the load must be shut down or deprived of energy, as shown in Fig. 5. The simulation results are shown in Fig. 7. From the results, it is observed that the load had to be shut down several times during the day for the setup without BES. However, the load has been fulfilled by the BES during periods of non-availability in the setup with BES, improving the system reliability and reducing the cost of electricity during the purchasing period.

The third scenario is simulated with the grid available, while solar energy is less available due to low solar irradiance. Fig. 8 shows the simulation results, and it is observed that the two setups provide almost similar results during off-peak times, as the difference between the two is less. However, the difference increases during the peak period, where the cost of energy purchased from the BES is less than the energy purchased from the grid.

The fourth scenario includes available grid and solar energy. Fig. 9 shows the simulation results, and it is observed that the cost is the same, especially during the solar energy availability period, as both setups utilize the available solar energy to its maximum potential. Moreover, the initial difference in cost is less, as the difference in the price of electricity between the off-peak grid rate and the BES rate is low. However, the difference becomes significant during the peak period, where a 35% reduction is observed, like in the first case. Meanwhile, no load has been shut down here due to the grid availability in the setup with BES.

Table 2 presents the cost comparison for the four simulated scenarios during the 24-hour operation of the BSS as a BES. Scenarios 3 and 4 reduce the cost of electricity by 8.8% and 8.5% respectively during the 24-hour operation. However, scenarios 1 and 2 show a negative sign or an increase in the cost of electricity

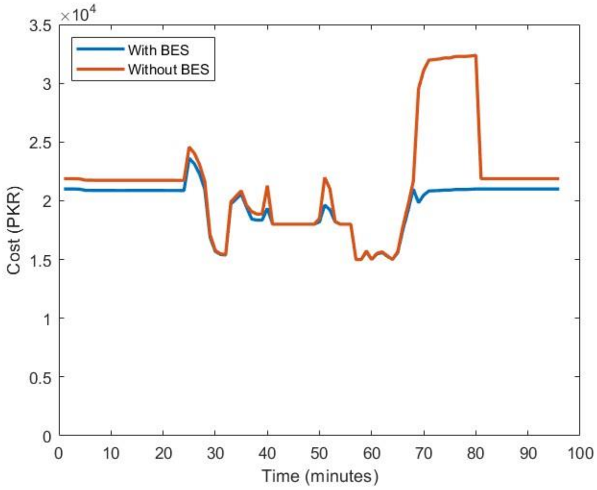

Fig. 8. Cost Comparison of Scenario-3

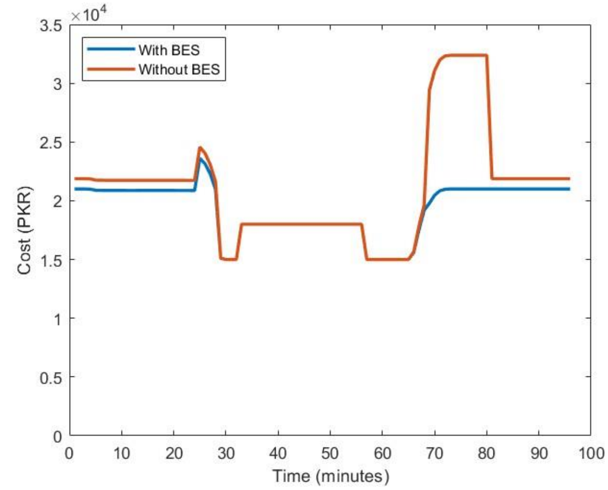

Fig. 9. Cost Comparison of Scenario-4

purchase. The first two scenarios are those where the grid is not available or is unreliable, resulting in the load being shut down. During the normal operation in the setup without BES, the load is shut down as the supply is not available; hence, the load does not purchase any electricity, reducing the cost of electricity. Due to the load-shedding methodology, the actual energy usage or purchase remains unclear. This highlights that although the price of electricity has increased, the system is now able to provide uninterrupted electricity to the consumer.

Table 2. Comparison of Electricity Cost Per Day

Scenario	Cost		Difference (%)
	With BES	Without BES	
1	1855118	1856971	-0.1
2	1881382	1795117	-4.8
3	1881382	2063391	+8.8
4	1856971	2029567	+8.5

A significant reduction is observed in all four scenarios, especially during peak load duration when an alternative cheap source of electricity is not available. The utilization of idle batteries at the BSS in the form of BES not only results in providing cheap electricity to the consumer but also enhances the utilization of the installed solar generation plant by offering storage during the solar availability period and providing uninterrupted electricity to the consumer. Moreover, the interconnection with the grid utility offers the optimal scheduling of battery charging strategies, which can further reduce the cost of electricity offered to the BSS for battery charging. In return, the BSS can offer battery energy capacity to the grid for stability and backup services. Although the BSS can act as a BES using the idle batteries by providing energy to external mobile or stationary loads, a detailed cost-benefit analysis of the BSS must be carried out to gain a better insight into the complete system's working and profitability.

7. CONCLUSION

The battery swapping station (BSS) addresses EV range anxiety and long charging times through quick battery swaps. However, its adoption faces challenges due to additional battery and swapping costs. To overcome this, the proposed model explores alternative income sources for BSS, utilizing idle batteries for grid stability, backup power, and storage. The model demonstrates up to a 35% cost reduction during peak load and 8.8% in 24-hour operations for external loads. Future improvements include the upgradation of the linear model towards a more complex integer model incorporating the uncertainty of energy and load demand for real-world optimization. The enhanced model will be integrated into a multi-disciplinary model focusing on energy, food, and transport sectors forming an energy, food, and transportation nexus (EFTN).

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