

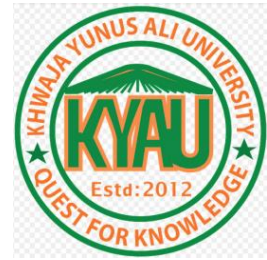
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Research Article

AN OVERVIEW OF POWER MANAGEMENT OF ELECTRICAL VEHICLES

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ABSTRACT

Electric vehicles (EVs) represent a significant approach to minimizing oil usage and cutting greenhouse gas emissions. When they are connected to the electrical grid for either charging or discharging purposes, they are referred to as gridable EVs (GEVs), which are crucial for effective energy management. This study evaluates the incorporation of GEVs within microgrid frameworks through technologies such as vehicle-to-home (V2H), vehicle-to-vehicle (V2V), and vehicle-to-grid (V2G). A detailed review of EV categories, power management strategies, and charging methodologies is provided, along with the challenges and solutions tied to them. We propose a coordinated optimization scheme based on a Multi-Agent System (MAS) to establish the most effective charging and discharging schedules, utilizing trip pattern forecasting through a regression by discretization technique. Additionally, the model includes economic incentives for both electric vehicle owners and their workplaces. A DSP-based hardware testbed is used to create a hybrid power source circuit, and the methodology is validated through simulations and experiments. By supporting cleaner urban environments and sustainable energy practices, our work improves environmental health and societal well-being.

Keywords— Solar Irrigation: SDG: Surplus Electricity Electric Vehicles (EVs), Energy Management, Gridable Electric Vehicles (GEVs), EV Forecasting.

01. Introduction

The majority of the transportation across the world relies on petroleum-based vehicles, which emit greenhouse gases. In addition, an increase in fuel rates motivates researchers to work on electric vehicles (EVs). In recent years, many existing automobile manufacturers and new dedicated companies have put a remarkable effort into transforming the conventional vehicle into an electric vehicle that provides a green and reliable solution. The solid lines represent the power flow, while the dotted lines are the information flow; meanwhile, the red dotted line, the pink dotted line, and the blue dotted line correspond to the transmission line information, V2G line information, and V2V line information, respectively. The GEV can offer its battery for active power exchange with the home grid. Also, the onboard or offboard bidirectional charger can offer the bidirectional active power conversion and provide the reactive power to the grid using its DC link capacitor.

The smart building can achieve energy savings through various energy-efficient technologies and can transmit the renewable energy harnessed from the building to the low-voltage (LV) network or other local devices. The GEV aggregators play a key role in allocating the power flow and the information flow between the grouped GEVs and the grid. According to the grid voltage level, the GEVs can be classified as three kinds of clusters for energy distribution.

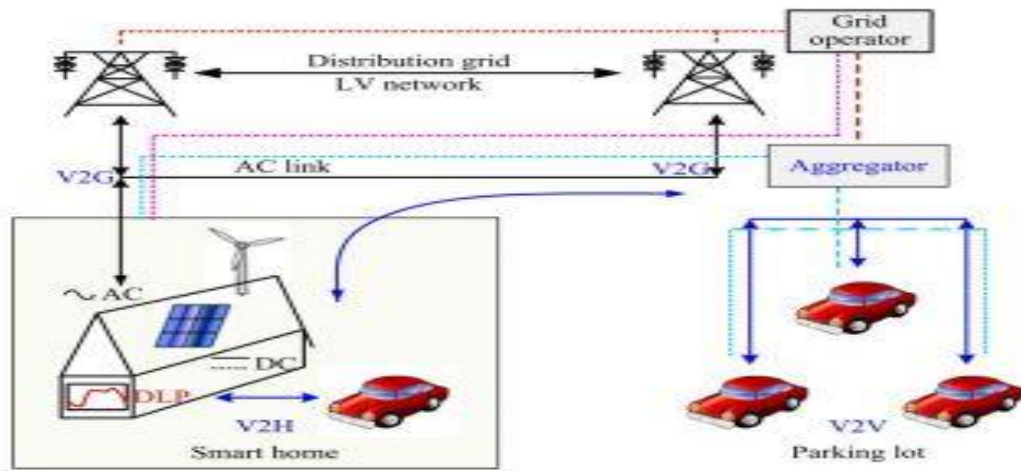


Fig I(a): Framework for V2H

The first kind of cluster is that GEVs are located at the LV network, which facilitates V2H and V2V operations. In a practical situation, these GEVs are allotted to residential areas, parking lots, and smart buildings. The second kind of cluster is that GEVs are located at the medium-voltage (MV) network for the V2G operation. In a practical situation, these GEVs are allotted to GEV charging stations, particularly for fast charging and discharging. The third kind of cluster is that GEVs are also located at the MV network but are not advised for use in the V2G operation. In a practical situation, these GEVs stop at the swapping stations for swapping their batteries so that all discharged batteries are collectively recharged or regenerated in the MV network. Moreover, in the first and second clusters, the GEV chargers also can offer reactive power support via their internal capacitors.

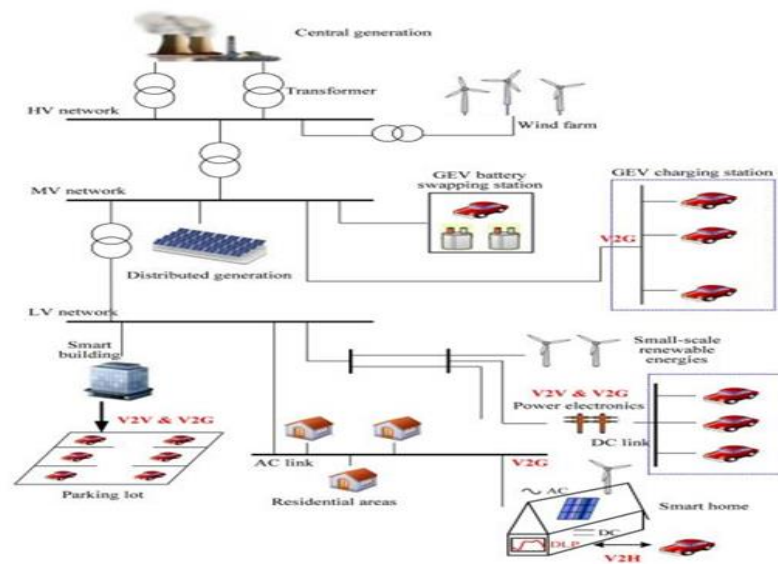


Fig I(b): Framework for V2V

2.0 MATERIALS AND METHODS

The power management (PM) system in EVs is formed by two layers: high-level software-based supervision and low-level hardware-based control, which can be divided into two control layers: low-level component and low-level control. Both hardware and software control layers work together to optimize the PM system in EVs. (Ehsani, M., et al., 2018; Chau *et al.* 2007). The major challenge of an energy management system (EMS) in an electric vehicle is to ensure optimal use and regeneration of the total energy in the vehicle. Regardless of the number of sources and the powertrain configuration, at any time and for any vehicle speed, the control strategy has to determine the power distribution between different energies. When two storage systems or two fuel converters are available, additional power distribution between the RESSs and between the fuel converters has to be determined. These decisions are constrained by two factors. First of all, the motive power requested by the driver must always be satisfied up to a maximum power demand already known. Then, the charge status must be maintained, allowing the vehicle to be charged continuously (Paganelli *et al.* 2001).

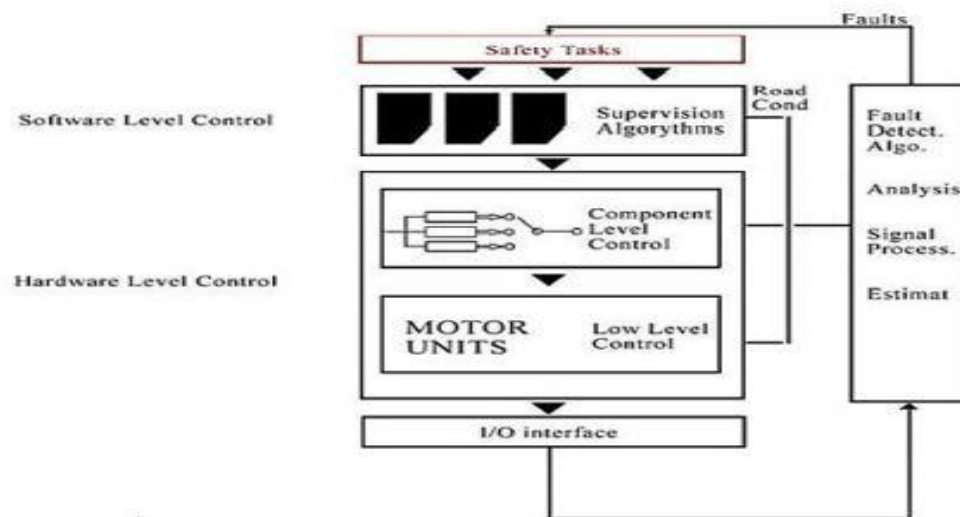


Fig II(a): Power management control layer

2.1 Hardware Level:

Power management control design starts with the hardware level, more precisely with the vehicle power train which is a must in every EV (Pisu, P et al. 2007). Presented in different approaches to management results, increase vehicle performance and robustness, and reduce energy loss in transmission (Chen, H et al., 2012; Salmasi, F. R., 2007).

Generally, there are 6 transfer architectures in BEV; the first is the conventional drivetrain with clutch (Fig. II(b)). The vehicle is equipped with an Energy Storage System (ESS) that delivers electrical energy to the main EM through a power converter. The mechanical energy provided reaches the front wheels through a quite long way, a clutch, a gearbox, and a differential.

In the second type, Fig. II(c), the clutch is deleted and the gearbox is replaced with a fixed-gear transmission unit while the entire architecture remains the same. This little enhancement simplifies the driveline configuration and reduces the size and weight of the transmission system (Malikopoulos, A. A., 2014, Xu, S et al. 2013).

By following the same logic, a third configuration, Fig. II(d), offers a further simplification. It groups the electric motor, the single-gear box, and the differential on the same level with wheels. The BEV is lighter, and mechanical transmission losses become minimal. The need to enhance the cornering performance in BEVs: each wheel gets its own fixed gearing and its own electric motor. Thus, it is possible to operate at different speeds. In some other configurations, the wheels were exploited. The in-wheel application reduces even more weight and complexity. Here, the vehicle operates in direct drive without a drive shaft; wheels are equipped with the fixed gearbox and driven directly by EMS. The same architecture is kept in the final configuration

but with more use of in-wheel application. The EM is built right in the wheel, and the drive train is reduced to zero. Each EM receives power from a dedicated power converter fed by the Energy Storage System.

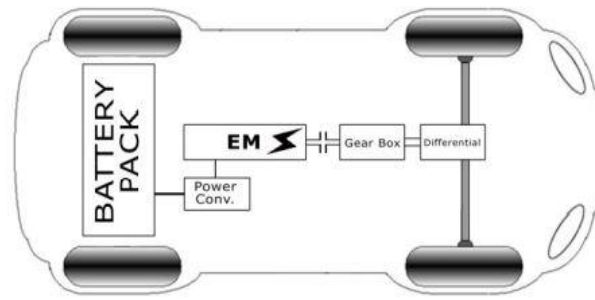


Fig II(b) : Conventional Drive train

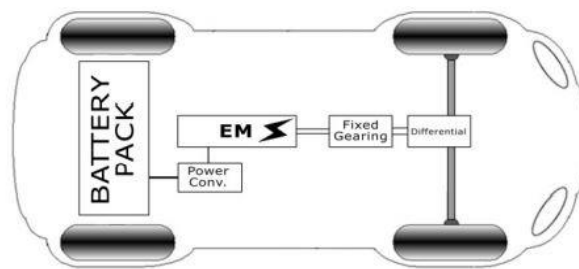


Fig II(c): Single-gear transmission architecture

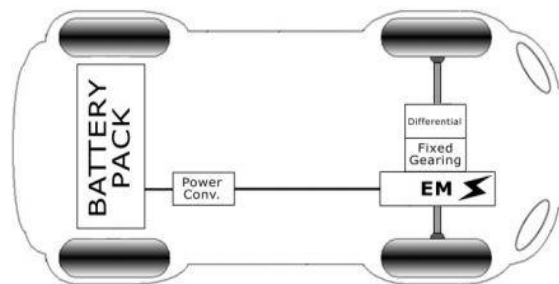


Fig II(d): Integrated single-gear and differential architecture

For HEV, mainly 4 architectures are available and aiming different vehicle purposes; Parallel Drive Train configuration Fig II(e) allows both ICE and EM to access transmission in parallel via couplers (Chen *et al.* 2012). The second architecture is Series Drive Train Fig II(f). Only the EM accesses the transmission shaft. Meanwhile, the ICE is to generate electrical power but not to support the EM in transmission. The generated electric power is led to power converter before reaching Battery Pack and EM (Iversen *et al.* 2014). By combining the previous configurations Fig II(g), the Parallel Series Drive Train is figured out, the ICE supports the EM in similar way to parallel mode, however, it keeps providing electric power through linked generator (Elbert, P *et al.* 2014). In final architecture Fig. II(h), by replacing the generator in previous vehicle structure and adding a second power converter to store electrical energy in-car produced in battery, HEV become more controllable and efficient (Xu, S *et al.* 2013). Both, HEV and BEV architectures use DC/AC converters to control electric motors feeding and DC/DC converters to manage two way energy transfer for battery charging or use (Tie, S. F *et al.* 2012, Salazar *et al.* 2013).

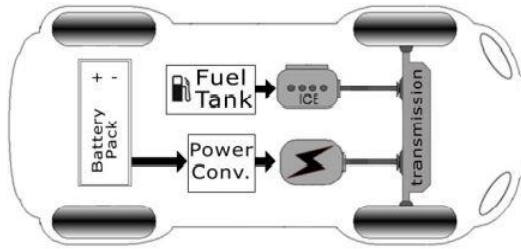


Fig II(e): Parallel structure HEV

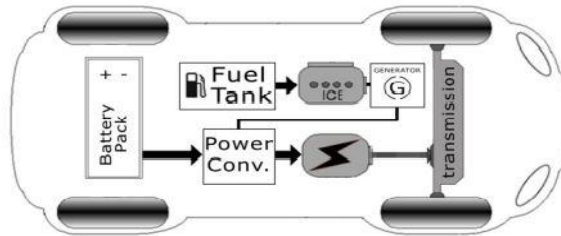


Fig II(f): Series structure HEV

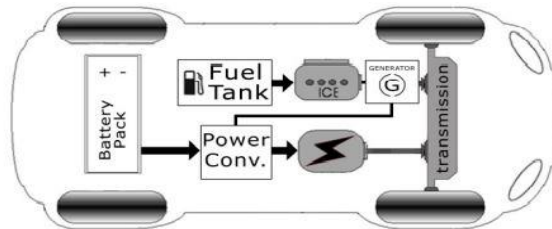


Fig II(g): Series-Parallel structure HEV

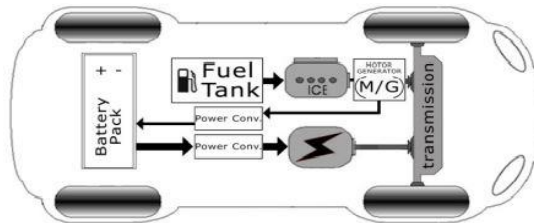


Fig II(h) : Complex structure HEV

2.2 Software Level:

In the high supervisory power management layer (PML), many algorithms have been developed. Depending on powertrain architecture, mainly five techniques proved reliability and delivered intended results: offline power management control (PMC) algorithms, online PMC algorithms, rule-based PMC algorithms, learning PMC algorithms, and GPS-enhanced PMC algorithms (Paganelli, G et al., 2001; Malikopoulos, A. A., 2014).

2.3 Modeling:

The modeling of V2H, V2V, and V2G systems should be based on the objectives and their constraints. The general objectives for V2H, V2V, and V2G are load variance minimization, cost minimization, cost-efficiency optimization, cost-emission minimization, power loss minimization, load shift and peak load reduction, reactive power compensation, and so on. Based on the aggregated sizes of the GEV battery and capacitor, V2H, V2V, and V2G have their individual objectives and constraints. A general modeling diagram for the V2H, V2V, and V2G systems is proposed as depicted in Fig. II(i). Based on this modeling diagram, the objective functions and constraints can be grouped and bounded to perform the desired optimization target.

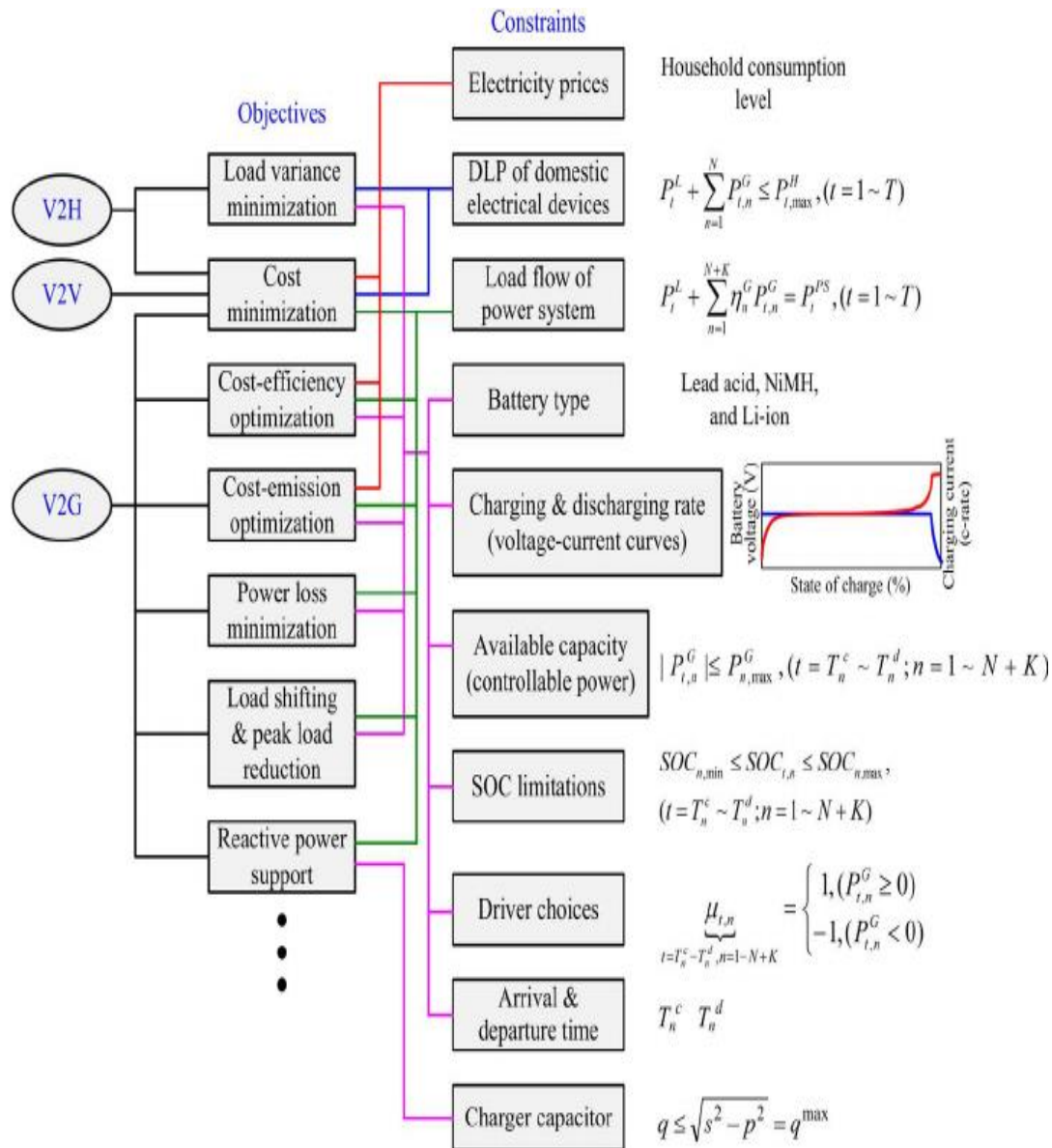


Fig II(i): Proposed general modeling diagram for V2H, V2V, and V2G systems

2.4 Battery Technology:

Battery is the key component of the GEV, which has a significant impact on the V2H, V2V, and V2G systems. First, the battery offers the energy for the GEV. Also, the battery plays the role of energy exchange between the GEV and the power grid. Furthermore, the battery energy can be further exchanged among GEVs. Table II(a) lists three main types of batteries, namely, the lead–acid (Pb–acid), the nickel–metal hydride (Ni–MH), and the lithium-ion (Li–ion), for GEVs (Kutkut, N. H., *et al.* 1997), (Burke, A. F., 2007). The Pb– acid type has the lowest energy density and lowest cycle life. Furthermore, it has the memory effect for charging, which needs to fully charge each time. Thus, the Pb–acid type is not preferred for modern GEVs.

Table II(a): Characteristics of GEV Batteries

Type	Pb-acid	Ni-MH	Li-ion
Specific Energy (Wh/kg)	30-40	60-120	90-160
Specific power (W/kg)	200-300	150-400	250-450
Cycle Life	400-600	600-1200	1200-2000

On the contrary, the Ni-MH and Li-ion batteries have much better performances, hence favoring modern GEVs. Fig. II(j) shows the cost-effectiveness of these three batteries. It can be found that Li-ion has the highest capital cost per unit power and unit energy, leading to the high initial cost of those high-performance GEVs. Thus, Ni-MH can still play a role for those economical GEVs. Nevertheless, both Ni-MH and Li-ion need to have a significant reduction in cost in order to improve their cost-effectiveness for the V2H, V2V, and V2G operations. Based on the specific energy, specific power, life cycle, and cost-effectiveness of these three main batteries (Panel, A. I. E., 2007), it can be identified that all of them are suitable for BEVs, Ni-MH is preferred for the light-duty economical PHEV and REV, and Li-ion is favorable for the heavy-duty high-performance PHEV and REV.

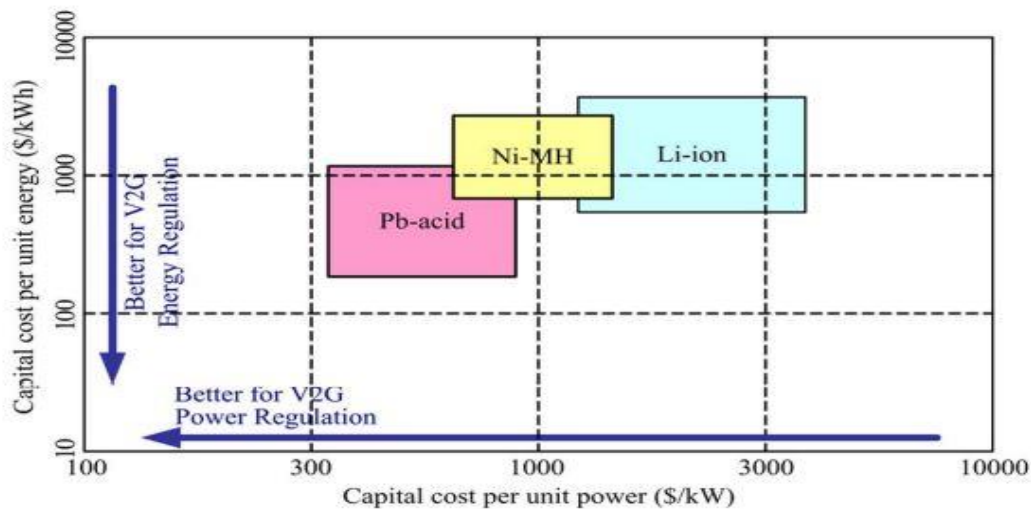


Fig. II(j): Cost effectiveness of GEV batteries.

Since there are many cells stacked in series to achieve the required voltage for the GEV, the battery reliability depends on the reliabilities of several hundred cells. Table II(b) compares the cell and battery reliabilities of a typical GEV, adopting various batteries to achieve the voltage level of about 312 V (Panel, A. I. E., 2007).

Table II(b): Reliabilities of GEV Batteries

Type	Pb-acid	Ni-MH	Li-ion
Cell voltage (V)	2	1.25	3.6
Number of cells	156	250	8
Battery voltage (V)	312	312.5	313.2
Cell reliability (%)	98.45	97.53	99.14
Battery reliability (%)	85.55	77.9	91.69

It can be seen that the cell reliabilities of these batteries are all over 97%. However, when the cells are connected in series, only Li-ion can offer the battery reliability of over 90%.

2.5 OPTIMIZATION SCHEME:

The mathematical formulation of the proposed EM scheme is described in this section. The proposed optimization scheme considers three basic assumptions, which are

- The randomness in trip patterns of urban household EVs on weekdays is minimal. Therefore, the randomness is not considered in this work.

- EVs are charged at home during the off-peak pricing intervals.
- EVs are always connected to the charging station at the workplace and at home.
- The selling price for the discharging power is always lower than the grid pricing at that interval.

The EMS is designed to optimize the cost of electricity usage for the workplace. The objective function to optimize the cost of the workplace can be expressed by

$$\text{Min } C = \sum_{t=1}^T \left(\sum_{i=1}^N C_{ev} E_{evi}^d(t) + C_{grid} E_{grid}(t) - \sum_{i=1}^N C_{grid} E_{evi}^c(t) \right)$$

$$C_{ev} = \begin{cases} C_{ev(op)} = C_{grid(op)} \\ C_{ev(mp)} = \frac{C_{grid(op)} + C_{grid(mp)}}{2} \\ C_{ev(p)} = \frac{C_{grid(op)} + C_{grid(np)} + C_{grid(p)}}{3} \end{cases}$$

Where, $C_{ev(op)}$, $C_{grid(op)}$, $C_{ev(mp)}$, $C_{ev(p)}$, $C_{grid(op)}$, $C_{grid(op)}$, $C_{grid(mp)}$, $C_{grid(np)}$, $C_{grid(p)}$

are the grid prices and selling cost of energy from EVs at off-peak, mid-peak, and peak intervals, respectively. The constraint function is given by

$$\sum_{i=1}^N f_i E_{evi}(t) + E_L(t) = E_{grid}(t)$$

$$f_i = \begin{cases} -1 \\ 0 \\ 1 \end{cases}; E_{evi} = \begin{cases} E_{evi}^d(t): f_i = -1 \\ 0: f_i = 0 \\ E_{evi}^c(t): f_i = 1 \end{cases}$$

The total energy discharged for all t intervals from the EV is the total energy available from the EV (E_{evi}^a)-

$$\sum_{t=1}^T E_{evi}^d(t) = E_{evi}^a$$

$$E_{evi}^a = E_{evi}^{aini} + E_{evi}^c$$

E_{evi}^c is based on the scheduling and can be calculated. The actual energy available for discharging can be calculated. Here E_{evi}^{aini} must be greater than the minimum energy requirement.

$$E_{evi}^{aini} = E_{evi}^{ini} - E_{evi}^{req} - Bat_{min}^{res}$$

Equation prevents the battery from discharging below the minimum reserve of the battery (Bat_{min}^{res}) and the required energy to travel the predicted miles E_{evi}^{req} .

$$E_{evi}^{max} = Bat_{cap}^{tot} - E_{evi}^{req} - Bat_{min}^{res}$$

$$E_{evi}^{diff} = E_{evi}^{max} - E_{evi}^{aini}$$

E_{evi}^{diff} is required to obtain the actual energy that is chargeable during mid-peak pricing (E_{evi}^{diff}) and restricts the battery from over charging. The energy E_{evi}^c required for travelling is determined by

$$E_{evi}^{req} = (\tau_i + \varepsilon) \cdot \eta_i$$

The optimal charging and discharging schedule (f_i) can be obtained based on the predicted information given.

$$E_{evip}^d = P_{ratedi} \cdot t_{dwti}^p$$

... ..

$$E_{evimp}^c = P_{ratedi} \cdot t_{dwti}^{mp}$$

The additional chargeable energy (E_{evip}^d) is based on E_{evimp}^c and t_{dwti}^{mp} and is given by

$$E_{evi}^c = \begin{cases} E_{evi}^{diff} & : E_{evi}^{diff} < E_{evimp}^d \leq E_{evimp}^c \\ E_{evimp}^c - E_{evi}^{aini} : E_{evimp}^c < E_{evi}^{diff} \leq E_{evimp}^d \\ E_{evip}^d - E_{evi}^{aini} : E_{evip}^d < E_{evi}^{diff} \leq E_{evimp}^c \\ E_{evimp}^c - E_{evi}^{aini} & : E_{evi}^a > E_{evip}^d \\ E_{evip}^d - E_{evi}^{aini} & : E_{evi}^a > E_{evip}^d \\ 0 & : E_{evi}^{aini} > E_{evip}^d \end{cases}.$$

The charging and discharging times are obtained by ((1)and (2) respectively.

$$t_c = \frac{E_{evi}^c}{P_{rated i}} \dots\dots\dots(1)$$

$$t_d = \frac{E_{evi}^a}{P_{rated i}} \dots\dots\dots(2)$$

The optimal charging and discharging schedule (f_i) can be obtained from t_c and t_d as per (3) .

$$f_i = \begin{cases} -1 & \forall & t_d \\ 0 & & \\ 1 & \forall & t_c \end{cases} \dots\dots\dots (3)$$

This optimal schedule is applied in (3) to obtain the optimized cost.

RESULTS AND DISCUSSION

This section verifies the proposed energy management scheme for a workplace with EV integration. A small office with one EV scenario is considered, as shown in Fig. III(a).

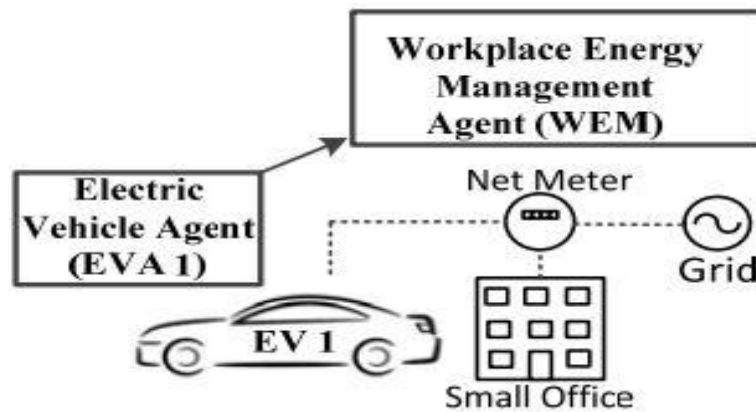


Fig. III(a): Workplace model under study.

The travel details are derived from the National Household Transportation Survey (NHTS) (Nissan Website, 2024). The dataset provides travel information on trip miles, dwell time, start time, and end time. In addition, the database provides other information such as the gender of the driver, the purpose of the travel, etc. The proposed work utilizes information on the start time, trip miles, and dwell time. Though the NHTS data is provided for ICE-based vehicles, its behavior or trip pattern is similar to that of an EV. In this work, a 2017 Nissan Leaf-s model is selected as the EV model. Table III(a) provides the details of Nissan leaf.

Table III(a): EV details [Nissan Website, 2024]

Model	2017 Nissan Leaf-s
Total battery capacity	30 kWh
Miles range	107 mi
Energy efficiency	0.24 kWh/mi
Onboard charger rating	6.6 kW
Charging time for full capacity	5 h

The real-world power consumption data for a small office in Houston is obtained from the Open-Ei database (TXU Energy Website, 2024). The grid pricing is based on a three-tiered plan of TXU Energy. Table III(b) provides the TOU values.

Table III(b): Li-tou pricing data [TXU Energy Website, 2024]

Pricing	Intervals	Cost (¢/kWh)
Off peak pricing	10:00PM -6:00AM	6.2
Mid-peak pricing	7:00AM-12:00PM, 7:00PM -9:00PM	9.8
Peak Pricing	1:00 PM-6:00PM	21.9

The initial cost is calculated without applying the EMS. Fig. III(b) depicts the 5-day power consumption of the small office. Fig. III(c) shows the cost of power consumption for a 5-day period without the EMS.

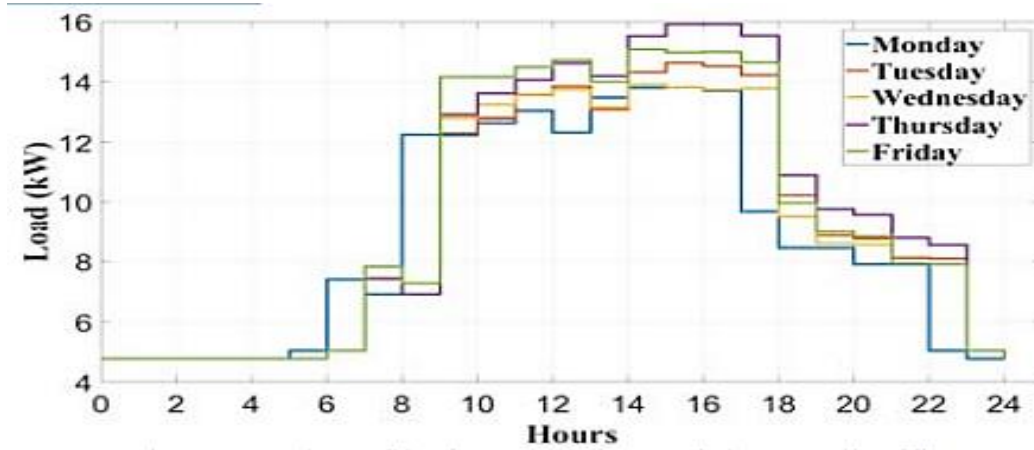


Fig. III(b): Load profile for weekdays of the small office.

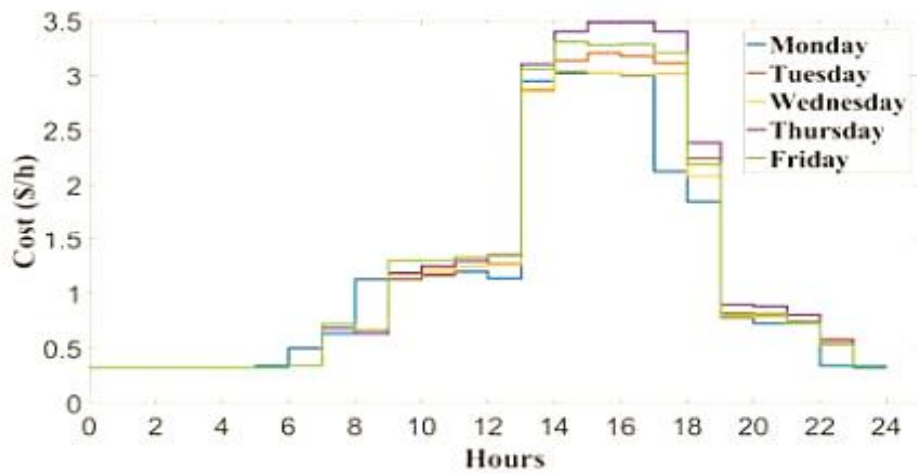


Fig. III(c): Cost incurred by the workplace without EMS

Based on the power consumption data and TOU pricing the total cost incurred by the office in a week is \$149.64 without applying the energy management scheme. The proposed EM scheme is applied for the same TOU pricing and load data. For detailed explanation of the proposed EM scheme, the trip pattern of an EV on a Thursday is considered. The initial step of the proposed energy management scheme is the EV forecasting. A java-based forecasting tool (Weka) is utilized to forecast the EV trip pattern based on the proposed

regression by discretization methodology. In this work, EV travel pattern prediction is based on three weeks of data. Fig. III(d) shows the predicted miles in hourly interval for each day. The EVA predicts the trip miles from 9:00h to 23:00h of that day based on data available till 8:00h of the particular day and the data of the previous weeks. From Fig III(d), it can be observed that the EV travelled 8 miles to reach workplace between 8:00h and 9:00h on Thursday. The forecasted departure time for the EV is 18:00h. Hence, the dwell time is 9 hours. This information is utilized for deriving the optimal schedule. The optimal charging and discharging values are obtained based on the proposed methodology discussed in CHAPTER II.

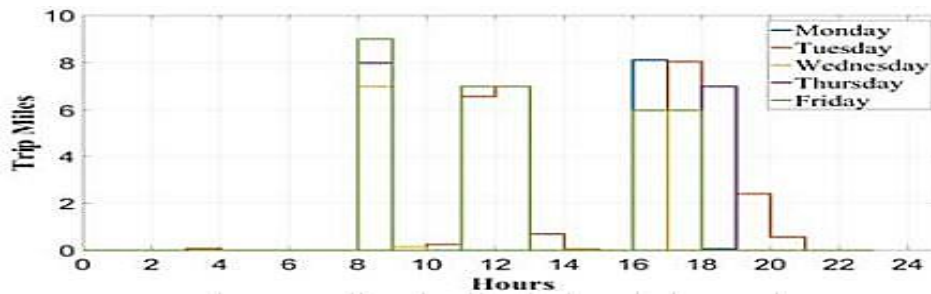


Fig.III(d): Predicted miles in hourly interval

The initial energy of EV during its arrival is 28.08kWh. The forecasted return trip miles is 7. Besides, a compensation for the forecasted error is added to the trip miles .(The mean absolute error (MAE) for the proposed prediction methodology is < 0.5 . Furthermore, the maximum depth of discharge for Nissan Leaf-S model is (80%). Therefore, the initial dischargeable energy is 20.15kWh. The EM scheme calculates that an additional energy of 1.92kWh can be charged during the mid-peak pricing interval without violating the maximum charging criteria. This additional energy can be sold at peak pricing interval.

Therefore, the maximum dischargeable energy is 22.07kWh as shown in Fig. III(e).

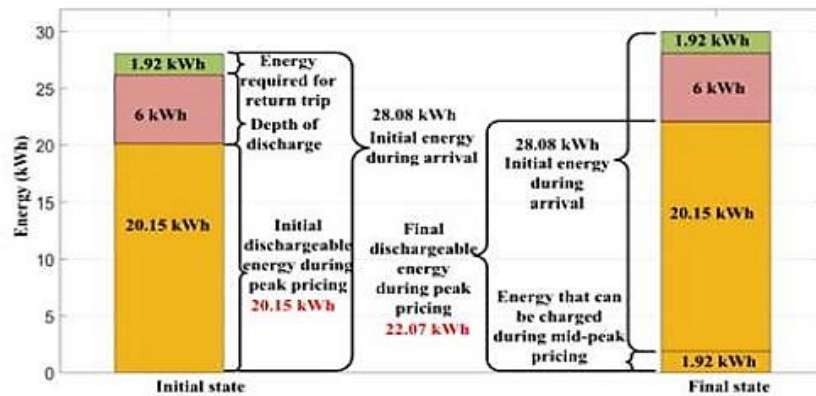


Fig. III(e): Initial and final charging and discharging profile

Fig. III(f) depicts the charging and discharging energy of the EV during office hours for the particular week. From Fig.25, it can be observed that the EV is charged by 1.92 kWh during the interval 9:00h-10:00h. Furthermore, during the peak pricing interval, the EV is discharged at the rate of 5.52 kWh for 4 hours (13:00–17:00).

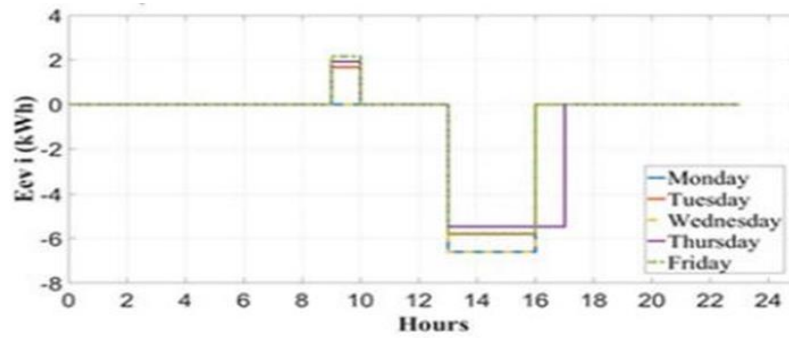


Fig. III(f): Charging and discharging power

It is evident from Fig. III(g) that the scheduling methodology utilizes the dwell time of the vehicle suitably to optimize the cost of the workplace and to maximize the benefit of the EV owner. The state of charge of the EV on Thursday is shown in Fig. 6.8, which provides the comparison between the cost incurred by the workplace before and after applying the energy management scheme.

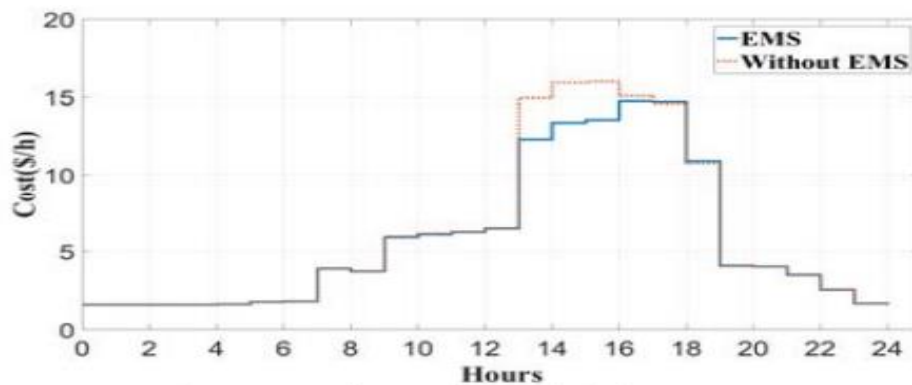


Fig. III(h): Total cost with and without EMS

It can be observed that the proposed energy management scheme reduces the cost of power consumption per day by 7% with just one EV integration. The profit will increase based on the number of EV integrations. The total profit to the EV owner is shown in Table III(c).

Table III(c): EV PROFIT

Day	Discharge (peak) kWh	Charge (Off-peak) kWh	Charge (Mid-peak) kWh	Cost of Charging (\$)	Cost of selling (\$)	Profit (\$)
Mon	19.8	19.8	0	1.34	2.5	1.15
Tu	17.352	15.672	1.68	1.22	2.19	0.97
Wed	19.8	19.8	0	1.34	2.5	1.15
Th	22.07	20.15	1.92	1.54	2.78	1.2
Fri	17.28	15.12	2.16	1.22	2.18	0.95

The profit obtained by an EV owner is predominantly dependent on the selling price and the trip pattern. Furthermore, the proposed scheme will be significantly economical to EV owners because the optimal scheduling is performed based on individual EV behaviors.

3.0 ACKNOWLEDGEMENT

We sincerely thank all those who supported the successful completion of this research. We are especially grateful to the researchers whose work laid the foundation for this study. Our heartfelt thanks also go to our family and friends for their unwavering support and encouragement throughout the process.

4.0 CONFLICTS OF INTEREST

The author declares no conflicts of interest regarding this research. All research was conducted ethically, with full transparency and objectivity. No financial, professional, or personal influences affected the outcomes. Any future conflicts will be disclosed as necessary.

5.0 AUTHORS CONTRIBUTIONS

Research concept and Research design – Hasibur Rahman and Md. Shafiqul Islam, Materials and Data collection –Hasibur Rahman and Afia Ibnat Ruxy, Data analysis and Interpretation – Md. Moien Uddin and Hasibur Rahman, Literature search and Writing article – Md. Moien Uddin, Critical review and Article editing – Hasibur Rahman, Final approval – All authors.

6.0 CONCLUSION

Electric vehicle (EV) power management was thoroughly examined in this study, with a focus on the ways in which V2H, V2V, and V2G technologies connect EVs to energy networks. A variety of pricing techniques, management strategies, and a coordinated optimization approach based on a multi-agent system were addressed. Simulation and experiment results confirmed the effectiveness of the proposed model. As EV use rises, efficient power management will be crucial for preserving grid stability, maximizing financial rewards, and easing the transition to a cleaner, more sustainable energy future.

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