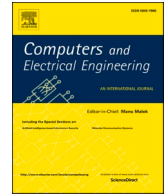




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Energy management algorithm development for smart car parks including charging stations, storage, and renewable energy sources

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ABSTRACT

In this study, a photovoltaic system and stationary energy storage unit integrated vehicle charging station energy management algorithm were developed using a long-short term based prediction model (LSTM). The aim of the proposed system is to develop intelligent car parks with controlled charging stations aggregated by centralized charging stations instead of individual or dispersed uncontrolled charging stations to eliminate the imbalance in the demands of charging. The system has four energy sources: grid, vehicle batteries, PV system, and the stationary battery group. By calculating the power demand for vehicles in the car park, a dynamic energy management algorithm has been developed that provides efficient use of energy resources by considering the power demand density. Moreover, the forecasting model has been created by LSTM not only to adjust charging timing and effectively use energy sources. The model was performed by forecasting not to take energy from the grid at critical times (overloaded times). The grid load is analyzed by the energy management algorithm and run for different times of the year, creating a load profile for 16 vehicles. The results of this study show that energy demand during the critical time interval can be reduced by 8–20 % solely through load shifting before and after the critical time interval without any additional resource support. Moreover, while the integration of only the PV system supports the grid by 15–20 %, the optimal utilization of other energy sources during the relevant time frame supports the grid by 65–75 %. In addition, by collecting charging stations at a central point, energy storage capacity is increased and effective energy management is achieved. In conclusion, it is proposed that the infrastructure of such a parking system should be set up before the use of electric vehicles increases significantly.

1. Introduction

The costs of pollution caused by conventional transport include, but are not limited to, healthcare costs, the re-cultivation of forests destroyed by acid rain, and monuments eroded by acid rain. The development of high-efficiency, clean, and safe transportation has

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therefore been one of the most emphasized R&D activities recently. Today, most drivers prefer internal combustion engine vehicles (ICEVs) because of lower purchase costs, without considering the long-term cost. In this context, some research has focused on the lifetime cost of both ICEVs and electric vehicles (EVs). They prove that the lifetime costs of EVs are less than those of ICEVs [1]. Also, ICEVs and EVs are compared in terms of their long-term cost; consequently, it is noticed that these types of vehicle's costs, when long-term costs such as energy costs are taken into account, are comparable [2]. Moreover, the efficiency of EVs is much higher than that of ICEVs, and EVs can reach maximum torque in a large speed range compared with ICEVs [3].

1.1. Challenges and opportunities for the widespread use of electric vehicles

EVs can reduce emissions by being powered by renewable energy [4]. EVs are not only environmentally friendly and quiet but also low cost in terms of energy and operating costs compared with conventional vehicles [5]. With the development of current battery technologies, the interest in more environmentally aware and more efficient vehicles is increasing daily. In this context, automotive manufacturers are tending to produce electric and hybrid electric vehicles (HEVs). While 120,000 EVs were sold in 2012, now that number of EVs is only meeting the demand of the one-week EV market, with 10 million EVs sold in 2022. It is expected that they will have a market share of 60 % by 2030 [6]. Additionally, the number of EVs is forecast to be 70 million in 2030 [6].

There are some problems with the spread of EVs. A considerable amount of time is required for recharging them; it takes a few hours to fully charge a modern EV. Charging time limitations severely hamper the availability of EVs, even for short-distance urban transport [7]. It is predicted that EVs and HEVs will develop over time and replace traditional internal combustion engines. Therefore, it is anticipated that overloads will occur in the electricity distribution system. To prevent this problem, it is vital to model charging stations. Charging stations should be supplied with renewable energy sources because the system will increase the need for electrically installed power.

Despite their advantages, EVs are not becoming widespread at the desired level because there are no common charging stations. The main reason for this is the fear of traditional vehicle users being stranded on the road [8,9]. To eliminate this disadvantage, charging stations can be set up in many car parks. On a typical day, cars are not actively used for long periods of time because they are often left in parking lots. Therefore, these long parking times can be considered an opportunity to recharge EVs in smart car parks [7]. Much research is focused on determining the best charging algorithm to prevent overloading of the grid by multiple EVs and HEVs being charged simultaneously. In addition, the owners of EVs minimize the charging price by considering their own consumption and market costs [10]. The purpose of these studies was to ensure the satisfaction of EV and HEV users while eliminating the negative effects [11].

Energy generation from renewable source is not a solution of load fluctuations without an efficient energy management [12]. There is a need for a control mechanism to control the power supplied to parked vehicles, which are supplied by the grid as well as by electricity production [13–15]. If carefully designed, the demand response from EVs might play a vital role in resolving these generation fluctuations, allowing grid operators to maintain a balance between supply and demand [16,17].

The challenges posed by EVs, however, should also be discussed. Unorganized EV charging will jeopardize the protection of the network, impose heavy costs on the parties concerned, and require the electrical installations to be improved [18]. While EVs primarily use the slow-charge mode to get their needed energy during night hours, there will always be factors such as long journey and failure to charge during parking hours. This implies that fast charging will be needed for approximately 15–20 % of the total EV fleet [19,20].

New installations, namely fast-charge and ultra-fast charge stations, are required by recent innovations in fast-charge electric vehicles to meet the high-power charging requirements of these types of EVs. Considering this information, we can state that the number of fast chargers and the availability of fast should be increased to meet the demands of EV owners. However, it should be considered that increasing EV use will adversely affect the grid. Likewise, fast charge stations support up to 150 kW, and the ultra-fast charge topology supports up to 350 kW of charging power [21].

1.2. Power demand management

Current research focuses on the optimization of EV and HEV grid infrastructure and the problems related to pricing. Primary studies in this area include smart grid designs and applications [22], large-scale economic charge distribution and risk management for EVs and HEVs [23], distribution network modification for these vehicles [24], and architectural and energy management strategies [25]. In addition to these, vehicle-to-grid energy flow algorithm development and renewable energy resource integration for charging stations [26,27] and determination of the location of public charge stations with regard to driver behaviours for maximally maintaining the existing activities of EV drivers [28] are also popular subjects.

Moreover, EVs can be an alternative to power systems by energy transfer from vehicle to grid (V2G) or vehicle to buildings [29,30]. In addition, batteries of EVs can be potential energy storage systems to solve the storage problem of renewable energy sources [31]. V2G approach with an optimal distribution of charging stations across the country may decrease the network losses and voltage fluctuations by approximately 15–30 % [32].

In many studies, EV grid adaptation has been discussed. The transition to electric vehicles requires an infrastructure of charging stations with information technology, ingenious, distributed energy generation units, and favourable government policies [33]. In addition, some studies show that the battery of the vehicle can be used as an energy storage system. Thus, charging systems can be developed to cut peaks and fill valleys in the energy consumption graph to solve the duck curve problem. This will greatly reduce the peak-to-valley gap of the power grid [34,35]. Various studies have been conducted to identify optimization strategies and to suggest solutions for various charging infrastructures. It has also been suggested that one of the most important factors in the spread of EVs is

the successful positioning of charging stations [34,35].

With the expansion of EVs and charging stations in the near future, it is necessary to plan energy production and distribution. To meet the energy demand, issues such as the development of new energy resources and the efficient use of existing energy resources are important [32,36]. In a study, cost-based and motivation-based demand response programs, with a mathematical model, were developed to evaluate the demands of EV charging and improve the stochastic performance of EVs [15]. Similarly, dynamic pricing on charging fee is proposed with an optimized schedule [36].

Additionally, to overcome the problem of integrating PV and EV charging stations into the existing grid, PV-integrated charging stations have been proposed [37]. Moreover, to overcome the stochastic online charging problem, a predictive control-based model has been proposed using EV users' charging periods and durations [38,39]. One of the most important limitations on designing smart charging station is widely varying parameters such as short-term energy consumption. This could be a major issue on modelling a smart parking. Nevertheless, the short-term energy demands can forecast by some prediction methods to model an algorithms for getting better energy management [35,40]. In terms of energy distribution and management, studies on smart charging stations and smart energy management algorithms are important.

This study focuses on the design of smart parking systems for EVs and HEVs, supporting other studies on EVs' smart parking in terms of vehicle-to-grid, vehicle-to-vehicle, and usage of renewable energy sources. In addition to the current literature, the present study has a smarter control algorithm including a forecasting algorithm that can manage energy transfer from energy sources such as grid, PV, battery pack, or car batteries that are allowed to share their batteries, and can shift the energy demand from an overloaded grid period to a non-overloaded period with the help of a forecasting algorithm. Hence, in the proposed smart car parking system, the intention is to centralize the charging stations at a single point, to meet the simultaneous energy demand without overloading the grid, to compensate for fluctuating energy use, and to improve instant energy storage capacity.

2. The proposed smart car park system

To minimize the negative effects on the grid from the spread of EVs and HEVs and even to enable them to be used as an auxiliary energy source to the grid, not only is the electrical grid supported, but the satisfaction of the EV users is also given importance. The proposed system offers innovations such as renewable energy support, a forecasting model, dynamic energy management, vehicle battery rental, time determination of charge, and energy transfer from vehicle to vehicle.

2.1. Parking lot physical parameters

In the proposed system, the maximum charging value is 50 kW per vehicle. 16 vehicles can be charged synchronously in the parking lot. Considering these values, the maximum power demand from the grid is determined as 800 kW.

For the PV system, the total peak panel power is determined as 45 kW. This installed power meets a significant proportion of the energy requirement of the smart parking system during peak hours. To get maximum benefit from the sun, the entire roof of the smart car parking system is designed to be covered with PV panels. According to the standard parking dimensions given in the parking

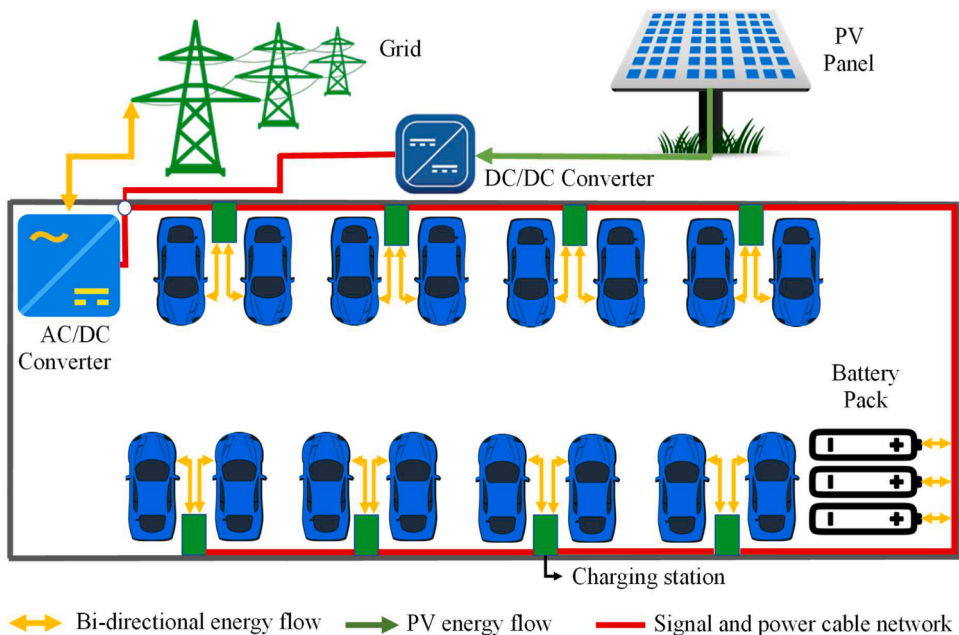


Fig. 1. Schematic representation of the designed parking system.

regulations [37], the parking area of a passenger car should be at least 20 m^2 including the manoeuvring area. In the designed system, the total area is 320 m^2 for 16 vehicles. The median power square per kW was defined as $5.9 \text{ m}^2/\text{kW}$ for the polycrystalline PV panel [41]. As the proposed car parking has 320 m^2 roof area, PV panel installation with 45 kW ($45 \text{ kW} \times 5.9 \text{ m}^2/\text{kW} = 265.5 \text{ m}^2$) power is theoretically possible. Thus, the total PV panel power is determined as 45 kW peak. For an installed power of 45 kW, 250 panels, one of which produces 180 W of power, are required. A schematic of the parking system is given in Fig. 1.

Because of the battery packs included in the smart parking system, many advantages are obtained. The battery packs are charged during periods when there is a minimum grid demand, when the PV panels are generating power, and when fewer or no vehicles are charging. In addition, some of the energy required for vehicle charging can be obtained from the battery packs during periods when the grid is overloaded. The designed system has a 50 kWh battery pack. PV panels in car park systems are important in terms of reducing grid demand during peak times, decreasing charge prices, and supporting clean energy production. However, there are costs associated with panel installation for the system.

2.2. Reservation interface program design

Finding a charging station for EVs and HEVs is not as easy as finding a gas station for conventional vehicles. However, even if there is a charging station, no available charger may be found because the charging process takes a long time. One of the biggest obstacles to the spread of EVs and HEVs in the studies carried out so far is the concern of vehicle users about not being able to find suitable charging stations.

Performing the charging process in a certain order is only possible with automation. With the designed smartphone application, drivers can make an online appointment by easily accessing the location of the smart car parks. Another concern of EV and HEV users is that their batteries could run out on the road. However, with the developed application, electric vehicle users could be able to see the charge rate of their vehicle batteries online when their vehicles are in the parking lot. Screenshots of the developed smart application are shown in Fig. 2.

To calculate the amount of power required and run the best algorithm, vehicle information is required, such as the energy capacity of the battery pack, SoC value, and user preferences. Users who want to share their battery capacity are also offered advantages such as lower payments. The purpose of battery sharing is to provide energy transfer between vehicles without overloading the grid.

The control algorithms were devised according to the energy management strategy. The reservation process algorithm of the system is shown in Fig. 3. When a reservation request is received, the number of vehicles in the parking lot and the battery charge status is first checked. The reservation request is then evaluated. If there is free space in the parking lot, the relevant parking space information is provided. If there is no free space in the parking lot, the available time slot information is provided. In the next stage of the reservation process, the user is asked for allowing battery-sharing or not. In the next step, the required power value is calculated and recorded in the system by receiving the battery charge request. Finally, the reservation process is completed.

2.3. General system structure of the proposed system

The proposed system comprises five principal elements: the grid, PV panel, battery pack, vehicle batteries, and automated system. As shown in Fig. 4, the most appropriate energy flow direction is determined by the automated system by measuring the energy levels of the system control groups. Crucial data for energy management, such as the energy level of the power sources, the power demand of charging stations, and the available instant power on the grid, are recorded by the PC.

2.4. Energy management strategy for the proposed system

In the designed system, there are various energy flows for different scenarios. Energy can come from the grid, storage unit, vehicle batteries, and PV panels, and the system is designed for bidirectional flow.

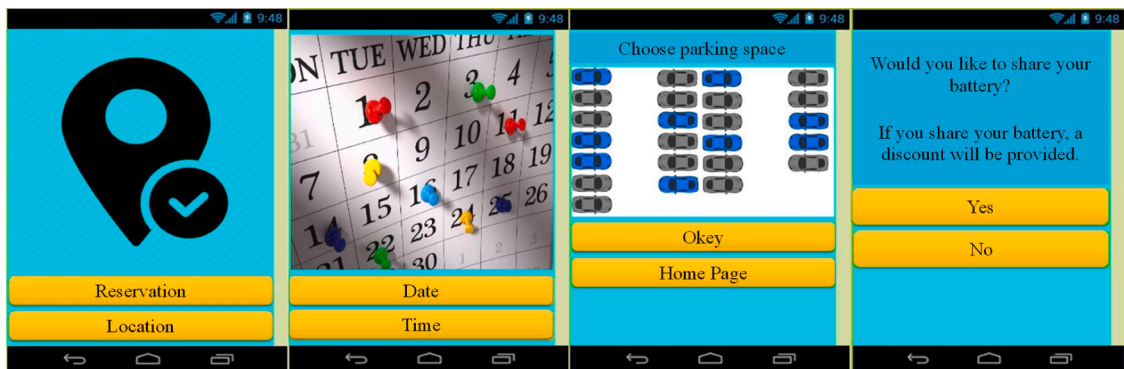


Fig. 2. Smart application screens.

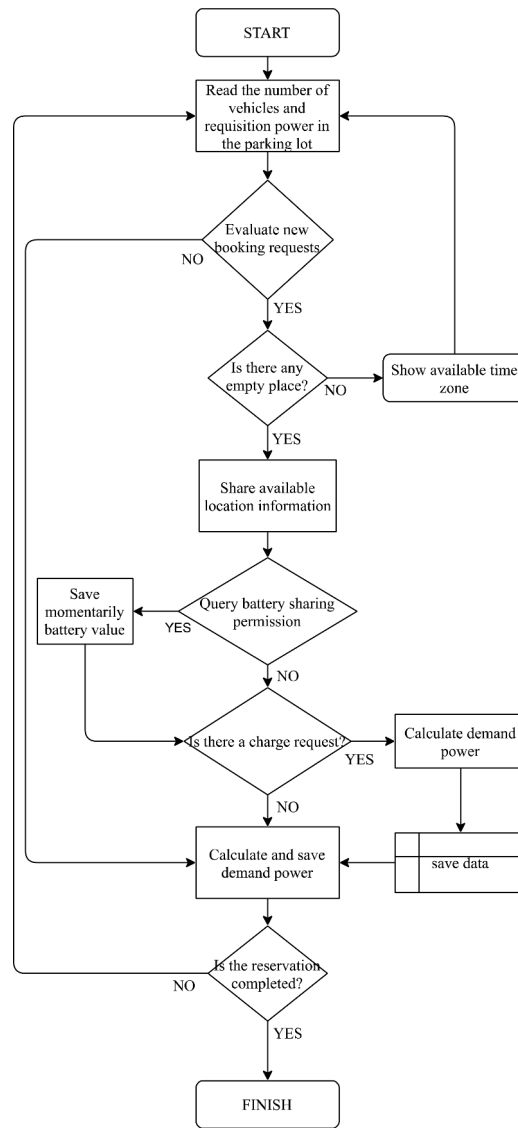


Fig. 3. The reservation process algorithm.

The system can turn to other sources by reducing the grid demand in different time zones, considering the load status of the grid. A graphic showing these changes on the demand side is shown in Fig. 5. Scenarios are created for 3 major zones. These zones are determined in relation to the grid loads. The first zone shows the early hours of the day when the grid is not overloaded, generally. The second zone consists of daylight hours when the grid is overloaded. The third zone is the time range in the evening and midnight when the grid is not overloaded in general. The algorithm generally considers the load demand of the grid, but it also has a dynamic energy management system for rare cases.

For instance, if the demand power is less than the power that can be drawn from the grid in zone 2, the automation system can behave as in zone 1 or zone 2 thanks to the dynamic management algorithm. The smart car park would attempt to draw minimum energy from the grid in zone 2. Therefore, incoming vehicles would be charged before entering time zone 2. In addition, vehicles arriving within zone 2 would be charged in zone 3 if the length of parking time is suitable. Thus, "load shifting" is performed in the peak demand period. The energy sources of the vehicles that need to be charged in zone 2 are PV, battery energy storage system, and EVs (battery pack) with charge sharing. When the total power of the three sources mentioned above is not enough for charging, the load will be supplied by the grid.

Battery groups and/or vehicle batteries are charged from the grid and PV panel during times when there is no overload on the grid, such as zones 1 and 3, as shown in Fig. 5. During times when the grid has peak demand (zone 2), the load is not supplied by the grid as much as possible. In case the batteries of the vehicles are full of the grid could be supplied by the system. All scenarios that may occur in the system are shown in Figs. 6 and 7. The lines in yellow, red, green, and blue represent the power flow in PV panels, grid, stationary

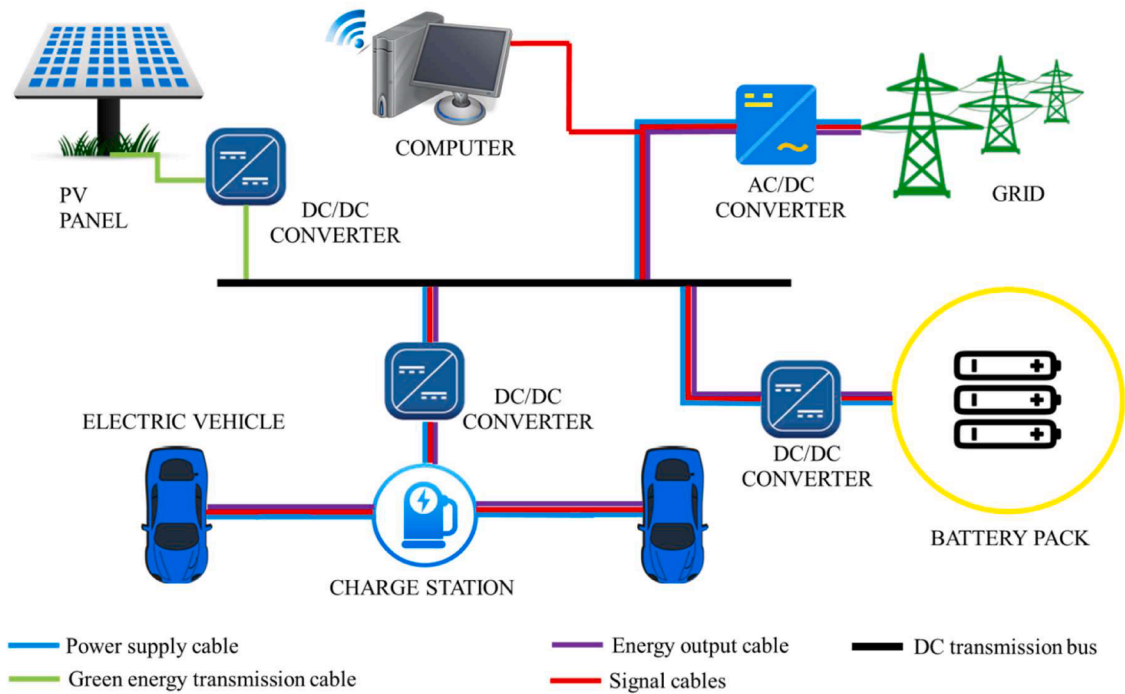


Fig. 4. Smart car-parking system control structure.

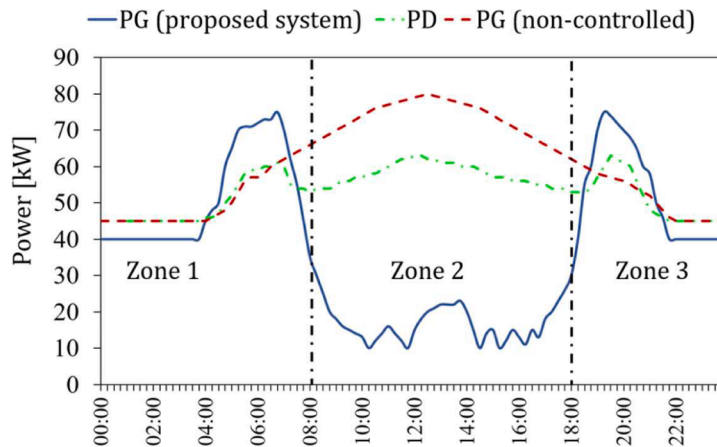


Fig. 5. Power graphs of grid demand according to different control strategies. (P_D is the power demand and P_G is the available grid power).

battery pack, and vehicles with battery sharing permission, respectively. The switches between the lines indicate that no energy flow is allowed in the open state and that energy flow is allowed in the closed state. The directions of the energy flow are expressed by arrows in the line unit. Drawing energy from the grid in these zones would not harm the grid. In addition, the system will primarily draw energy from PV in both three zones as PV generates energy. The scenarios that can draw energy from the grid as a second priority after PV have been performed in zones 1 and 3 in Fig. 6. Scenarios 2, 3, 4 indicate the condition that PV can meet the demand for energy while other scenarios do not have enough energy on PV in the figure below. Therefore, demanded energy can be drawn from PV as a single source in scenarios 2, 3, and 4; meanwhile, demanded energy can be met by PV and the grid when demanded energy is higher than the energy generated by PV. In addition, when the sunshine does not reach the PV, all the energy would be met from the grid since there will be no power generation in the PV, as shown in scenarios 6, 7, 8. Lastly, the battery pack will be charged by both PV and/or grid when needed (see in Fig. 7, scenarios 1, 2, 4, 6, 8).

On the other hand, Fig. 7 demonstrates the scenarios that are performed for zone 2. As Fig. 5 shows, there is an overload on the grid in this zone. Therefore, we reduced energy usage in zone 2. To reach this goal, three energy sources would be used before drawing energy from the grid. However, every energy source may not be suitable for use in some cases. All possible scenarios are shown in

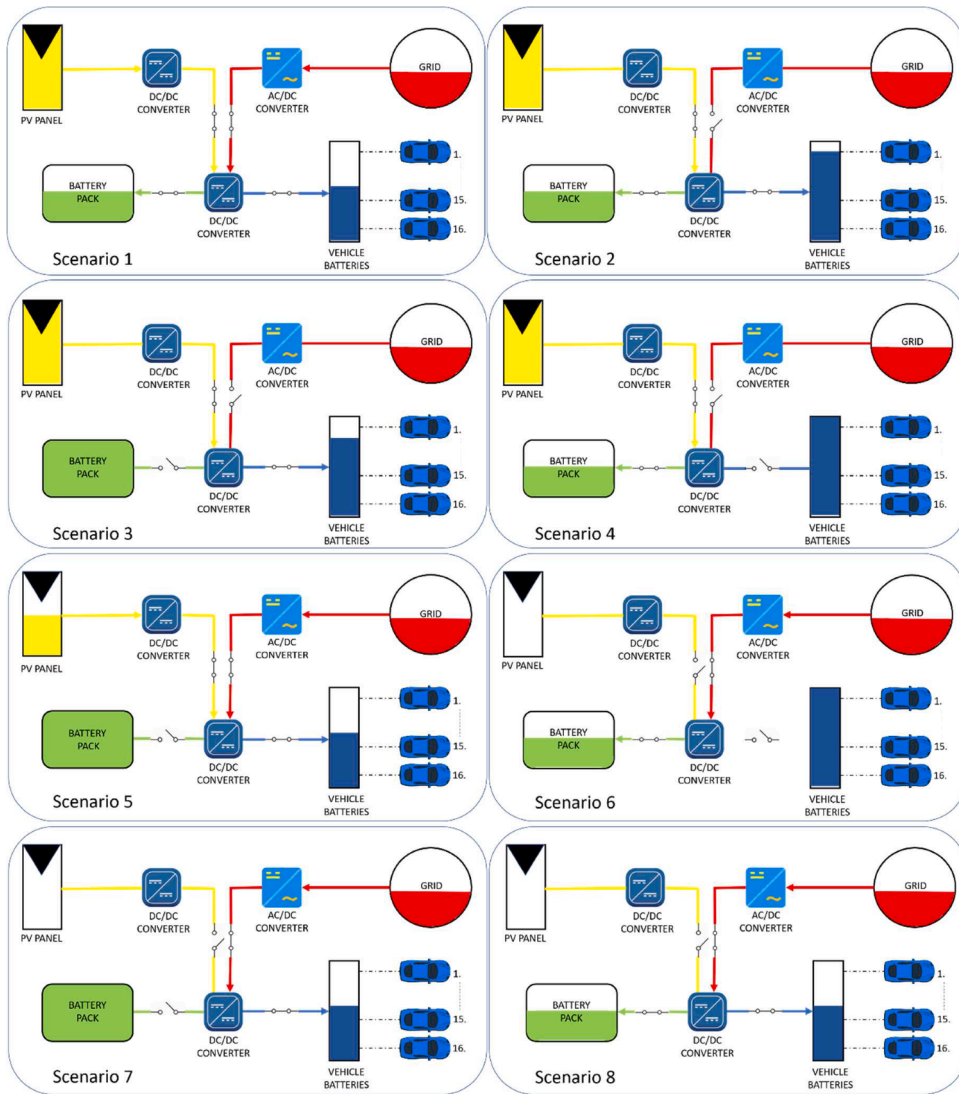


Fig. 6. Scenarios showing the energy flow in zones 1 and 3.

Fig. 7. Energy drawing order is PV, stationary battery pack, and batteries of EVs having battery sharing permission. For example, only energy would be drawn by PV when the energy generated by PV is enough to supply the system, as shown in Scenario 1. Additionally, the system will be powered by PV and stationary battery pack when PV is not sufficient but the total energy of PV and stationary battery pack is sufficient to supply the system (scenario 3). In addition, if PV and stationary battery packs cannot meet the energy demand, batteries of EVs having battery sharing permission would be used. Although forecasting, demanded energy can be drawn by the grid when such sources are not enough (scenarios 4, 6, 7). In addition to these scenarios, the generated energy from PV could be more than the demanded energy, the stationary battery pack could be full, and there may be no need for energy transfer from an EV with battery sharing permission to another EV. At that time, energy from PV or battery packs or EVs with battery sharing permission would be transferred to the grid (scenario 2, 5). Thus, the system will support the grid instead of being an extra load on the grid when it is overloaded. Finally, energy transfer can be performed only between EVs with battery sharing permission when EVs need to be charged without using any other sources when there is no energy on PV and stationary battery pack in zone 2 (scenario 8).

Control algorithms

The operating mode determination algorithm of the system is shown in Fig. 8. In this algorithm, the value of the power demand (P_D) is read with the data received from the instant demand power data, and these data are compared by reading the energy resource values. With this control algorithm, the status of the energy sources and estimated PV (P_{PV}) and grid (P_G) statuses are continuously compared by reading from the system. The appropriate operating mode is activated according to the results of the comparison. According to the results, three operating modes can be activated. In the first operation mode, ($P_D < P_G$, P_D is the power demand and P_G is the available grid power), the value of the power demand of the system is below the power value that the grid can provide. The second operating

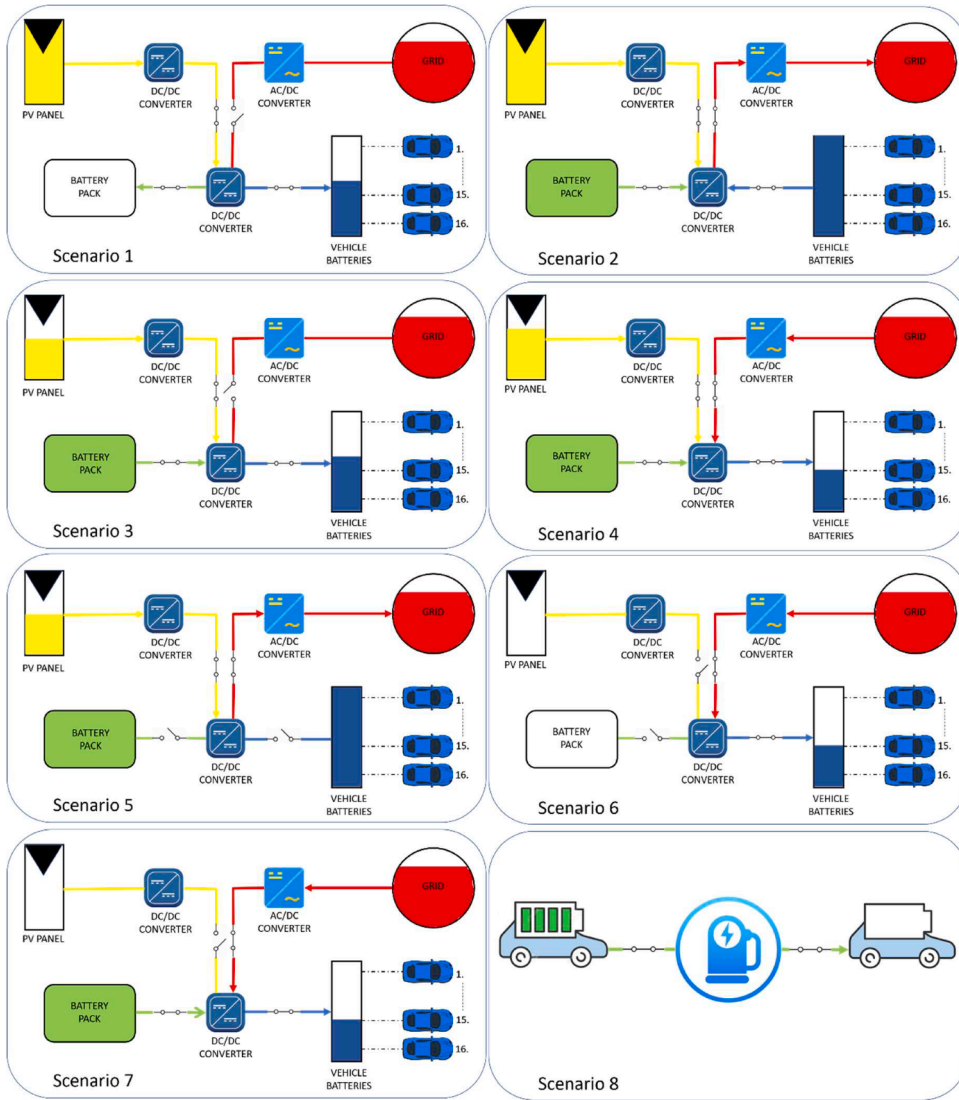


Fig. 7. Scenarios showing the energy flow in zone 2.

mode ($P_D = P_G$) is activated when the power demand is equal to the power value that the grid can provide. In the third operating mode ($P_D > P_G$), it is indicated that the value of the power demand cannot be met by the grid, which is the overload status of the grid.

The control algorithms of the operating modes are created by considering the instantaneous state of the energy sources. Each operating mode control algorithm is based on preventing grid overload. First, PV panels are selected as the first energy source to be used by checking whether there is currently energy production from them. The grid is preferred as the secondary energy source. However, only an allowable amount of energy is transmitted to prevent overloading when power is drawn from the grid. In cases where the power value drawn from the PV panels and the grid cannot meet the power demand, stationary battery packs are activated as the third energy source. If the energy level of the stationary battery packs is not sufficient, EVs that have given permission for battery sharing are used as the final energy source. If all these energy sources are still insufficient to meet the demand, the worst scenario occurs and grid overload occurs. Similar to this order of preference for energy sources, a priority order has been created within the energy consumption units. Charging vehicle batteries takes first place in energy consumption.

If the power value that can be drawn from the PV panels and the grid is above the power required for vehicle battery charging, the second energy consumption unit is determined as the charging process of the stationary battery packs. If the stationary battery (P_B) packs are full of vehicle batteries with battery sharing permission are selected as the final energy consumption unit for later use. As an example of the operating mode control algorithms, the control algorithms created for operating modes 1 and 2 are shown in Figs. 9 and 10.

As shown in Fig. 9, first, we check whether there is an estimated PV power. If there is PV generation, the production amount is compared with the demand power. If PV generation is less than the demand power, the remaining power is supplied from the grid. If PV

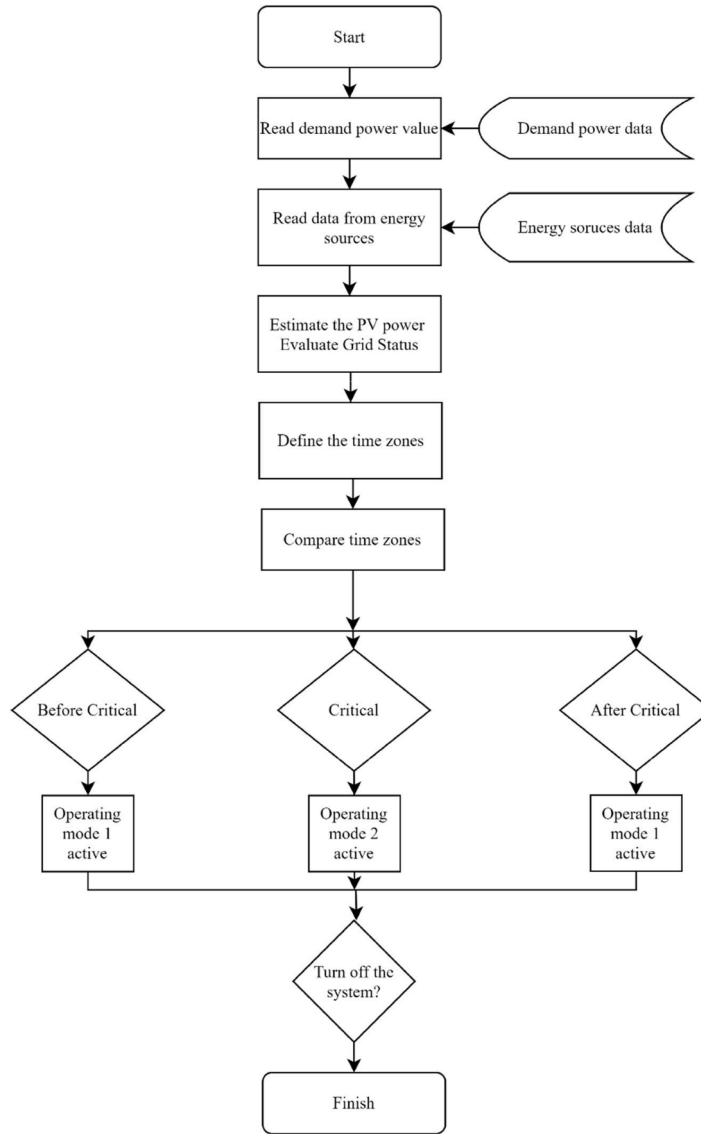


Fig. 8. Operating mode determination algorithm.

generation is greater than the demand power, the power to be used for vehicle charging is determined by $P_T = P_D$. At the same time, the charge amount of the stationary battery pack is checked. If the charge value is less than 80 %, the stationary battery pack is charged by using $P_{PV} - P_D$ power. If the charge of the stationary battery pack is greater than 80 %, power as much as $P_{PV} - P_D$ is transferred back to the grid. If it is anticipated that there will be no PV generation, then all power is supplied from the grid.

If the PV generation power is less than the demand power, it is checked whether there is power available for charging ($P_B > 20\%$) in the facility batteries. If $P_{PV} + P_B$ power is greater than the demand power, $P_T = P_{PV} + P_B$ is performed. As Fig. 10 shows, first it is predicted whether there will be PV production or not. If there is PV generation, demand is compared with power. If the PV generation power is greater than the demand power, P_T power is used for charging the vehicles by performing $P_T = P_{PV}$. If there is no PV production, $P_{PV} = 0$. If $P_B(20\%, P_B = 0)$ is taken and it is checked whether there is a battery SoC value opened for sharing in the vehicles. When $P_{EV} = 0$, if $P_{PV} + P_B + P_{EV}$ power is greater than the demand power, $P_T = P_{PV} + P_B + P_{EV}$ is performed. If it is not greater, the remaining amount is withdrawn from the grid (P_G) to meet the demand power.

2.5. Forecasting model for power demand and renewable energy resources

An LSTM-based forecasting model was developed in addition to the energy automation created to minimize the grid loads mentioned earlier. In this way, the system is enabled to direct the energy flow by estimating the energy production and consumption on a daily and hourly basis [42].

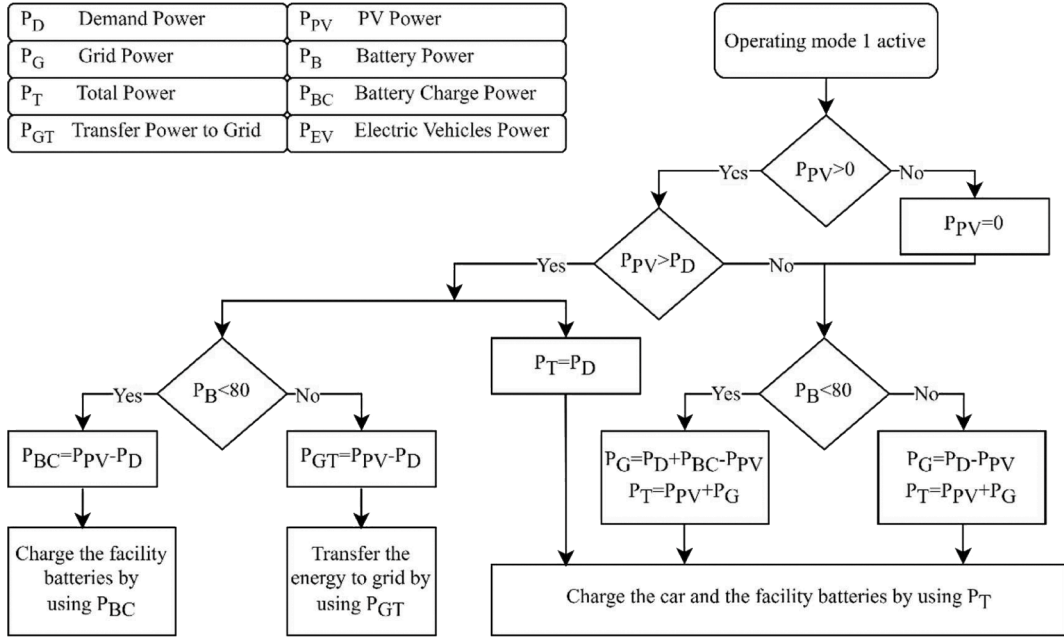


Fig. 9. Operating algorithm for modes 1 and 3.

Within the scope of this study, the uncertainty of the energy produced by the PV system is a challenge in terms of energy management. Therefore, a predictable method will contribute to an effective energy management system. In this section, the energy production forecasting model of the proposed PV system is based on the LSTM [43]. LSTM networks presented in 1997 by Hochreiter and Schmidhuber to find a solution for the "vanishing or exploding of gradient" problem, which is a shortcomings of RNNs [44]. Recurrent neural networks (RNNs) are among the models with the deepest structure in neural networks and are more suitable for using data in sequential order [45].

Fig. 11 shows the LSTM model structure, including gates, inputs and outputs. In the LSTM model, the Forget Gate determines which part of the cell status information should be forgotten, depending on the previous output value and current input values.

$$f_t = \sigma(W_f X_t + U_f h_{t-1} + b_f) \tag{1}$$

Eq. (1) describes the forget gate. Here, W_f and U_f are weight matrices, X_t is current input, h_{t-1} is the output at time $t - 1$, and b_f is bias vectors in Eq. (1).

The input gate has two layers as \tanh and sigmoid. These layers are used to create a candidate vector as shown in Eq. (2). To control what information of the \tanh layer will be added to the current cell state, which is also named as input gate and presented in Eq. (3)

$$\tilde{C}_t = \tanh(W_i X_t + U_i h_{t-1} + b_i) \tag{2}$$

$$i_t = \sigma(W_i X_t + U_i h_{t-1} + b_i) \tag{3}$$

The section that determines the data to be sent to the rest of the LSTM network is the output gate and is given in Eq. (4).

$$o_t = \sigma(W_o X_t + U_o h_{t-1} + b_o) \tag{4}$$

The cell state and hidden state definitions are shown in Eqs. (5) and (6), respectively.

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

$$h_t = o_t * \tanh(C_t) \tag{6}$$

Here, $W_b, U_b, W_z, U_z, W_f, U_f, W_o$ and U_o are weight matrices. b_b, b_z, b_f and b_o are bias/trend vectors. X_t represents the current input, h_t and h_{t-1} represent outputs at time t and $t-1$, respectively.

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{7}$$

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{8}$$

The hyperbolic and sigmoid tangent functions are expressed in Eqs. (7) and (8), respectively.

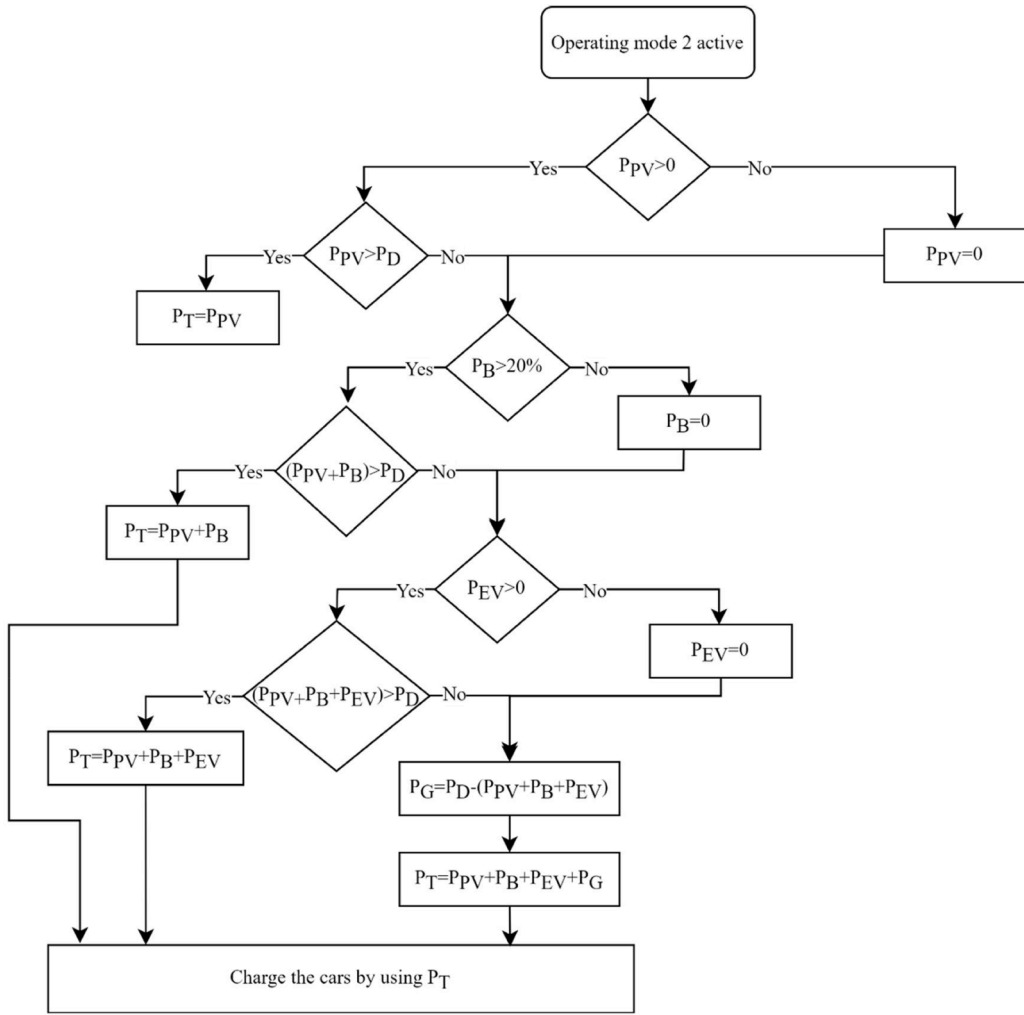


Fig. 10. Operating algorithm for mode 2.

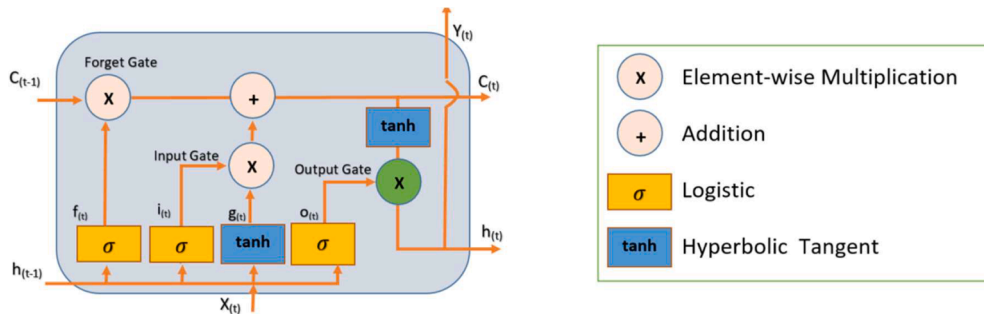


Fig. 11. LSTM model structure.

The PV output power was estimated using the current, radiation, temperature, and humidity data of the PV system in previous years. The LSTM network structure created for this process is shown in Fig. 12.

In the first LSTM layer used in the model, 10 hidden-layer neurons were used, and 30 hidden-layer neurons were used in the second LSTM layer. In the dropout layer, weight updates in the LSTM model were added randomly to prevent overfitting. A total of 5591 trainable parameters were used in the entire model. Finally, the estimated PV output power was obtained using the fully connected layer. Fig. 13 shows how effectively the LSTM generates forecasting. The entire prediction process and results are created with

normalized data between -1 and $+1$ depending on the \tanh activation function.

The LSTM model was trained with a dataset created by selecting random days in four different seasons. In the estimation process made with the network created after the training. The actual and predicted values were obtained, as shown in Fig. 13. A total of 444 PV energy production data belonging to three different days were calculated.

The performance metrics were also produced based on the normalized prediction results. The performance of the estimation process made with the LSTM model was obtained as 0.083 and 0.055 in terms of RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) parameters, respectively, using actual and predicted data.

RMSE and MAE are calculated in Eqs. (9) and (10) respectively;

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_{actual} - P_{predicted})^2} \quad (9)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |P_{actual} - P_{predicted}| \quad (10)$$

The success rate of the prediction model was also calculated as 0.981 using R^2 score which is another traditional regression success metric. This result can also prove the success of the prediction performance.

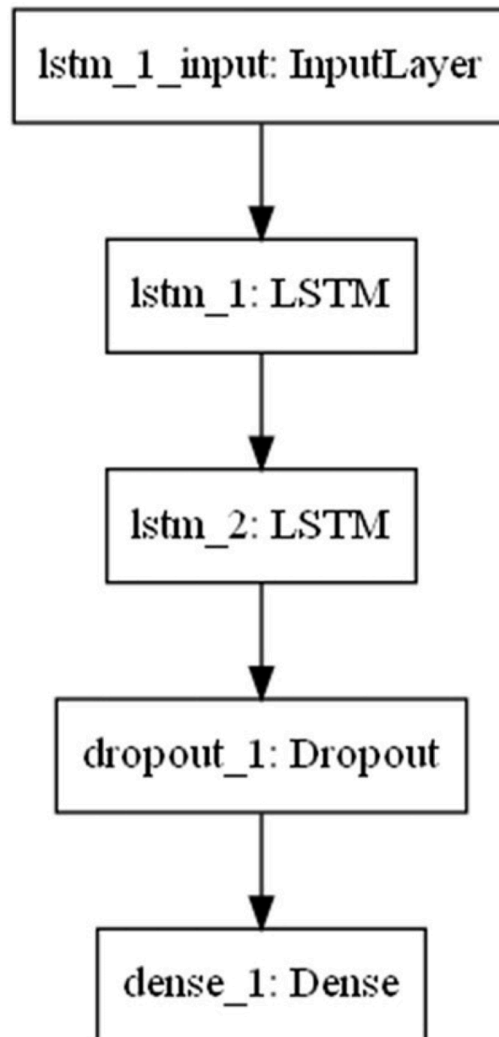


Fig. 12. Structure of LSTM network.

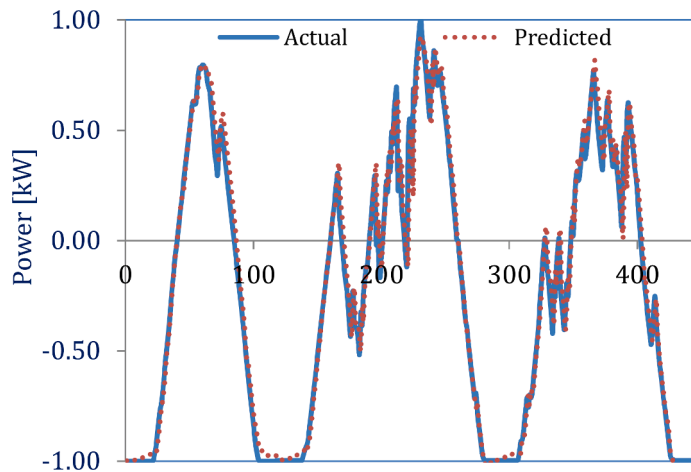


Fig. 13. Comparison of actual and estimated data of PV.

3. Simulation studies

In this study, PV energy production estimation is made using Python (3.9) programming language and various machine learning libraries in PyCharm development environment. PV and transformer data used in the program are real data provided by the grid. The simulation was conducted using the C# programming language in the Visual Studio 2019 development environment. Random generation of the parameters and their execution under appropriate scenarios were performed for a parking lot daily routine. For simulating the system, the considered data of daily incoming and outgoing vehicles in a car park are listed in Table 1.

The simulation was used to model 80 vehicles entering and exiting various stations in the parking area during the day. It is assumed that these vehicles enter the parking lot using a randomly assigned method, with the station number, park entrance times, planned parking times, initial battery charge rates, and battery sharing request parameters. In addition, the charging request is positive for each vehicle that enters, and the battery target filling rate is defined as 100 %.

The software first detects in which of the 3 different time zones the vehicles entered the parking lot. Here, to decrease the load consumed in the critical time slot, the charging start and finish times of the incoming vehicle are updated accordingly for load shifting. In this way, the proposed algorithm aims to reduce the total load required in the critical time slot by performing an optimization according to the parameters of each new vehicle. For this purpose, vehicle battery charging processes in the parking lot are operated, especially considering the transformer load and PV generation data at critical hours. For instance, PV-grid and stationary batteries are used for vehicle battery charging in non-critical zones. Moreover, PV and stationary batteries are used in the critical time slot to minimize the load on the grid for power optimization. In this context, a user interface is also presented in Fig. 14 to simulate the scenario automatically or manually.

Although actual data are used in PV and grid loads while modelling the system’s operating efficiency, vehicle input- outputs and charging demands are randomly generated. The energy graph of stations about vehicle charge level is given in Fig. 15 to better analyse the responses of the smart parking system. It represents between 07:00 and 22:00 time periods on the horizontal axis, and the total energy output per vehicle is shown according to the duration of stay in the parking lot on the vertical axis. In Fig. 15, each column shows the total daily energy throughput of one charging station, and each colour indicates the energy consumed by a vehicle. For example, column S1 consists of 4 different colours. The lengths of these four bars are different from each other. The total length of the bars shows that a total of 600 kWh of energy was drawn from the charging socket S1 for that day (07.00 – 22.00). Each of the short bars

Table 1

System parameters for the simulation study.

Input/output parameters of the system		
<ul style="list-style-type: none"> • Day and time • Vehicle Id • Station Id • Battery sharing status • Battery shared load • Total vehicle load • Total energy from the grid • Total energy to the grid • Estimated grid load • Estimated PV load • Instant load 	<ul style="list-style-type: none"> • Entry time to the parking lot • Planned length of stay in the parking lot • Vehicle battery initial level • Vehicle battery target level • Battery charging initial time • Battery charging finish time • Battery charge actual status • Vehicle charging request • Energy from facility batteries (instant) • Energy from car batteries (Instant) • Minimum level of the facility battery group • Actual capacity of the facility battery group 	<ul style="list-style-type: none"> • Vehicle battery capacity • Vehicle charging request • Battery sharing request • Battery sharing status • Battery shared load • Battery sharing request • Energy from PV (Instant) • Energy from the grid (Instant) • Vehicle battery actual status • Total vehicle number • Vehicle battery capacity

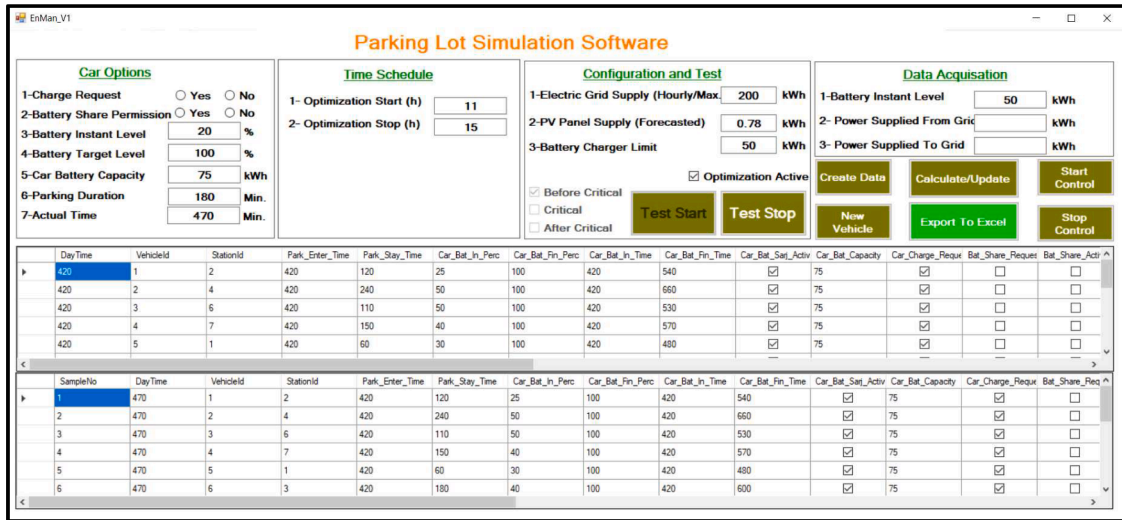


Fig. 14. Parking lot simulation software.

of different colours shows the total consumption of a vehicle. In one day, 4 different vehicles used a total of 600 kWh of energy from the S1 socket. Approximate energy consumption values of vehicles are 250 kWh, 100 kWh, 75 kWh, and 175 kWh, respectively. Although these values are random, the total energy drawn from the S1 socket is important for the study, not the value of each vehicle.

All power graphs (P_G , P_D , P_V , P_B and EVs) are given in Figs. 16, 17, 18, and 19, respectively, to measure the response of the system according to different scenarios in the four seasons. The PV values and grid power are taken from real data. However, the charging demand power of EVs and battery pack power are created randomly. The proposed system has been tested across four seasons, contingent upon variations in parameters such as grid and PV instantaneous power, stationary battery state of charge, the number of vehicles with battery sharing permission, and energy capacities, the critical time interval, under the station-based energy demand depicted in Fig. 15.

For instance, the results for the date of 30/10/2020 are depicted in Fig. 16. Fig. 16(a), (b), and (c) display the energy automation, while Fig. 16(d), (e), and (f) represent the system without automation, showcasing respectively the grid-demand power, power supplied to the system, and distribution of energy from sources during the critical time interval. The critical time interval when the grid is overloaded is between 10:00 and 14:00. As mentioned before, the system is designed to perform forecasting in order to do not to be additional load to the grid. When comparing Fig. 16(a) and (d), the predictive model facilitates load shifting approximately one hour prior to the critical time window (09:00 - 10:00), thus reducing demand power within the critical timeframe. In this scenario, the energy demand during the critical time interval is decreased by approximately 18 % through load shifting. Furthermore, juxtaposing Fig. 16(c) and (f), energy management enables a reduction in grid loading during the critical time interval, with contributions of

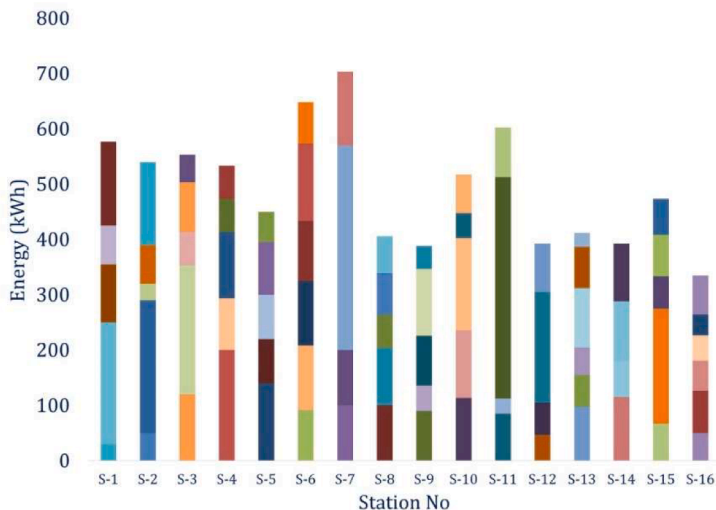


Fig. 15. Station-based energy demand of the vehicle.

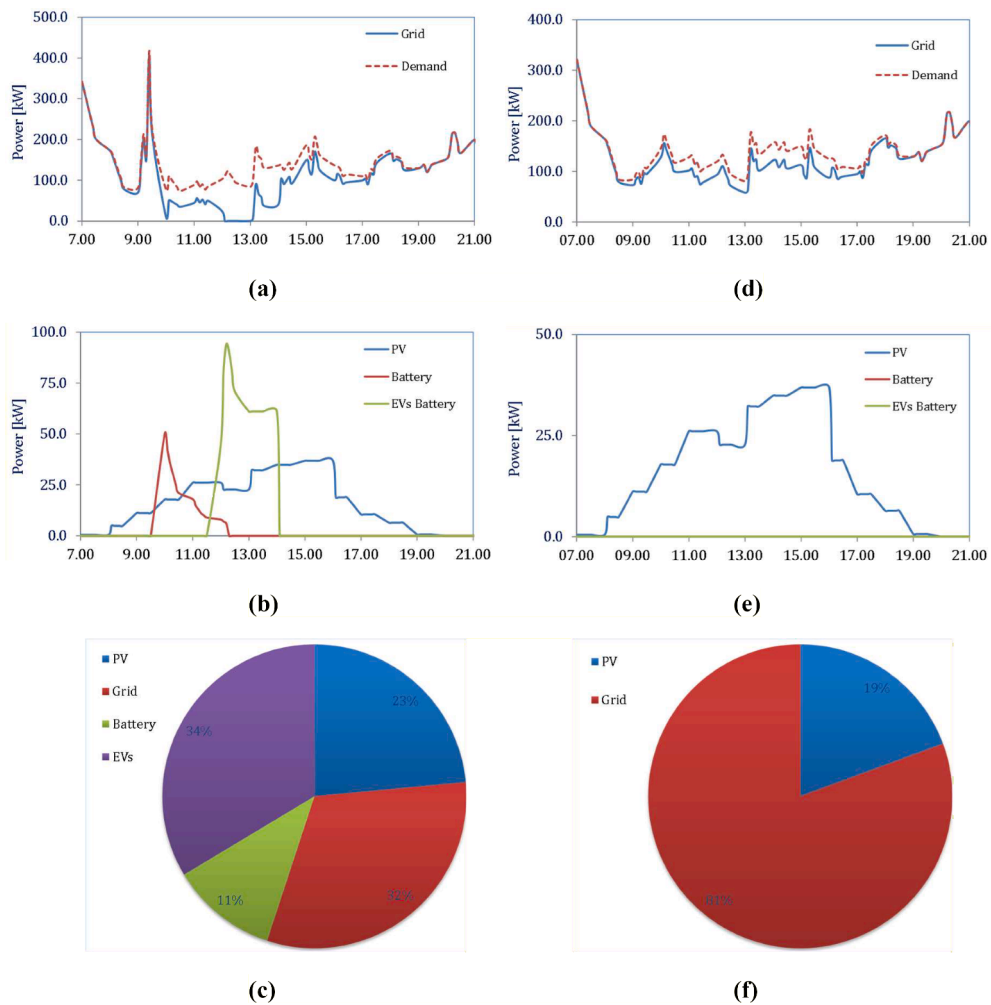


Fig. 16. Energy consumption– production and distribution graphs based on autumn (30/10/2020) data, the results of the proposed system (a), (b), (c) and the non-controlled system (d), (e), (f).

approximately 34 % from EVs with battery sharing permission and 11 % from stationary battery packs, resulting in a decrease in grid loading from 81 % to 32 %.

To test the automation of the system on a winter day, the energy production and consumption graphs with and without automation are compared to the system in Fig. 17. The critical time interval is between 11:00 and 15:00. When Fig. 17(a) is examined, the demand load is shifted both before and after the critical time interval, resulting in a reduction of approximately 20 %. During this timeframe, the grid loading rate has been decreased from 86 % to 25 %, as depicted in Fig. 17(c) and (f). Particularly, the high energy capacity of vehicles with battery sharing permission has contributed to a 48 % reduction in grid loading during this timeframe. On the other hand, with only PV support, grid support remains limited, providing a contribution of 14 %.

The effect of automation on the system is shown in Fig. 18 on a spring day. The critical time interval on the indicated day is between 11:00 and 17:00. While graphs show automated system outcomes in Fig. 18(a), (b) and (c), graphs illustrate system outcomes without automation in Fig. 18(d), (e) and (f). In this scenario, the extended duration of the critical time interval may pose challenges in reducing grid loading. During this timeframe, while the ongoing energy production from the PV system significantly contributes to lowering grid demand power, the contribution of stationary battery pack support may remain limited to its capacity, emphasizing the significance of the number of vehicles with battery sharing permission and their energy capacities. Within this context, during the critical time interval, as evident from Fig. 18(a), the demand power has been reduced by a modest rate of approximately 8 %. When analysed comparatively in Fig. 18(c) and (f), grid support through PV assistance stands at 15 %, while in the proposed system, both the partial shifting of demand power and additional energy source utilization have elevated this rate to 68 %. Notably, vehicles with battery sharing permission play a significant role, providing approximately 45 % of the energy support. Consequently, in scenarios with extended critical time intervals like this, a high rate of battery sharing among EVs greatly facilitates energy demand management.

The test data for the system during the summer season is illustrated in Fig. 19. The critical loading period for the grid is selected to be between 13:00 and 18:00. During this timeframe, as depicted in Fig. 19(d), (e), and (f), in the absence of energy management

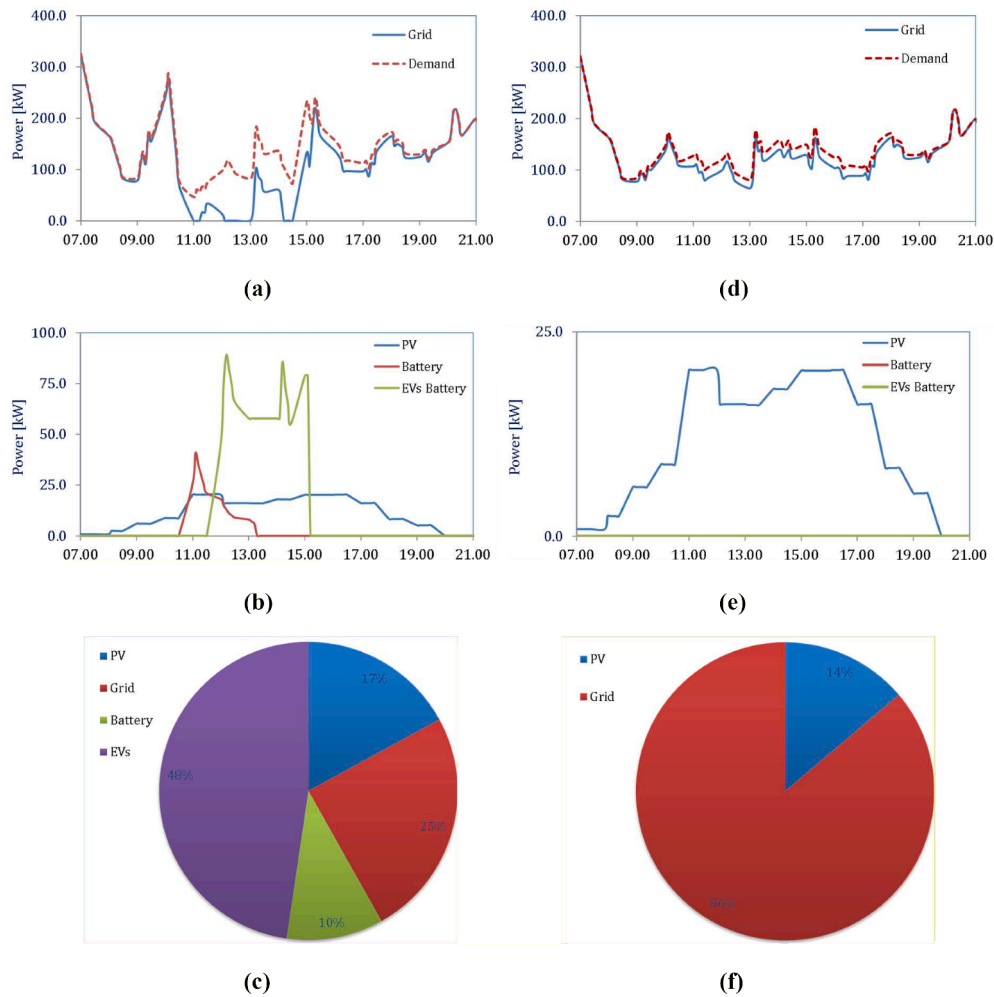


Fig. 17. Energy consumption– production and distribution graphs based on autumn (30/01/2020) data, the results of the proposed system (a), (b), (c) and the non-controlled system (d), (e), (f).

automation, a transfer of energy to the grid via the PV system has been achieved at a rate of 18 %, resulting in a grid loading rate of 82 %. Conversely, the implementation of energy management automation has led to a shift in energy demand during the critical time interval, reducing it by approximately 14 %. Additionally, the inclusion of the stationary battery pack has provided limited support to the grid, contributing at a rate of 7 %. When considering the utilization of EVs with battery sharing permission, the grid power demand can be reduced to the level of the 34 s, while in the absence of their use, or their absence entirely, it can be reduced to as low as 72 %.

4. Results and discussion

The advantages and opportunities of the system developed in this study compared with traditional systems are given in [Table 2](#). In the table, the most strategic system specifications are determined by considering the literature and compared with the developed system and others. Load shifting is of great importance to eliminate overloads in the grid. Having this feature of the system will reduce the infrastructure (grid) installation requirements. The most basic way to perform load shifting is to have a stationary storage unit. Thus, vehicle charging demands occurring at peak time intervals can be met from the storage unit and not from the grid. Integration of renewable energy sources into charging stations allows EVs that do not emit gas emissions to maintain these characteristics. Thus, energy costs are also reduced and distributed generation is supported. Centralizing charging stations in a particular region will reduce infrastructure costs and maximize energy efficiency. Applications such as vehicle-to-grid and vehicle-to-vehicle charging will increase the flexibility of the system.

Unfortunately, load shifting is not possible in traditional systems and renewable integrated systems. There must be an external storage unit to perform load shifting. Conventional systems cannot reduce grid demand in any way. Because in these systems, there is no alternative energy source other than the grid. Even if renewable energy integrated systems can reduce the load demand, they cannot reduce the peak load demand. The reason for this is that energy cannot be obtained from PV during the peak load time slot (17.00 –

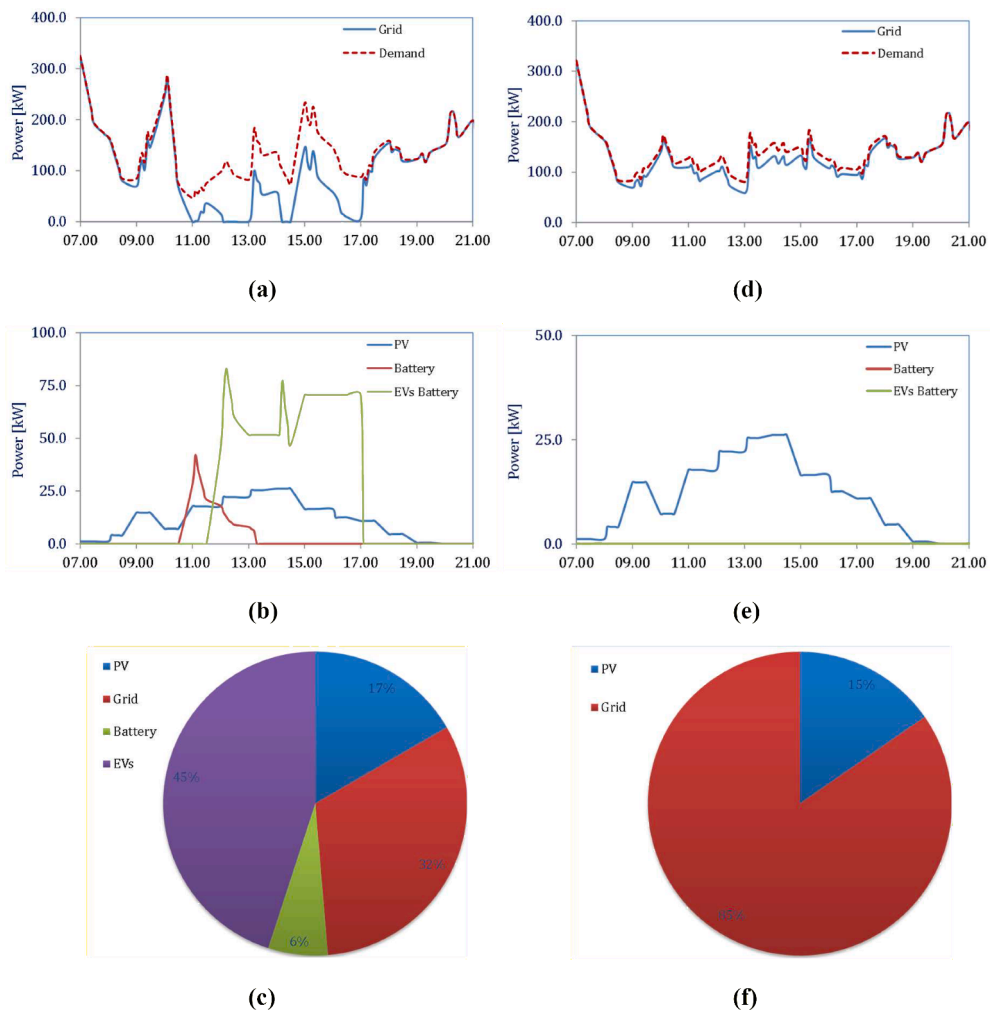


Fig. 18. Energy consumption– production and distribution graphs based on spring (30/04/2020) data, the results of the proposed system (a), (b), (c) and the non-controlled system (d), (e), (f).

22.00) of the grid. Renewable energy sources reduce the total cost. Renewable energy systems with energy storage provide much greater cost reduction by means of load shifting and arbitrage features.

Table 2 also shows the cost analysis between traditional electric vehicle charging stations and the proposed system. In car parks consisting of only a charging station, the establishment cost is limited to the chargers only. This is the lowest establishment cost system. In systems with integrated renewable energy sources, the establishment cost can increase between 30 % and 100 % depending on the size of the renewable system. The system proposed within the scope of this study includes a stationary energy storage unit along with a renewable energy production system. Additionally, a control algorithm needs to be developed to manage all these systems. This increases the establishment cost by 50 % to 200 % compared to traditional systems. A significant part of this cost is closely related to the size of the renewable energy production and stationary energy storage system [46–48].

As a result of the study, it was observed that there is a great difference between the management of the system with a control algorithm and the random charging of the vehicles. The energy demands of electric vehicles are very difficult to meet by the grid, especially in the peak time slot. This situation may cause voltage sag and power quality problems in the grid, or as a next stage, instability can cause a blackout event.

5. Conclusion

In this study, we have addressed the challenges posed by the increasing adoption of electric vehicles (EVs) and the consequent rise in energy demand from the grid. Traditional vehicles rely on internal combustion engines fuelled by fossil fuels, whereas electric vehicles utilize energy storage systems instead of power generation plants. As EVs become more prevalent, grid-dependent vehicles will replace those powered by internal combustion engines, leading to a surge in electricity demand from the grid. To mitigate the demand on the grid and ensure the sustainability of the energy supply, we have proposed energy management algorithm development

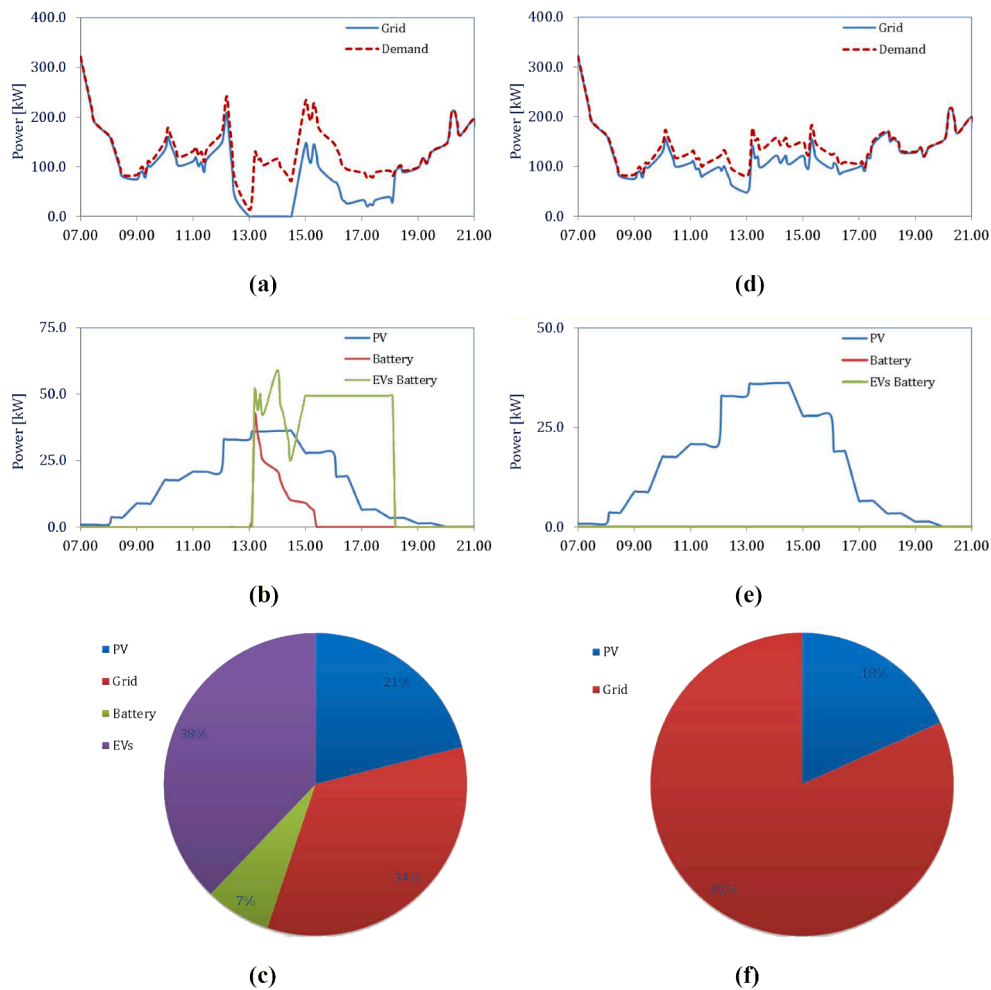


Fig. 19. Energy consumption– production and distribution graphs based on summer (30/07/2020) data, the results of the proposed system (a), (b), (c) and the non-controlled system (d), (e), (f).

for smart parking systems, including charging stations, storage, and renewable energy sources. This algorithm optimizes energy distribution between vehicles, the grid, storage systems, and photovoltaic (PV) panels to minimize grid load while ensuring efficient charging.

Integrating renewable energy sources into electric vehicle charging stations represents a significant step forward. Moreover, incorporating stationary battery energy storage and EVs with battery sharing systems into these stations enables load shifting, allowing vehicles to be charged independently from the grid during peak demand periods. The proposed energy management-based smart parking system has been simulated and analysed for different times of the year based on randomly generated demand loads specific to a 16-vehicle capacity. The simulation results indicate that while the integration of only the PV system supports the grid by 15 % to 20 %, optimal utilization of other energy sources during critical time frames can support the grid by 65 % to 75 %, with contributions of 30 % to 50 % from EVs with battery sharing permission and 5 % to 12 % from stationary battery packs. Furthermore, energy demand during critical time intervals can be reduced by 8 % to 20 % solely through load shifting before and after the critical time interval without any additional resource support.

The study contributes to existing literature by introducing a comprehensive automation system that schematizes energy flows within smart parking systems. Moreover, the integration of a forecasting model into our system has yielded more efficient results in reducing energy consumption from the grid during critical periods. While increasing the capacity of PV panels and battery units simplifies energy management without relying on grid power, it also entails higher costs. Therefore, enhancing energy storage capacity through increased participation in battery sharing programs presents a cost-effective solution. In conclusion, the development of controlled and collective charging stations represents a viable strategy for accommodating the growing demand for electric vehicle charging while minimizing the strain on the grid. Future research should focus on further optimizing energy management algorithms and expanding the capacity of renewable energy sources and energy storage systems in smart parking systems. Additionally, numerical data from our simulations underscore the effectiveness of our proposed solutions, providing valuable insights for the implementation

Table 2
System comparison between the proposed system and others [23,24,28,29,36,37,46–48].

Compared Systems/System Specifications	Conventional charging stations (only grid) [36]	Grid-Based Charging Stations with RES [28]	Proposed System (Grid + RES + Energy Storage + Centralized Carpark + Energy management)
Load shifting	✗	✗	✓
Energy storage	✗	✗	✓
Reduce power demand on the grid side [36,37]	✗	✓	✓
Reduce peak power demand on the grid side [36,37]	✗	✗	✓
Renewable energy sources	✗	✓	✓
Cost reduction (Energy)	✗	✓	✓
Time management	✓	✓	✓
Battery sharing (V2V) [23,24]	✗	✗	✓
Mobile application compatibility	✗	✓	✓
Centralized charge station system structure	✓	✓	✓
Bi-directional energy flow V2G – G2V [23,24]	✗	✗	✓
System complexity (per unit) [46, 47,48]	x 1	x 2	x 4
Establishment cost (per unit) [46, 47,48]	x 1	x 2	x 3

of sustainable energy management strategies in smart parking systems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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