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Energy Consumption and Grid Interaction Analysis of Electric Vehicles Based on Particle Swarm Optimisation Method

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Abstract: The widespread adoption of electric vehicles poses certain challenges to the distribution grid, which refers to the network of power lines, transformers, and other infrastructure that delivers electricity from power plants to consumers. This higher demand can strain the distribution grid, particularly in areas with a high concentration of electric vehicles. Grid operators need to ensure that the grid infrastructure can handle this additional load and prevent overloading and consequences in terms of additional losses. As part of the task, a methodology was developed for the assessment of the electricity consumption of battery electric vehicles in Slovenia. The approach used for the calculation includes the number of electric cars, average consumption, distance travelled and efficiency of the system. Additionally, the results of the modelling approach for an integrated distribution grid model in terms of steady-state simulations are presented. The regular situation of the power losses within the distribution grid is managed together with an optimal result. In this sense, an application of the particle swarm optimisation-based strategy is suggested to minimise reliance on grid systems.

Keywords: electric vehicles; distribution grid; optimisation; power losses

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1. Introduction

The field of e-mobility constitutes one of the steps towards a more sustainable society. At the same time, its development is closely related to the trend that energy consumption increases with development. It is necessary to ask how to save energy that is obtained in an environmentally friendly manner. When electric vehicles (EVs) are used, the E-mobility positively affects both individuals and the environment. Battery electric vehicles (BEVs) are means of transport with electric motors and a battery for storing electricity, which can be charged from the grid. They ensure a reduction in greenhouse gas emissions, which enables a cleaner and quieter local environment, a reduction in dependence on the import of petroleum products, and the efficient use of our own energy from renewable energy sources (RES). At the same time, their development is based on the ever-increasing energy utilisation from RES. Of course, we must not forget that the electrification of road traffic will require us to greatly expand and strengthen the electric power network and construct numerous charging stations along with any associated charging infrastructure. Urban air quality is generally poor, especially on urban roads that have many crossroads, due to the influence of variations in traffic flow, vehicle acceleration, driving mode, speed etc. [1,2]. The issues of climate protection, zero emissions during driving and protection of local air quality encourage that the transport system involves these challenges [3].

As a part of the paper, the total electricity consumption for electric vehicles was estimated. For example, some similarities could be found in [4], where the real-world driving data of electric taxis are assigned. In addition to this, authors in [5] address a need by developing a simple EV instantaneous energy consumption model, while a linear analytic expression and robust nonlinear regression models related to the energy consumption of EVs are assumed in [6,7]. From the modelling framework, some important insights (the energy consumption characteristics analysis, EV movement behaviour and rationality and validity of the model) were discussed [8]. In addition to this, the authors present an architecture for EV simulation when there are barriers or heavy traffic [8,9]. Based on real-world data, the aforementioned simulation could be related to open data and the different forecasting models for EV power suppliers [10–13].

Besides those already mentioned, further important aspects include the duration and characteristics of the battery charging process [14,15] and the demand-side management strategy based on the day-ahead load-shifting technique [16], as well. The formulation is intended to simulate a consumer's interaction with the grid. The main goals are to minimise the power carried from the distribution grid, minimise the operating costs, or decrease the peak load demand considering that the user has storage elements and can also handle demand response in specific loads [17–19].

In the distribution grids, power losses are linked to the line current. The line currents can be reduced with the adequate placement of capacitor banks and distribution generations [20]. The problem to clarify is to consider the optimal location and size of a specific number of distribution generation units in a known distribution grid. For clearing up and without loss of generality, such an optimisation problem could be formulated to minimise the real power losses [21]. Two plug-in electric vehicle charging scenarios are modelled using a charging time probability distribution [22].

Based on the load profiles, frequency and efficiency data, we can obtain the monthly consumption of electricity used in Slovenia. The presented procedure includes the number of electric cars, the average consumption, the distance travelled and the battery's efficiency. Vehicle models can be divided into segments based on vehicle characteristics (mini, small, medium-sized and large). In contrast, with the expected increasing number of electric vehicles, greater difficulties are expected in determining the electricity consumed for charging the associated battery packages. The results of the modelling approach with the considered distribution grid model in terms of steady-state simulations are also added to this. The modelling approach for an integrated distribution grid model, along with steady-state simulations, can provide insights into the behaviour and performance of the distribution grid under regular operating conditions. Modelling results, orientated to the power losses, are mainly highlighted. In essence, optimal results obtained from the simulations can guide decision-making processes for improving grid efficiency and reducing reliance on the grid system. In this context, an application of a particle swarm optimisation (PSO)-based strategy is suggested to achieve these goals. The PSO method can be applied to analyse electric vehicles' energy consumption and grid interaction in several ways. In essence, the PSO method is a population-based optimisation algorithm that can be used to find optimal solutions in complex search spaces. Its contribution to grid interaction could lie in determining optimal locations for placing charging stations, while it could also optimise the energy consumption of electric vehicles by finding the most efficient driving strategies [17,18,21]. This paper, however, is more focused on the grid interaction and load balancing area. In other words, it focuses on an algorithm that can optimise the scheduling of EV charging to minimise peak loads and distribution losses, ensuring both grid stability and reliability.

An overloading of the distribution grid due to increased demand from electric vehicles could represent a problem, one which could lead to several potential consequences, including voltage fluctuations, power outages and reduced reliability of electricity supply. The distribution grid may not be designed to handle the sudden surge in electric vehicle charging demand resulting in increased distribution losses. This could very well impact the overall efficiency of the grid. Under the current scenario, where the number of electric vehicles is relatively small compared to conventional vehicles, any potential consequences could be handled. Our research is mainly focused on load management techniques that can help to optimise the scheduling and distribution of electric vehicles charging loads with a focus placed on increased distribution losses. We demonstrate that integrating energy storage systems, such as stationary batteries, with electric vehicle charging infrastructure can help manage peak loads and stabilise the grid.

The research on energy consumption and grid interaction of electric vehicles has implications for policymakers, energy providers and consumers alike, and can even be applied in practice to help in planning grid infrastructure investments to accommodate the growing electric vehicle fleet. For example, policymakers can prioritise grid reinforcement, charger placement strategies and the integration of renewable energy sources to ensure grid stability and reliable electric vehicle charging. Energy providers can benefit from research findings in order to optimise grid management and balance load distribution. They can implement smart charging programmes, demand response initiatives and load management techniques to ensure efficient use of grid resources, reduce peak loads, and avoid grid overloads. Research insights can raise consumer awareness of the environmental benefits of electric vehicles and encourage sustainable mobility choices. Beyond this, research findings help consumers understand optimal charging practices, including off-peak charging and smart charging options.

2. Road Transport Electricity Consumption

In general, the knowledge of the electricity consumption of different types of vehicles at both public and domestic charging stations is insufficient. In this manner, and with the expected increasing number of electric vehicles, greater difficulties are expected in determining the electricity consumed for charging the associated battery packages. If we want to obtain information about energy consumption in different terms, it makes sense to use different approaches for modelling electric vehicles with all the associated components or methods for assessing electricity consumption. The objectives of approaches are related to the methodology and setting up the procedures and technical solutions for the collection of data on electricity consumption in road transport, conducting the pilot data collections in order to test new methodologies and analysing the results of data collections, especially with the usage of approaches for modelling electric vehicles.

In road transport, cars use renewable liquid fuels and fossil fuels supplied by fuel distributors. Data could be obtained on fuel sales and consumption from fuel distributors and, as such, estimated energy consumption. With alternative drives–battery electric vehicles, hybrids and plug-in hybrids–the situation regarding monitoring energy use in traffic becomes quite complicated. Battery electric vehicles use only electricity instead of conventional fuel. Electricity is stored in a battery pack, which is charged using charging stations for electric vehicles. The battery pack powers one or more electric motors that run the electric vehicle.

Based on our experience in defining the usage of fuels in road transport, we propose the following equation for calculating the use of electricity (in Slovenia) E in kWh (1).

$$E = no\_car \cdot cons_{\mathrm{avg}} \cdot l_{\mathrm{annual}} \cdot (1/v_{\mathrm{charging}})/100 \tag{1}$$

In (1), no_car stands for the number of electric cars, $cons_{\mathrm{avg}}$ is the average consumption (km·kWh/100), l_{annual} is the distance travelled (km) and ν_{charging} is the efficiency of the battery. Equation (1) considers a limited set of factors and provides an approximate estimation of electricity consumption for electric vehicles. In reality, there are indeed numerous other factors that can influence the electricity consumption of electric vehicles, such as driving style, road conditions, weather conditions and even the use of ancillary systems in electric vehicles, such as headlights, audio systems and climate control, all of which contribute to the electricity consumption. The following present data for individual variables in the equation. The number of electric cars (both registered for the first time and existing, i.e., old) can be obtained from the records of the Ministry of Infrastructure, namely, from the open data portal [23]. The number of electric vehicles for 2015, 2017, 2019 and 2021 is presented in Table 1. In 2015, there were 288 battery electric vehicles, while in 2021, there were 5413.

Table 1. The number of electric vehicles.

Year	2015	2017	2019	2021
No.	288	779	1998	5413

Table 2 shows how the number of the most common models changed in 2015, 2017, 2019 and 2021, as well as separately for BEVs. The most common models for each year were analysed and then combined for the entire period.

Table 2. Some most common BEV models.

Model	2015	2017	2019	2021
ZOE	41	155	338	807
i3	19	151	358	485
LEAF	30	81	253	344
Model S	30	54	82	105
e-Golf	8	67	151	138

Consumption of BEV vehicles can be determined through the manufacturers' energy consumption data. However, for a more realistic estimate of consumption, we turned to the portal, where users voluntarily enter the energy consumption of their vehicles [24]. The portal has the decent options of filtering entries by year, type of fuel and vehicle, but it also allows the omission of irrelevant results. Beyond this, vehicle models could be divided into segments based on vehicle characteristics (mini, small, medium-sized and large). Since segments combine cars well according to characteristics that impact fuel consumption, we expect that specific energy consumption should differ between segments. In addition to this, and given that we have a considerable number of models, the estimate of average consumption for an individual segment could be good enough for calculating energy consumption by segment. The average consumption for each segment was calculated according to the number of registered vehicles in that segment, as seen in Equation (2).

$$cons_{\mathrm{avg,seg,k}} = \Sigma share_{\mathrm{i}} \cdot cons_{\mathrm{i}} / \Sigma share_{\mathrm{i}} \tag{2}$$

In (2), $cons_{\mathrm{avg,seg,k}}$ is the average energy consumption of vehicles in segment k, $share_{\mathrm{i}}$ is the share of model i within segment k within registered vehicles in the selected year, and $cons_{\mathrm{i}}$ is the energy consumption of model i. Table 3 shows the average energy consumption of electric vehicles calculated considering common vehicles and the average consumption by individual segments.

Table 3. Average consumption by segment.

Segment	Share [%]	[kWh/100 km]
Mini	19	15.3
Small	40	16.2
Medium-sized	32	15.7
Large	9	19.6

The annual distance travelled is determined from roadworthiness test data [23]. Along with the age of the vehicles, this is a good indication of the annual mileage. For the exact calculation of the annual distance travelled, we used data from two consecutive roadworthiness tests.

3. Results of the Modelling Approach

Electric vehicle energy consumption models can be analytical, statistical or computational [25]. Analytical models are mainly based on fundamental theoretical equations, while statistical models are built based on real-world driving data analysis. Computational models for energy consumption estimation determine relationships between input and output variables. The input variables refer to the factors affecting the electric vehicle energy consumption, which represents the output variable. Most of the classic approaches are based on the analysis of the past average energy consumption per distance for defining the future energy consumption estimation. This approach does not consider the changes that can occur in response to driving conditions. The presented research focused on applying a database of several load profiles for electric-drive vehicles based on car-use profiles of current vehicles. All presented results are valid for 2021. The construction of load profiles corresponding to charging, driving and parking patterns finally consisted of an estimation of the amount of electricity consumed from the grid when electric vehicles are parked, and their users need to recharge them. Three load profiles are applied through the applied modelling process in the following order: night, office and highway profiles (Figure 1).

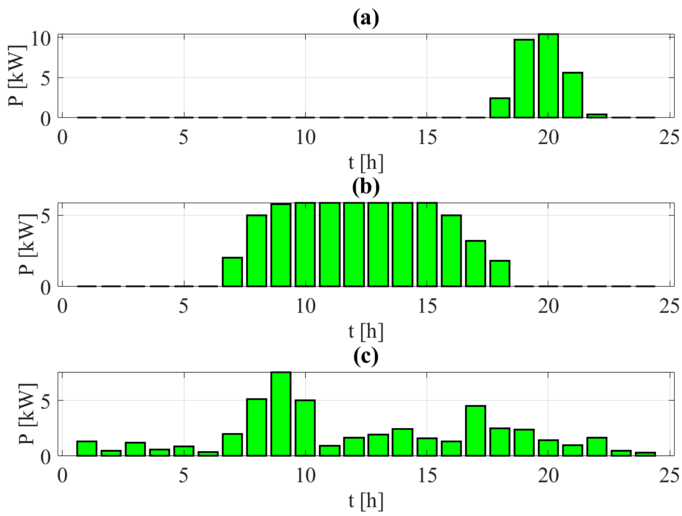

Figure 1. Load profile corresponding to night (**a**), office (**b**) and highway (**c**) charging.

Another variable that shows significant characteristics is within the frequency of appearing f for individual power P in kW. For BEV, the lower power is dominant in the sense of appearing over a given length of time (Figure 2).

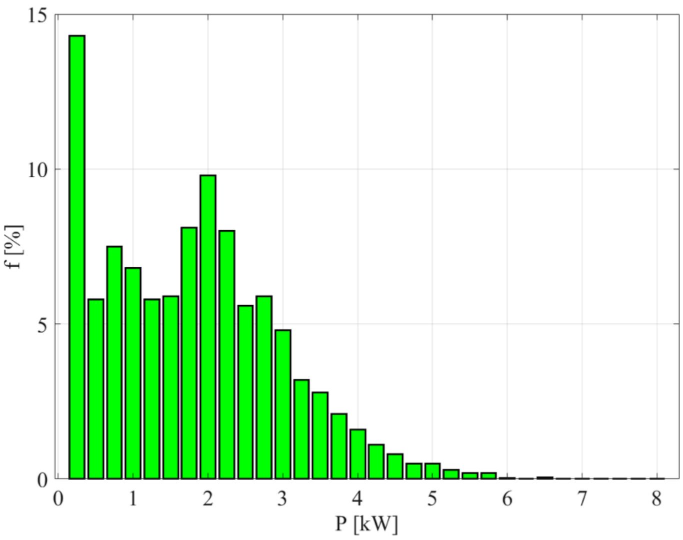

Figure 2. The frequency of appearing for individual power.

In general, the development of load profiles and frequency-power curves for electric-drive vehicles involves considering different factors that impact the energy consumption and charging patterns of these vehicles. One important factor is vehicle type, such as battery electric vehicles or plug-in hybrid electric vehicles, both of which may have quite different load profiles, especially since plug-in hybrid electric vehicles have both an electric motor and an internal combustion engine. Beyond this, charging infrastructure availability and the power levels at which electric vehicles are charged, together with the seasonal and daily energy load diagrams, also constitute important factors. The daily energy load diagram typically experiences a peak in the summer months due to increased energy consumption for cooling purposes, while in regions with cold winters, the season peak in energy load usually occurs in the winter time. This is due to the increased demand for heating during the colder months. In the current Slovenian scenario, where the number of electric vehicles is relatively small compared to conventional vehicles, the impact on the daily energy load diagram and the peak values is not particularly important. However, as the adoption of electric vehicles increases, their contribution to the energy load will become significant.

From the EV designer's point of view, the battery can be examined as a black box with a variety of performance criteria such as power, specific energy, capacity, amp-hour, voltages and energy efficiency, etc. [26]. The capacity of a battery is decreased if the current is drawn more quickly. For example, drawing 2 A for 6 h does not catch the same charge from a battery as running it at 6 A for 2 h [26,27]. As aforementioned, together with the electric motor characteristics and inclusion of gear ratios, lead to different (lower) efficiencies for different velocities.

Based on the load profiles, frequency and efficiency data, the monthly consumption of electricity could be obtained (Figure 3). The weighting is carried out using the number of electric cars, average consumption and distance travelled discussed in the previous section. Results are valid for 2021. The shared use of electricity is estimated at 14.5 GWh, with a mean monthly value equal to 1.21 GWh.

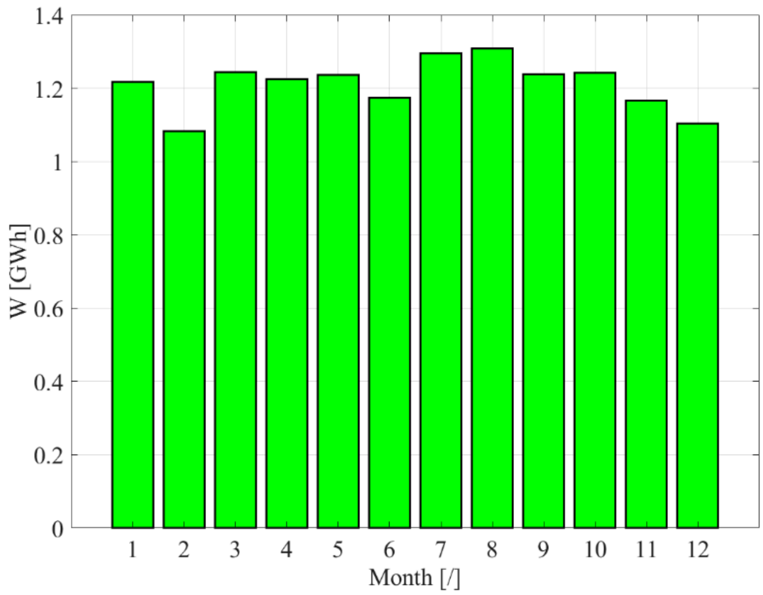

Figure 3. Monthly consumption of electric energy.

4. Optimisation Process and Results

The distribution grid is connected to the transmission grid via distribution-transformation stations. It consists of transformer stations and electric lines of different voltage levels, which are intended for the distribution of electricity to the end consumers. In addition to this, smaller electricity producers are connected to the distribution network. Distribution grids were built as passive grids, which essentially means that power was able to flow from the higher voltage level to the low voltage network. If a distributed generation was connected to the low voltage grid, the power flows could change, which could cause unusual voltage conditions, overloading of individual grid elements, increased currents, losses and incorrect operation of the protection devices within the specific conditions. Often, it is recommended to estimate from the point of distribution grid operator view the maximum possible production of distributed generation. Beyond this, the widespread adoption of electric vehicles poses certain challenges to the distribution grid, which refers to the power lines of the grid, transformers, and other infrastructure that delivers electricity from power plants to consumers.

This paper involves a modelling approach for an integrated distribution grid model regarding steady-state simulations. Both data collection and grid representation can be found in our previous works [28–31]. In this sense, relevant data about the distribution grid, including the existing infrastructure, network topology and load profiles, are considered, while special attention is directed to a graphical representation of the distribution grid, including its components and their interconnections. An estimation of the various components of the distribution grid, such as transformers, switchgear and conductors, is crucial along with power demand at different points within the distribution grid. However, the loads can be calculated as constant impedance loads (3), where $Z_{\mathrm{Load,a}}\ (i)$, $Z_{\mathrm{Load,b}}\ (i)$ and $Z_{\mathrm{Load,c}}\ (i)$ represent the complex impedances of loads across all three phases for any node. $U_{\mathrm{a}}\ (i)$, $U_{\mathrm{b}}\ (i)$ and $U_{\mathrm{c}}\ (i)$ are the voltages in node i. Similarly, distributed generation can also be taken into account within the calculation.

$$I_{\mathrm{Load,x}}\ (i) = U_{\mathrm{x}}\ (i)/Z_{\mathrm{Load,x}}\ (i),\ \mathrm{x} = \{\mathrm{a, b, c}\} \tag{3}$$

The next step is the calculation of the current in all branches of the network. This can be calculated using Equation (4), where $I_{\mathrm{a}}\ (k)$, $I_{\mathrm{b}}\ (k)$ and $I_{\mathrm{c}}\ (k)$ are the currents in branch k, $I_{\mathrm{Load,a}}\ (i)$, $I_{\mathrm{Load,b}}\ (i)$ and $I_{\mathrm{Load,c}}\ (i)$ are the load currents in node i for which connection (5) is valid. $I_{\mathrm{a,h}}$, $I_{\mathrm{b,h}}$ and $I_{\mathrm{c,h}}$ are the currents in the branches connected below branch k, while within $\boldsymbol{Y}_{\mathrm{ground,k}}$ the earth capacitances for individual phases for branch k are presented.

$$\boldsymbol{I}_{\mathrm{x}}\ (k) = \boldsymbol{I}_{\mathrm{Load,x}}\ (i) + \Sigma \boldsymbol{I}_{\mathrm{x,h}} + \boldsymbol{Y}_{\mathrm{ground,k}} \cdot U_{\mathrm{x}}\ (i),\ \mathrm{x} = \{\mathrm{a, b, c}\} \tag{4}$$

$$i = k + 1 \tag{5}$$

Currents are summed from the farthest node towards the balance one. Once these are all added up, we can proceed to the next step, where the voltages at the nodes are calculated. The calculation starts at the balance node and proceeds in steps to the farthest node.

The short-circuit power of the high-voltage grid at the points where individual substations are connected constitutes important input data for calculations. This information is used to determine the data of the foreign network. Modelling the network is then carried out by modelling the 110/20 kV and 110/10 kV transformers. Following this, medium-voltage lines are modelled, which are represented in the model with the help of the π-model of lines. For the purposes of calculating the energy flows in the medium voltage network, the load and production of electricity by the individual transformer stations are usually considered. The calculation assumes the symmetry of all three phases.

An optimisation process, together with a concept of distribution grid operation with the application of batteries and a photovoltaic (PV) power plant, was applied in this section. This process involves integrating energy storage and renewable energy generation into the existing distribution grid to enhance its efficiency and sustainability. Therefore, to minimise the power from the grid in a photovoltaic plant with battery storage, we can employ an optimisation method that aims to maximise the self-consumption of solar energy and minimise reliance on the grid.

4.1. Optimisation Method

In the PSO algorithm, each particle defines a potential solution in the search space. The position update equation aims to adjust the particle's position based on its current position, velocity, and the best positions found by both the particle itself and the swarm. Generally, the position update equation in PSO consists of cognitive and social components. The cognitive component represents the particle's individual learning and thus adjusts the particle's position towards its own best position that it has found so far. The social component instead represents the influence of the swarm's collective knowledge. It adjusts the particle's position towards the best position found by any particle in the swarm.

An application of the PSO-based method is suggested to minimise reliance on grid systems. It is initialised with a population of random solution particles that are related to a position s and velocity v. All of the solution particles have criterion for choice estimated by the objective function. In that manner, the principles of holding its inertia and modifying the solution particles' position in accordance with their and swarm's most optimal positions are included [31,32]. So, the specific particles improve their velocity $v_{\mathrm{i,new}}$ by the velocity (6) where i is the number of particles, $v_{\mathrm{i,old}}$ describes the old velocity, while $P_{\mathrm{best,i}}$ and G_{best} denote the best result of particle i and the best result of all particles at a specific point. Coefficients c_1, c_2 are the acceleration parameters and R_1, R_2 are the random numbers categorized between 0 and 1. In the presented case, the old position of the particles $s_{\mathrm{i,old}}$ is updated according to a power value at an observed hour. Afterwards, the position of each particle $s_{\mathrm{i,new}}$ is adjusted according to (7) [31,33]. Equation (7) is valid for the unit time step.

$$v_{\mathrm{i,new}} = v_{\mathrm{i,old}} + c_1 \cdot R_1 \cdot (P_{\mathrm{best,i}} - s_{\mathrm{i,old}}) + c_2 \cdot R_2 \cdot (G_{\mathrm{best}} - s_{\mathrm{i,old}}) \tag{6}$$

$$s_{\mathrm{i,new}} = s_{\mathrm{i,old}} + v_{\mathrm{i,new}} \tag{7}$$

4.2. Results of General Principles

The objective function used in the optimisation approach can be tailored specifically to minimise losses. This means that the optimisation algorithm will prioritise solutions that result in lower overall losses within the grid depending on production (*pro*), consumption (*con*) and battery condition (*bat*) (8). The boundary values related to consumption are equal to 0.5 kW and 5.8 kW, while production is for a photovoltaic power plant with an installed power of 5 kWp. The capacity of the battery is instead limited to 10 kWh, while battery charging power with an alternating current is up to 3.3 kW.

$$Obj = Min\ (pro+;\ con-;\ bat-) \tag{8}$$

The proposed technique and approach to enhance the operation of distribution grids with the integration of batteries and photovoltaic power plants are demonstrated in Figures 4–6, where PV production ($\mathrm{a_2}$) and general consumption ($\mathrm{a_1}$) are shown, together with battery storage state (b), power grid situation (c) and consumption fulfilment from intern systems ($\mathrm{d_1}$) or from the power grid ($\mathrm{d_2}$). The basic state for 24 h is presented in Figure 4. Results obtained via the PSO method are optimal in the sense of there being minimal reliance on the grid. The power grid state shows considerable involvement in the morning hours, while after PV generation, the battery provides an almost sufficient amount of energy.

In the case of lower (Figure 5($\mathrm{a_1}$)) or higher (Figure 6($\mathrm{a_1}$)) energy consumption, the grid state is significantly different. If the peak value of the consumption state reaches a value below 3 kW, the grid interaction after the morning hours is negligibly small, while in the case of consumption higher than the daily PV production (Figure 6), this aforementioned interaction reaches as close as a base state. Proposed techniques demonstrate the potential for optimising the operation of distribution grids by integrating batteries and PV power plants, leading to increased efficiency, renewable energy use, loss reduction and, consequently, grid reliability. For example, losses that appeared in cases of lower energy consumption

(Figure 5) decreased to 47%, while the higher energy consumption (Figure 6) led to increasing levels of up to 88%. The renewable energy utilisation (Figures 4(a_2), 5(a_2) and 6(a_2)) stands for the integration of RES into the charging infrastructure. Therefore, for example, within an electric vehicle area is an important aspect of promoting sustainable transportation.

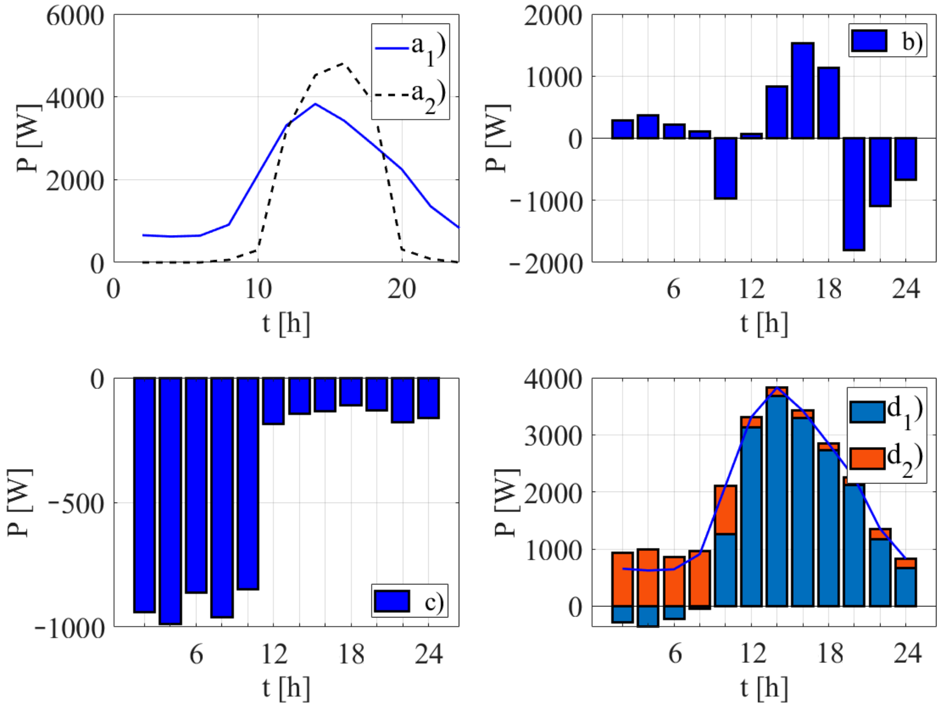

Figure 4. Scenario 1: PV production (**a$_2$**), general consumption (**a$_1$**), battery storage state (**b**), power grid state (**c**) and consumption fulfilment from intern systems (**d$_1$**) or from the power grid (**d$_2$**).

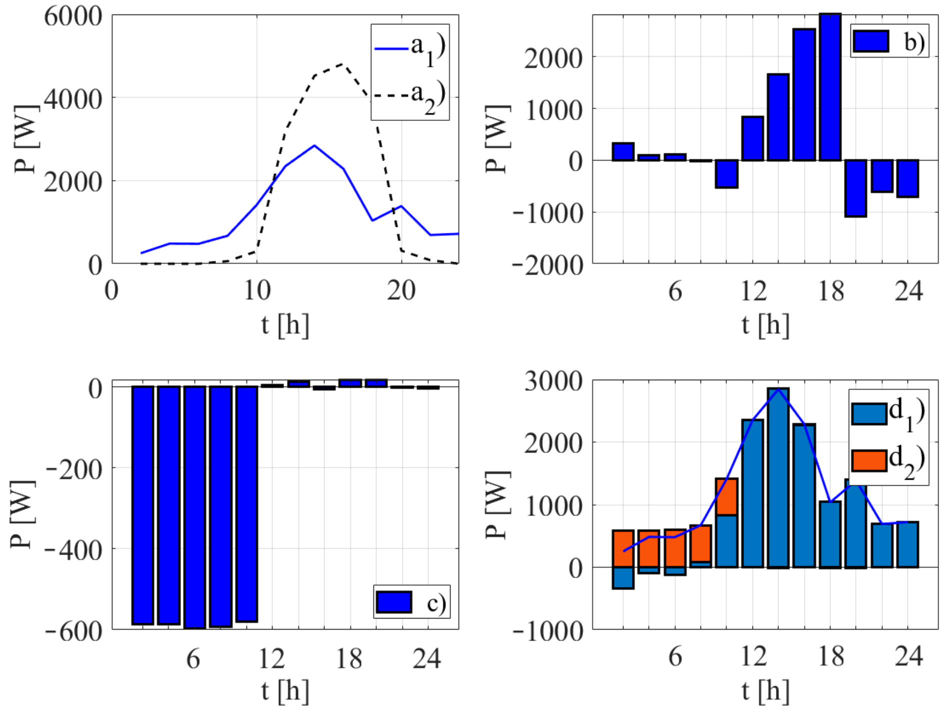

Figure 5. Scenario 2: PV production (**a$_2$**), general consumption (**a$_1$**), battery storage state (**b**), power grid state (**c**) and consumption fulfilment from intern systems (**d$_1$**) or from the power grid (**d$_2$**).

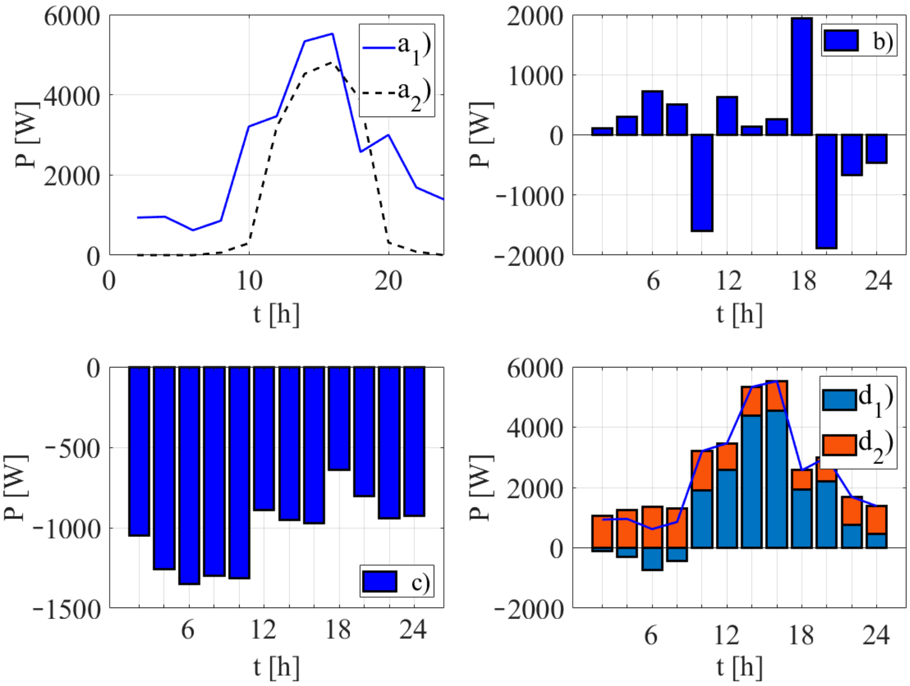

Figure 6. Scenario 3: PV production (**a_2**), general consumption (**a_1**), battery storage state (**b**), power grid state (**c**) and consumption fulfilment from intern systems (**d_1**) or from the power grid (**d_2**).

4.3. Electric Vehicles Integration

When integrating electric vehicles and solar power systems into the distribution grid, there are considerations and optimisation strategies to minimise losses and enhance system efficiency. For example, both proper voltage regulation and power factor correction techniques ensure efficient energy transfer and minimise losses in the distribution grid. Additionally, an implementation of demand response programs to incentivise electric vehicles charging during off-peak hours or when solar power generation is high could be included. This helps balance the load and minimise strain on the grid during peak periods. Beyond this, deployment of high-efficiency EV charging infrastructure to minimise losses during the charging process and the use of smart charging infrastructure and vehicle-to-grid technology within an optimal EV charging and discharging, considering grid conditions, renewable energy generation and user preferences, help in the sense of system losses minimisation and a grid stability support.

In fact, once the power flow calculation is finished, the grid losses can be defined through taking into account the current through the grid branches or on the basis of the power flow through the grid branches. The losses could also be evaluated based on the consideration of the differences in voltage amplitudes and angles on both sides of the lines. Figure 7 presents the voltage, current, active and reactive powers of the first phase within the grid, while consequently, the losses are calculated and shown in Figure 8. Results are presented without the impact of the EV charging process. The situation before 0.6 s is valid for the regular situation within the distribution grid, while the optimal results are shown between 0.6 s and 1.2 s. The power that determines energy consumption during the optimal operation could be reduced by 14% (decreasing from 0.91 MW to 0.78 MW), while the power associated with the storage and release of energy in reactive components such as inductors and capacitors is also lower (28%, decreasing from 0.24 MVAr to 0.17 MVAr). A part of the system where photovoltaic and battery systems are available reduces the grid losses (Figure 8, curve a_1), while overall grid losses ΔP are, as a result, reduced by nearly 5% (from 31.31 kW to 29.74 kW). In this sense, losses related to the photovoltaic and battery system (Figure 8, curve a_2) should also be considered.

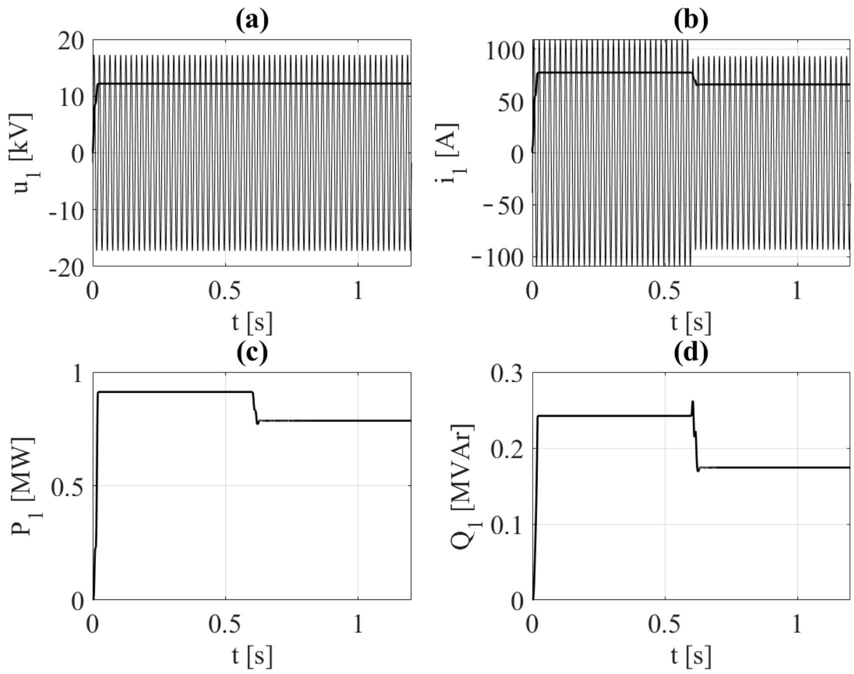

Figure 7. Voltage (**a**), current (**b**), active (**c**) and reactive (**d**) powers of the first phase. Situation without the impact of the EV charging (before and after the optimisation process).

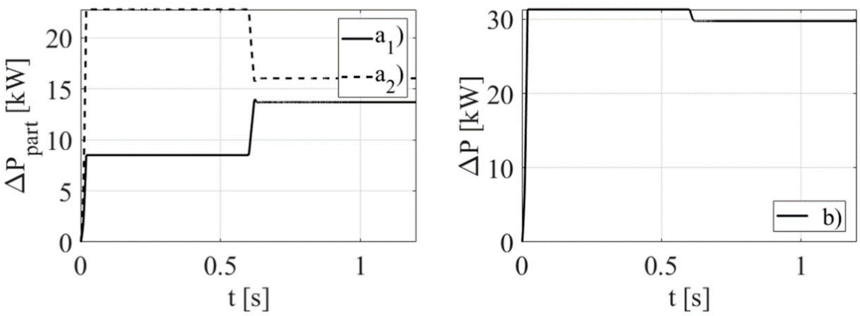

Figure 8. Losses (part ($\mathbf{a_1}$,$\mathbf{a_2}$) and overall (**b**)) within the grid. Situation without the impact of the EV charging (before and after the optimisation process).

When electric vehicles are added to the distribution grid, there can be an impact on losses within the grid. The additional charging can introduce new load dynamics and affect the overall efficiency of the grid. The charging process requires a certain amount of active power, which increases the demand on the grid. Of course, if the infrastructure is not properly designed or upgraded to handle the increased load, this can result in higher losses due to higher currents flowing through the distribution lines. If 100 kW of electric vehicles are added to the distribution grid, then the total charging load from EVs connected to the grid is 100 kW. This value, therefore, represents the combined power demand of all the EVs connected to the grid at a given time. The additional load from EVs increases the overall power demand on the distribution grid. This increased load can put additional stress on the grid infrastructure, including transformers, cables, and other equipment. In Figures 9 and 10, the situation with added electric vehicles is shown. Overall losses ΔP in a regularly operating distribution grid are 5.2% higher compared to the losses shown in Figure 8 (from 31.31 kW to 32.94 kW). However, in an optimised scenario (0.6 s to 1.2 s), these losses can be reduced to the levels observed when there are no electric vehicles in the system. In the presented case, the agreement is less than 0.4% (31.31 kW vs. 31.19 kW).

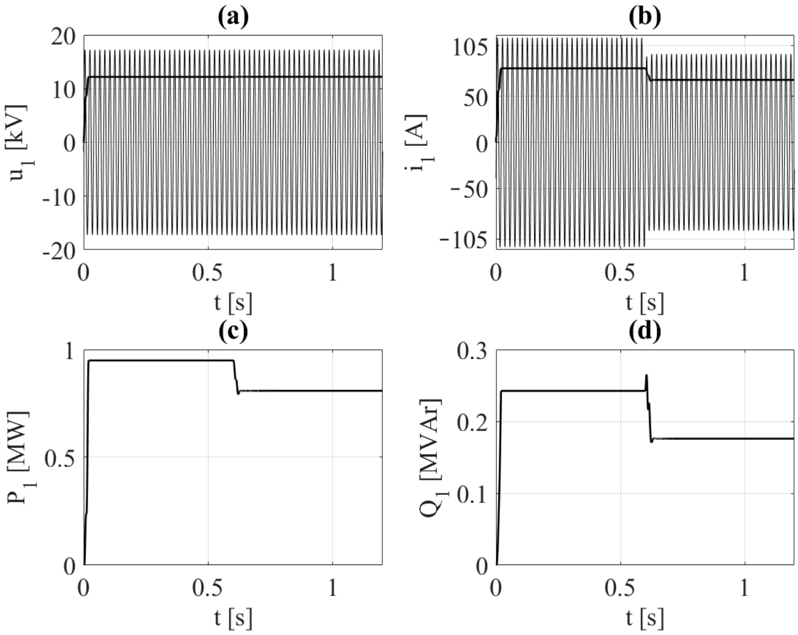

Figure 9. Voltage (**a**), current (**b**), active (**c**) and reactive (**d**) powers of the first phase. The situation with the impact of the EV charging (before and after optimisation process).

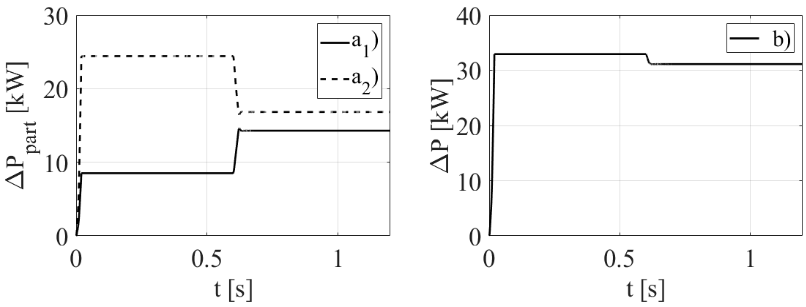

Figure 10. Losses (part (**a$_1$**,**a$_2$**) and overall (**b**)) within the grid. The situation with the impact of the EV charging (before and after optimisation process).

By applying the modelling approach and optimisation techniques, we found that the optimal solution means a reduction of losses within the distribution grid. Related to the results in Section 3, the losses within a Slovenian distribution grid as a result of electric vehicle inclusion reached up to 0.24 GWh per time unit and could be reduced by approximately 5% through optimisation process inclusion. The presented value was obtained through the ratio 14.5 GWh (Section 3) vs. 100 kWh. The difference between 32.94 kW and 31.31 kW is thus crucial and plays an essential role. However, the actual extent of loss reduction will depend on various factors, such as the grid's characteristics, the availability of data, the accuracy of the model, and the effectiveness of the optimisation algorithm.

5. Conclusions

In road transport, cars use renewable liquid fuels and fossil fuels supplied by fuel distributors. Different data on fuel sales and consumption are normally obtained from such fuel distributors. With alternative (electric) drives, the situation becomes much different. The distribution grid needs to accommodate the deployment of charging infrastructure at various locations, including homes, workplaces, public car parks, and along motorways. Planning the distribution grid's capacity and configuration should consider the locations and power requirements of charging stations to ensure adequate power supply and minimise the need for expensive grid upgrades. As more electric vehicles are introduced into the market and more people purchase them, there will be an increased demand for electricity. Over the last period, battery electric vehicles have increased in number. For the purposes of the task, the vehicles were divided according to the segment they belonged to, namely, the following four segments were formed: mini, small, medium-sized and large. When integrating electric vehicles, batteries and solar power systems into the distribution grid, there are considerations and optimisation strategies to minimise losses and enhance system efficiency. In some cases, the distribution grid might require reinforcement or upgrades to handle the increased demand from EVs. This could involve installing new transformers, upgrading distribution lines, and implementing advanced monitoring and control systems. Grid operators and utilities must assess the existing infrastructure and make necessary investments to ensure a reliable and resilient grid. In the context of the modelling approach and optimisation mentioned earlier, it is suggested that losses within the distribution grid can be reduced. By employing techniques such as particle swarm optimisation and considering various factors, the grid's operation can be optimised to minimise losses. So, it is highly important for utilities and grid operators to carefully consider the impact of EVs on distribution grid losses and take appropriate measures to ensure grid efficiency, reliability, and sustainability while also accommodating the growing EV market.

This research expands our understanding of the energy consumption patterns and charging behaviour of electric vehicles. It provides insights into factors that influence energy consumption. This enhanced understanding may help stakeholders accept informed decisions regarding electric vehicle adoption, charging infrastructure planning and grid management. Beyond this, this research contributes to the literature by addressing the ways in which vehicle charging demand results in increased distribution losses and consequently impacts the overall efficiency of the grid.

Several potential future directions can further advance this field as the long-term charging behaviour of electric vehicle users, potentially considering factors such as charging patterns over extended periods and the changes in charging preferences over time. This knowledge should provide valuable insights for grid planning, infrastructure development, and policy formulation. In addition to this, research in this area could explore advanced grid management techniques to optimise the integration of electric vehicles into the grid. This includes developing sophisticated algorithms for load forecasting, demand response optimisation and real-time grid balancing to ensure grid stability, minimise peak loads and even maximise the use of renewable energy sources. Future studies could centre on the increased demand for electric vehicles leading to several unwanted consequences, such as voltage fluctuations, power outages and reduced reliability of electricity supply.

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