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Optimal Electric Vehicle Parking Lot Energy Supply Based on Mixed-Integer Linear Programming

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Abstract: E-mobility represents an important part of the EU's green transition and one of the key drivers for reducing CO_2 pollution in urban areas. To accelerate the e-mobility sector's development it is necessary to invest in energy infrastructure and to assure favorable conditions in terms of competitive electricity prices to make the technology even more attractive. Large peak consumption of parking lots which use different variants of uncoordinated charging strategies increases grid problems and increases electricity supply costs. On the other hand, as observed lately in energy markets, different, mostly uncontrollable, factors can drive electricity prices to extreme levels, making the use of electric vehicles very expensive. In order to reduce exposure to these extreme conditions, it is essential to identify the optimal way to supply parking lots in the long term and to apply an adequate charging strategy that can help to reduce costs for end consumers and bring higher profit for parking lot owners. The significant decline in photovoltaic (PV) and battery storage technology costs makes them an ideal complement for the future supply of parking lots if they are used in an optimal manner in coordination with an adequate charging strategy. This paper addresses the optimal power supply investment problem related to parking lot electricity supply coupled with the application of an optimal EV charging strategy. The proposed optimization model determines optimal investment decisions related to grid supply and contracted peak power, PV plant capacity, battery storage capacity, and operation while optimizing EV charging. The model uses realistic data of EV charging patterns (arrival, departure, energy requirements, etc.) which are derived from commercial platforms. The model is applied using the data and prices from the Croatian market.

Keywords: parking lot; optimal scheduling; optimal investment; battery storage; PV capacity; mixed-integer programming

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Citation: Jakus, D.; Vasilj, J.; Jolevski, D. Optimal Electric Vehicle Parking Lot Energy Supply Based on Mixed-Integer Linear Programming. *Energies* **2023**, *16*, 7793. https://doi.org/10.3390/en16237793

Academic Editors: Rodolfo Araneo, Massimo Panella and Antonello Rosato

Received: 27 October 2023
Revised: 19 November 2023
Accepted: 21 November 2023
Published: 27 November 2023

1. Introduction

The EU strategy to steer member states away from the fossil-fuel-based transport sector, aiming for a minimum of 30 million zero-emission vehicles on its roads by the end of 2030, represents an ambitious goal and a great electricity grid infrastructure challenge. To meet these goals, it is projected that over 1 million charging stations for electric and hydrogen vehicles will need to be installed by 2025, with an even greater number expected by 2030. Despite significant investments in charging infrastructure, which is likely to be subsidized through different incentive programs and financial mechanisms, additional incentives directly focused on end consumers such as purchase rebates, tax exemptions, tax credits, and additional benefits are needed. As per the estimations from the Vehicle Technologies Office of the Department of Energy (DOE), the expense associated with an EV lithium-ion battery pack witnessed an 87% decrease from 2008 to 2021, substantially contributing to the overall reduction in EV costs. Regardless of all these benefits and incentives, the e-mobility sector growth will significantly be defined by the electricity prices at the parking lot (PL) level [1]. In order to achieve long-term stable prices for electric vehicle (EV) charging it is necessary to rely on electricity production technologies that are not exposed to the large fluctuations in electricity production costs which we are experiencing today in electricity markets worldwide.

The decline in PV and battery storage technology costs makes them ideal options for long-term hedging against volatile electricity market prices. In order to determine the optimal capacities of PV plants and battery storage systems (BSSs) which can be used to supplement grid supply it is necessary to carefully examine particular market conditions and assess parking lot utilization in the long term. In that sense, higher investment in the supply of parking lots which include PV plants and battery storage can in the long run increase parking lot profitability and bring a reduction in charging costs for end consumers. In addition to this, investment in a PV plant and battery storage increases parking lot operational flexibility; it can reduce costs associated with peak power but also allows the investor to reduce grid connection costs and its effect on the distribution grid (under voltages and grid congestion). This paper describes an optimization model that can be used to determine the optimal investment in EV parking lot supply which combines grid supply, PV plant production, and battery storage supply while also optimizing battery storage utilization in combination with EV charging optimization. The proposed model is formulated as mixed-integer linear programming.

1.1. Literature Review

Utilizing PV plant production and BSSs in EV parking lots offers a promising avenue for reducing EV supply expenses and minimizing the effect of EV charging on the power system loading. Usually, EV charging algorithms can be clustered into two major groups: centrally controlled coordinated charging and decentralized controlled charging [2,3]. In both scenarios, charging EVs at the PL level is executed optimally to prevent or minimize the adverse impacts of unplanned EV charging events, which may necessitate upgrades to the current electricity network infrastructure. Numerous prior studies have introduced coordinated charging strategies that overlook influencing factors such as EV departure time, EV capacity, consumer energy requests, and crucial components of energy tariffs affecting PL energy costs [4]. In [5], the authors propose a metaheuristic approach based on the particle swarm optimization (PSO) and shuffled frog leaping (SFL) algorithms for optimal dynamic scheduling of EVs in a PL with an objective function related to minimization of the grid charging costs. The authors apply the proposed method under the dynamic charging paradigm in which EVs' arrivals are dynamic in nature and EVs may come and go as they please. The main problem of methods that use different metaheuristic techniques is the computational time, which can be a limiting factor for the application of these methods in online operation, especially if there are many EVs that need to coordinate in a very small time slot. In the work by Hao et al. [6], a novel optimization model is presented, leveraging a virus search colony algorithm. This model is designed to enhance the performance of EV parking lots, taking into account uncertainties associated with grid prices in the demand response program (DRP). In [6], in addition to grid supply, the authors also consider the possibility of producing energy for PL needs from renewable energy sources (PV, wind) and hydrogen fuel cells. On the other hand, in the proposed approach, the authors do not consider investment and operational costs related to these technologies, and given the solution, the approach based on the virus search colony algorithm is limited to relatively short time interval simulations. In the study by Jannati et al. [7], an efficient energy management model is suggested for an electric vehicle (EV) parking facility within the framework of a demand response program. The proposed configuration incorporates an electrolyzer and fuel cell as a hydrogen storage system, aiming to minimize the operational costs of the parking lot. In [8], the authors propose an algorithm for parking lot management which is used for optimal scheduling of electric vehicles considering supply from solar generation with the objective of minimizing the grid power import during peak pricing periods. In [9], the authors propose a more formal approach for estimating the size of a stationary BSS for PLs in a constrained grid while considering EV travel patterns, charging needs, and the driver behavior of EVs. The BSS sizing and PL charging optimization is performed in a two-step process, with BSS sizing using the region reduction method and PL charging optimization based on nonlinear programming. The BSS sizing is determined in relation to grid limits and investment profitability is not considered in the BSS sizing process. In most of the papers, the proposed approaches do not consider BSS and DG investment problems in combination with the PL operation problem. In the study conducted by Zhang [10], the author examined the energy cost implications of daytime charging at parking lots situated near commercial areas versus nighttime charging at an EV parking facility associated with a residential building. The analysis incorporated stochastic considerations for the arrival and departure times, as well as the initial state of energy of the EVs, using a dynamic programming framework. In the study by Ahsan et al. [11,12], a multi-objective optimization framework designed for the intelligent management of electric vehicle (EV) charging and discharging is introduced. Their approach aims to not only maximize revenue and savings for smart buildings but also enhance the overall efficiency of EV operations. The authors show that EVs can save 50–69% in charging costs while performing V2X operations. In [13], the authors address the optimal energy management of EV parking lots under peak-load-reduction-based demand response (DR) programs considering uncertainty. The papers propose various energy management strategies and optimization models to maximize the load factor and minimize costs for EV parking lot owners while considering the stochastic nature of EV arrival and departure times, as well as the uncertainty in the state of energy of EVs. In [14], the authors propose an optimization method that maximizes the charging station profit while reducing the power purchased and sold to the grid during high solar availability without exceeding the charging rate limit.

An increase in EVCS profitability and a reduction in distribution network loading can be achieved by incorporating renewable generation and BSSs as supplementary power sources for EV charging. The authors in [15] conducted a study focusing on the design of a fast EVCS for EVs, with integrated renewable energy sources and BSSs. Unlike other research papers, this study adopts a comprehensive model of the EV charging process, taking into account the arrival time and state of charge of electric vehicles. The proposed solution approach, that utilizes a genetic algorithm, aims to identify the optimal EVCS power supply configuration that maximizes EVCSs' profitability, which is measured by its net present value. In terms of the necessity of the re-use of retired EV batteries and the capacity allocation of PV combined energy storage stations, the authors in [16] present a method of economic estimation for a PV charging station based on the utilization of retired electric vehicle batteries. The NPV is adopted to evaluate the cost and benefit of the PV charging station with the second-use battery energy storage during the lifecycle. In [17], the authors introduce diverse configurations of hybrid energy systems designed to fulfill the power needs of EVCSs located in the northwestern region of Delhi, India. The optimization algorithm aims to minimize the overall NPV and LCOE, while ensuring an adequate level of power supply reliability. The study presented in [18] employs three metaheuristic algorithms—PSO, the salp swarm algorithm (SSA), and the arithmetic optimization algorithm (AOA)—to determine the optimal structure, focusing on the number and power of chargers. The inclusion of renewable energy and BESSs mitigates the impact on the grid, enhances profitability, and, notably, PSO emerges as the most effective algorithm in maximizing the NPV of the EVCS structure, outperforming AOA and SSA.

The levelized cost of charging (LCOC) for electric vehicles is a critical metric for evaluating the economic feasibility and competitiveness of EVs compared to traditional internal combustion engine vehicles (ICEVs). In [19], the authors calculate the LCOC for 30 European countries. The study reveals a considerable variation in charging expenses among countries and diverse charging methods. The findings indicate that leveraging self-produced PV energy for EV charging, rather than relying solely on grid electricity, can substantially reduce the LCOC.

The above-listed research papers, along with many others, consider the problem of optimal parking lot operation (EV charging) through coordinated central/distributed EV charging control. Certain approaches that consider the use of a BSS and DG to reduce grid congestion and PL energy costs usually only consider operating costs and do not provide the means to optimize both investment decisions and PL operation costs. The prevailing trend across these papers [15–18] involves utilizing a metaheuristic approach to determine the optimal power supply for EVCS, while concurrently employing a heuristic approach for EV charging management. It is essential to note that the exclusive reliance on heuristics for determining optimal EV charging may be suboptimal, as it inherently lacks the capability to automatically consider the impact of charging strategy and EVCS power supply on critical cost components such as peak power costs, grid connection costs, and charging costs. The proposed paper distinguishes itself by adopting a mathematical programming approach, a more comprehensive method that incorporates, among other aspects, all these factors into the optimization process, offering a more robust and nuanced solution.

1.2. Research Questions and Contributions

In this paper, we propose a method for minimizing parking plot power supply costs through optimal PV/BSS investment and coordinated EV charging. To determine the optimal power supply investment and EV charging, a mixed-integer linear program (MILP) is implemented on a test case for a representative year with 15 min model resolution. Through optimal investment in PV/BSS and optimal EV charging the owner can reduce grid supply costs and peak power costs as well as grid connection costs, which are associated with maximum expected peak power. The BSS is used for load shifting as well as for storing the excess PV production which cannot be used immediately when it is produced. In addition to this, BSS is used for energy arbitrage: by purchasing energy during periods of low electricity prices (charging the BSS), and using it later for EV charging when the prices are higher (discharging the BSS), thus obtaining an economic benefit at the parking lot level.

Currently, electricity markets show a high level of price volatility, with record-breaking high electricity prices due to numerous reasons, some of which are still the topic of different debates. One of the main reasons for switching to electric vehicles, despite generally higher technology costs in relation to vehicles with a combustion engine, is low-cost driving due to high motor efficiency and historically low electricity prices. Recent trends in electricity markets have raised concerns about how the e-mobility sector can cope with the high electricity prices. The investment in PV/BSS at the parking lot level also provides a long-term measure to hedge against the potential risks of rising electricity prices. In order to make a strategic decision to invest in a solution that includes PV/BSS one needs to take into account not only PV/BSS investment costs but also operating costs, as well as equipment replacement costs. In the proposed method, the approach optimizes investment considering all the mentioned costs while weighing the costs of such an investment in relation to benefits, which can be achieved through optimal parking lot operation, primarily through PV production, BSS arbitrage, peak shaving at PL level, and grid-connection cost reduction. The proposed method takes into account costs and profits considering the project's whole lifetime. The main objective is the minimization of the parking lot net present costs, which are calculated as the difference between the present value of all costs (investment, operational, equipment replacement, and financing costs) and profits over the project's lifetime.

The key contributions of the paper can be summarized as:

1. The mathematical formulation, based on MILP, of an optimal parking lot power supply solution combining different important investment/management aspects.
2. A detailed analysis of different parking lot supply options as well as the effect of different reimbursement mechanisms for PV energy production surplus on system design and costs.
3. A comprehensive analysis of the optimal parking lot solution for a Croatian test case based on realistic data with a sensitivity analysis for relevant parameters.

The rest of the paper is structured as follows: In Section 2, a detailed mathematical formulation of the proposed approach is given. Section 3 is dedicated to a comprehensive case study focused on the Croatia test case, including a thorough discussion of the results. Finally, the relevant conclusions are provided in Section 4.

2. Mathematical Model

2.1. Model and Input Data Description

In this section, a detailed description of the optimal PL power supply investment/ management model is given together with the description and assumptions related to the input data used in the analysis. The general overview of the considered system is illustrated in Figure 1, and it consists of three main components connected to the power grid: the EVCS, PV plant, and BESS.

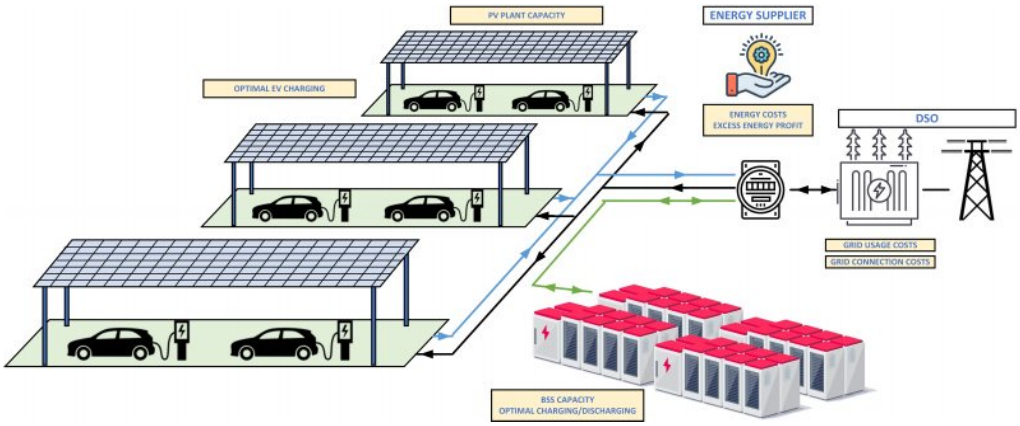

Figure 1. Parking lot power supply diagram.

The operation of the whole parking lot is managed by the charging controller, which manages the charging process of electric vehicles in a centrally coordinated manner based on data received from users (arrival/departure time, energy requirement, battery capacity, initial charge). Given that the long-term decisions related to options of investment in PV plant and battery storage systems need to be made before parking lot realization, the assessment of the optimal power supply solution, as well as optimal parking lot operation, is based on parking lot dynamics, which is defined by expected predefined EV data. The EV data used in this study is derived from real measurements from existing parking lots and the study is focused on specific test cases related to EV parking lots located near office buildings with typical EV workplace usage patterns. The study considers both battery electric vehicles (BEVs) and plug-in hybrid vehicles (PHEVs) since we simulate EV energy demand and arrival/departure dynamics based on real-life measurements from charging stations that allow charging of both types of EVs. Regardless of this, the proposed model can be applied to other use cases. The stochastic behavior of EVs is captured from real measurements, and relevant parameters such as EV arrival/departure time, charging duration, and required energy are represented through probabilistic distribution functions [20].

Usually, real measurements from EV chargers show a low charger utilization rate [21] given the still relatively low share of EVs in the transport sector. In [22], the author addresses the issue of regularizing the parking order at EVCSs in public commercial areas and proposes an economic penalty strategy for assessing parking fees, including fixed and dynamic penalties, based on a traffic flow model and price–consumption model that enhances EV charging facility utilization. The majority of available data indicate that charger utilization rate is in the range of 5–15%. The utilization rate for DC fast chargers is even lower, with estimates of average utilization rates between 3 and 5% [23]. With these low utilization rates, parking lots cannot achieve profitability levels even with optimized power supply solutions. In the future, the utilization of EV parking lot chargers will grow as the market and investor expectations mature. Given this, in the analysis, the EV charging data are simulated using obtained probability distribution functions but for a higher parking lot charger utilization rate.

Data used for modeling PV production can be obtained for the specific location where the PV plant is located, considering all relevant parameters such as shading effects, internal losses, inverter efficiency, temperature influence, etc. In the proposed model, the PV plant's production is modeled using average 15 min time-series data, with production expressed in relation to plant nominal power (per unit—p.u.). The proposed model determines whether or not to invest in a PV plant and, along with this, the PV plant's optimal capacity. The model also assumes that the excess power can be exported to the grid, and in that case the parking lot receives additional income. For cases in which the PV energy surplus is not used for financial reimbursement (PV production used exclusively for self-consumption), the energy price for selling excess energy is zero-valued.

The parking lot energy costs are calculated according to the time-of-use (ToU) tariff scheme which is currently used in Croatia for the majority of household/business consumers, with two different daily prices (peak/base load). The total energy price can be decomposed into parts related to energy production, transmission, and distribution. In addition to this, the consumers are required to pay a renewable energy source support tax, with unit prices irrelevant to time of use. Also, most of the ToU tariff schemes include peak power pricing, which is calculated based on the maximum power consumption in any settlement/accounting period (in Croatia on a monthly basis). The proposed model accounts for all these important parameters that define charging station energy costs, but it can also be easily adapted to a dynamic market pricing scheme. Through the optimal management of EV charging and investment in PV production and BSSs we can reduce grid supply costs as well as peak power and associated costs. Also, by partially fulfilling energy needs through PV production it is possible to reduce the amount of energy supplied by the grid, and with this the costs related to the renewable energy sources support tax.

2.2. Mathematical Formulation

As indicated previously, the objective Function (1) minimizes the total parking lot net present costs, which are calculated as the difference between the present value of all PL costs and the present value of PL profits over the project lifetime. The costs are separated into four major groups: investment costs, T_{inv}^{PV}; equipment maintenance costs, T_{main}^{PV}; operational costs, T_{EE}^{PV}; project financing/loan costs, T_{loan}^{PV}; and equipment replacement costs, T_{repl}^{PV}. On the other hand, in the model, the parking lot profits only refer to the profits from PL energy export to the grid during periods of excess PV plant production, T_{prof}^{PV}. The model does not include PL profits from EV charging since this category of profit is defined by consumer behavior and the charging station owner's pricing policy, it can be considered fixed.

The objective function is minimized over the set of variables Ψ which can be separated into two major groups:

- Power supply investment decision variables: PV plant investment (P_{inst}^{PV}, b^{PV}), BSS investment (E_{BSS}^{cap}, b^{BSS}), grid connection purchase power ($P^{contracted}$).
- PL management variables: EV charging($P_{t,i}^{EV}, E_{t,i}^{LOT}, SOE_{t,i}^{LOT}$), PV plant production ($P_t^{PV}$), BSS operation ($P_t^{ch}, P_t^{ds}, P_{max,t}^{BSS}, E_t^{BSS}$), grid supply and associated costs ($P_t^{grid_+}, P_t^{grid_-}, b_t^{grid}, P_{grid}^{max_m}$).

$$\min_{\Psi} \ T_{TOTAL}^{PV} = T_{inv}^{PV} + T_{main}^{PV} + T_{EE}^{PV} + T_{loan}^{PV} + T_{repl}^{PV} - T_{prof}^{PV} \tag{1}$$

The total investment costs can be represented with Equation (2). As stated in Equation (2), only a portion of the total investment costs are self-financed while the remaining amount is financed through a loan. The parameter f represents the portion of the total investment that is financed through a long-term loan.

$$T_{inv}^{PV} = \left(c^{PL}N^{PL} + c^{PV}P_{inst}^{PV} + c^{BSS}E_{cap}^{BSS} + c^{conn}P^{contracted}\right)(1-f) \tag{2}$$

The part of the investment that is financed through a loan is assumed to be paid through a series of payments made at equal annual intervals. The annuity required to return the loan, which is used to partially finance the investment in the PL and optionally the PV plant and BSS, is calculated using (3) based on loan terms (k—interest rate, L—loan payback period). It is straightforward to modify the proposed model in a way that accounts for different financing terms for different PL power supply components.

$$T_{annuities} = \frac{T_{inv} \cdot f \cdot k}{1 - (1+k)^{-L}} \tag{3}$$

$$T_{loan}^{PV} = \sum_{n \in L} \frac{T_{annuities}}{(1+d)^n} \tag{4}$$

The maintenance costs include the parking lot expenses that are tied to the upkeep and repair of the parking lot and power supply equipment and components present throughout the operation. In the proposed model, the maintenance costs are represented simplistically, with maintenance costs proportional to equipment rating or number of units. The parking lot maintenance costs are proportional to the number of parking lots while the PV plant and BSS maintenance costs are proportional to the PV plant's install power and BSS capacity. It is worth noting that the PV install power and BSS capacity will be equal to zero if the algorithm determines that such supply options are not optimal; in that case, the maintenance costs will also be equal to zero (Equations (18) and (22)). The maintenance costs increase over the years of equipment exploitation and can be easily introduced in the model by changing Equations (5)–(7). The net present value of the total maintenance costs is given by Equation (8).

$$T_{main}^{PL} = c^{PL} \cdot N^{PL} \cdot M^{PL} \tag{5}$$

$$T_{main}^{PVs} = c^{PV} \cdot P_{inst}^{PV} \cdot M^{PV} \tag{6}$$

$$T_{main}^{BSS} = c^{BSS} \cdot E_{cap}^{BSS} \cdot M^{BSS} \tag{7}$$

$$T_{main}^{PV} = \sum_{n \in N} \frac{T_{main}^{PL} + T_{main}^{PVs} + T_{main}^{BSS}}{(1+d)^n} \tag{8}$$

For certain equipment it is necessary to include replacement costs in the calculation when making long-term investment decisions given that the equipment life span is shorter than the project lifetime. In the proposed model, the replacement costs are only considered for the BSS if the model initially includes a BSS in the parking lot supply. A similar modeling approach can be extended also to other power supply equipment and components. For the BSS, the life expectancy is mostly driven by usage cycles. Most battery manufacturers provide a warranty for a specific time period and usually guarantee capacity retention in a percentage related to the initial BSS capacity. Also, when estimating the BSS replacement costs, it is necessary to account for technology maturity and cost reduction. Figure 2 illustrates the anticipated BSS power and capacity costs across various battery storage durations (2, 4, 6 h). The cost projections for a BSS were adjusted to the 2020 value. When considering the USD/kWh basis, longer-duration batteries exhibit a reduced capital cost, while on a USD/kW basis, shorter-duration batteries display a lower capital cost. For a more in-depth exploration of cost projections, readers are directed to [24]. From Figure 2, it can be seen that the replacement costs of a BSS when appearing several years after the initial investment have a significantly lower unit cost, which needs to be accounted for in the analysis.

$$T_{repl}^{BSS} = \frac{c_{repl}^{BSS} \cdot E_{cap}^{BSS}}{(1+d)^z} \tag{9}$$

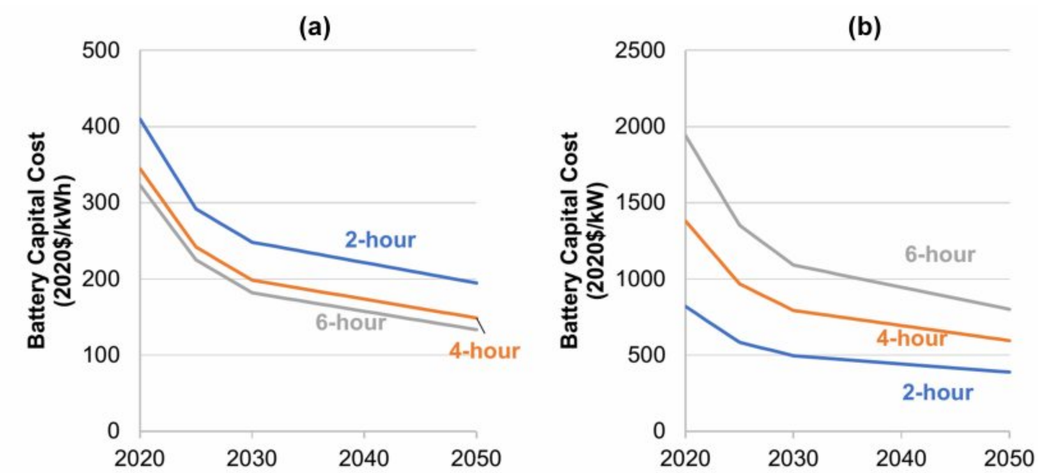

Figure 2. BSS cost projections [24]. (**a**) Shows the values in USD/kWh, while (**b**) shows the costs in USD/kW normalized to the 2020 value.

For connecting the parking lot to the grid it is necessary to pay the grid connection charge, which is usually proportional to the grid contracted power. The expected parking lot maximum peak power will depend on the EV charging strategy and user demand as well as on the possibility of providing power in critical peak load moments from the PV plant and BSS. Equation (10) provides the expected peak load over the period of a representative year (optimal contracted power) that defines the grid connection costs, which are also included in the total investment costs (Equation (2)). In this way, the potential benefit of including a PV plant and BSS in the PL's power supply in order to reduce the grid connection charge is also taken into account. The monthly peak power is determined by Equation (11) and used to calculate the associated monthly peak power costs in Equation (16). The energy imported/exported to the grid is defined by Equations (12)–(15). From Equation (15) it can be seen that the export of power from the PL to the electrical grid is only possible in periods when the PV plant is actively producing energy. This limits the possibility of exporting energy and accumulating associated profit from the energy previously stored in the BSS regardless of its origin. Equations (13) and (14) limit the possibility of simultaneous grid energy export/import, but due to the nature of the objective function it can be omitted, given that simultaneous grid energy export/import would increase PL energy costs.

$$P_m^{Gmax} \leq P^{contracted} \qquad \forall M^{big} \in M \tag{10}$$

$$P_t^{grid} \leq P_m^{Gmax} \qquad \forall t \in m, \forall M^{big} \in M \tag{11}$$

$$P_t^{grid} = P_t^{grid+} - P_t^{grid-} \qquad \forall\, t \in\, T \tag{12}$$

$$0 \leq P_t^{grid+} \leq\, M^{big} \cdot b_t^{grid} \qquad \forall\, t \in\, T \tag{13}$$

$$0 \leq P_t^{grid-} \leq\, M^{big} \cdot \left(1 - b_t^{grid}\right) \qquad \forall\, t \in\, T \tag{14}$$

$$P_t^{grid-} \leq\, P_t^{PV} \qquad \forall\, t \in\, T \tag{15}$$

The annual PL energy costs, grid usage, renewable energy source (RES) tax, and peak power costs are given in Equation (16). It can be seen from Equation (16) that the grid usage costs and RES tax costs are only applied to the energy imported from the grid. The net present value of PL annual energy costs, grid usage, RES tax, and peak power costs over the project lifetime is given with Equation (17), considering the discount rate d. During the project lifetime, these costs are assumed to increase with a fixed annual rate r.

$$\begin{aligned} T_{EE}^{annual} = \sum_{t \in T} \left(c_t^{E_{H/L}} + c_t^{Grid_{H/L}} \right) \cdot P_t^{grid_+} \cdot \Delta t + \\ + c_t^{RES_{H/L}} \sum_{t \in} P_t^{grid_+} \cdot \Delta t + \\ + c^{peak} \sum_{m \in M} P_{grid}^{max,m} \end{aligned} \tag{16}$$

$$T_{EE}^{PV} = \sum_{n \in N} \frac{T_{EE}^{annual} \cdot (1+r)^n}{(1+d)^n} \tag{17}$$

The proposed model assumes that the data regarding solar production for the potential PV plant located at or near the PL location are known. The PV production is expressed in p.u. values in relation to the PV plant's install power, which is determined by the proposed optimization model. Equation (18) defines the limits regarding the PV plant's maximum power that is limited by different factors restricting the available area for plant construction. The PV plant's production for time interval t, if selected for construction, is defined by Equation (19).

$$0 \leq P_{inst}^{PV} \leq P_{inst}^{PV.max} \cdot b^{PV} \qquad \forall\, t \in\, T \tag{18}$$

$$P_t^{PV} = P_t^{PV.pu} \cdot P_{inst}^{PV} \cdot \eta_{inv} \qquad \forall\, t \in\, T \tag{19}$$

In the case of excess PV plant production, where energy is exported from the PL to the grid, the PL receives additional profit. In Croatia, for example, if in a particular energy tariff the amount of energy delivered to a network exceeds the amount of energy taken from the network, then the energy supplier is obliged to take the excess energy at a price of 0.8 times the energy consumption price (not including grid usage costs) in a particular tariff. This amount represents additional profit for a grid user—in this case the charging station operator. This is expressed by Equation (20). The net present value of the PL profit due to excess power production over the project lifetime is given by Equation (21), considering discount rate d. Given that the model assumes an increase in power supply costs with a fixed annual rate r, the annual profits related to excess PV production also increase with the same rate—Equation (21).

$$T_{prof}^{annual} = 0.8 \cdot c_t^{E_{H/L}} \cdot \Delta t \sum_{t \in T} P_t^{grid_-} \tag{20}$$

$$T_{prof}^{PV} = \sum_{n \in N} \frac{T_{prof}^{annual} \cdot (1+r)^n}{(1+d)^n} \tag{21}$$

The maximum BSS capacity is defined by Equation (22), where b^{BSS} represents a binary decision related to investment in BSS, which limits the battery capacity either to zero or to the upper limit $E_{cap}^{BSS.max}$. It is worth noting that due to Equation (28), which links the BSS capacity and maximum charging/discharging power, the BSS charging and discharging power for all hours will be reduced to zero when binary variable b^{BSS} is equal to zero. Equations (23) and (24) represent the BSS's state of energy at the first hour and all other sequential hours in a simulated period considering the BSS's charging/discharging efficiency. The BSS's upper and lower state of energy limits are defined by Equation (25). Constraints (26) and (27) limit simultaneous charging and discharging of the BSS.

$$0 \leq E_{cap}^{BSS} \leq E_{cap}^{BSS.max} \cdot b^{BSS} \tag{22}$$

$$E_1^{BSS} = E_{int}^{BSS} + \left(P_1^{ch} \cdot \eta_{ch} - \frac{P_1^{ds}}{\eta_{ds}}\right)\Delta t \tag{23}$$

$$E_t^{BSS} = E_{t-1}^{BSS} + \left(P_t^{ch} \cdot \eta_{ch} - \frac{P_t^{ds}}{\eta_{ds}}\right)\Delta t \qquad \forall\, t \in T \tag{24}$$

$$DoD \cdot E_{cap}^{BSS} \leq E_t^{BSS} \leq E_{cap}^{BSS} \qquad \forall\, t \in T \tag{25}$$

$$0 \leq P_t^{ch} \leq x_t \cdot M^{big} \qquad \forall\, t \in T \tag{26}$$

$$0 \leq P_t^{ds} \leq (1 - x_t) \cdot M^{big} \qquad \forall\, t \in T \qquad \forall\, t \in T \tag{27}$$

Usually, the CC-CV method is applied for charging Li-ion batteries. When the BSS voltage and state of energy are below a certain threshold a constant current (CC) method is applied, resulting in a slow increase in voltage [25]. In this regime, we assume that the BSS can be charged with maximum power P_{max}^{ch}. When the BSS voltage reaches a certain value, the charging regime switches to constant voltage to avoid battery damage and permanent BSS characteristic degradation. In this regime, the BSS voltage is kept constant, and the charging current is reduced exponentially with the BSS state of energy reaching the battery capacity limit. In this operating regime, the maximum charging power is reduced and the charging time is prolonged, with the state of energy approaching battery capacity. Constraints (28)–(31) represent an accurate linear BSS charging model in which the maximum charging power is reduced when the BSS state of energy approaches the BSS capacity according to the BSS charging characteristic shown in Figure 3. Thus, the BSS's maximum charging power can be mathematically expressed with Equation (31), which can be incorporated into the model through the linear expressions (32) and (33).

$$\frac{E_{cap}^{BSS}}{k = 4} = P_{max}^{ch\_ds} \tag{28}$$

$$0 \leq P_t^{ds} \leq P_{max}^{ch\_ds} \qquad \forall\, t \in T \tag{29}$$

$$0 \leq P_t^{ch} \leq P_{max,t}^{ch} \qquad \forall\, t \in T \tag{30}$$

$$P_{max,t}^{ch} = \left\{ \begin{array}{cc} P_{max}^{ch\_ds} & 0 \leq E_t^{BSS} \leq E_{limit}^{CC\_CV} \\ P_{max}^{ch\_ds} \frac{E_{cap}^{BSS} - E_t^{BSS}}{1 - E_{limit}^{CC-CV}} & E_{limit}^{CC\_CV} \leq E_t^{BSS} \leq E_{cap}^{BSS} \end{array} \right\} \qquad \forall\, t \in T \tag{31}$$

$$P_{max,t}^{ch} \leq P_{max}^{ch\_ds} \qquad \forall\, t \in T \tag{32}$$

$$P_{max,t}^{ch} \leq P_{max}^{ch\_ds} \frac{E_{cap}^{BSS} - E_t^{BSS}}{1 - E_{limit}^{CC-CV}} \qquad \forall\, t \in T \tag{33}$$

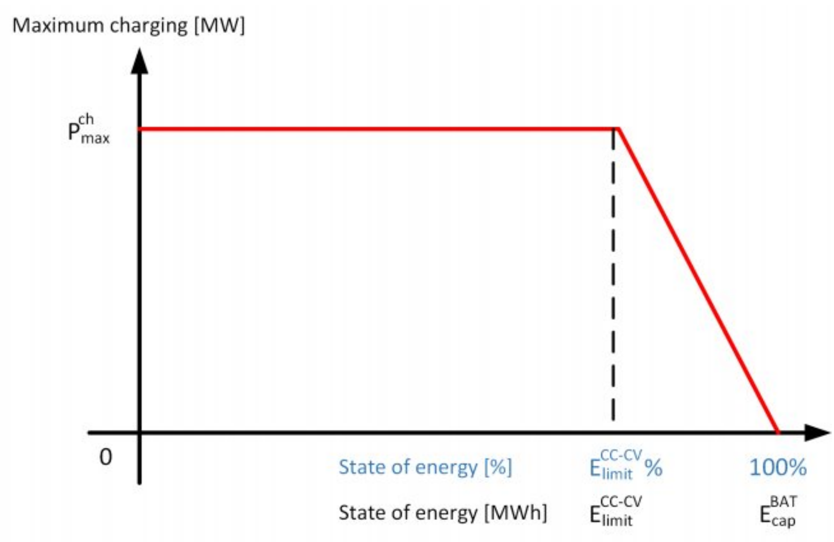

Figure 3. Linear approximation of BSS maximum power charging characteristic.

Equation (34) represents the power balance equation at the PL level, which needs to be satisfied for every time interval along the modeled time span. In the test case considered in this paper, the time span covers a period of one representative year with a 15 min time resolution.

$$P_t^{grid} + P_t^{PV} + P_t^{ds} = P_t^{ch} + \sum_{i \in PL} P_{t,i}^{EV} \qquad \forall\, t \in\, T \tag{34}$$

The electric vehicle dynamic is modeled based on measured characteristics obtained from existing chargers. These characteristics are described using probabilistic distribution functions that model EV arrival time, parking duration, total energy requirement, and car battery capacity. For every EV charger inside the modeled PL, probability distribution functions are used to model dynamic charger utilization. Given this, the model assumes that the EV arrival times, parking duration, total energy demand, initial EV battery charge status, and capacity are known. The model is used to optimize EV charging while minimizing PL investment and operational costs and satisfying EV owners' energy requirements. Constraint (35) sets the state of energy at charger i and time t to zero when the EV is not connected to charger i. Constraints (36) and (37) define the EV's state of energy connected to charger i at the time of arrival and other sequential time intervals before disconnecting from the charger. Equation (38) defines the relative state of the energy requirement that is defined by EV users at the time of disconnection. This condition ensures fulfillment of the EV user's requirements which can be fulfilled at the time of EV disconnection or prior to that if this minimizes PL operation costs. Equation (39) calculates the relative EV state of energy in relation to the EV's battery capacity.

$$E_{t,i}^{LOT} = 0 \qquad \forall t \quad \text{when there is no EV at charger } i \tag{35}$$

$$E_{t,i}^{LOT} = E_{on\_arrival}^{LOT_i} + \eta_{ch} \cdot\; P_{t,i}^{EV} \Delta t \qquad \forall t \;\; \text{when EV arrives at charger } i \tag{36}$$

$$E_{t,i}^{LOT} = E_{t-1,i}^{LOT} + \eta_{ch} \cdot\; P_{t,i}^{EV} \Delta t \qquad \forall t \;\; \text{when EV connected to charger } i \tag{37}$$

$$E_{t,i}^{LOT} \leq\; E_{t,i}^{LOT.cap} \qquad \forall t \;\; \text{when EV connected to charger } i \tag{38}$$

$$SOE_{t,i}^{LOT} = \frac{E_{t,i}^{LOT}}{E_{t,i}^{LOT.cap}} \qquad \forall t \text{ when EV connected to charger } i \tag{39}$$

$$SOE_{t,i}^{LOT} = req_{t,i}^{LOT} \qquad \forall t \text{ when EV disconnects from charger } i \tag{40}$$

Similar to Constraint (35), Constraint (41) limits the EV charging power to zero in time interval t if there is no EV connected to charger i. The EV charging model, the same as the BSS charging model assumes a CC-CV charging regime, with slower charging rates when approaching full EV battery capacity. Given this, the upper limit of the EV charging power is defined with Constraints (42) and (43).

$$P_{t,i}^{EV} = 0 \qquad \forall t \text{ when there is no EV at charger } i \tag{41}$$

$$P_{t,i}^{EVmax} = \left\{ \begin{array}{cc} P_{max}^{EV} & 0 \leq SOE_{t,i}^{LOT} \leq E_{limit}^{CC\_CV} \\ P_{max}^{EV} \frac{1-SOE_{t,i}^{LOT}}{1-E_{limit}^{CC-CV}} & E_{limit}^{CC\_CV} \leq SOE_{t,i}^{LOT} \leq 100\% \end{array} \right\} \qquad \forall t \text{ when EV connected to charger } i \tag{42}$$

$$P_{t,i}^{EV} \leq \min\left\{ P_{inst}^{ch}, P_{t,i}^{EVmax} \right\} \qquad \forall t \text{ when EV connected to charger } i \tag{43}$$

The proposed objective Function (1), subject to Constraints (2)–(43), is formulated as mixed-integer linear programming (MIP) and solved using the Gurobi solver [26] using the Pyomo optimization package [27,28].

3. Case Study

3.1. Input Data

The proposed method is tested on a case study in a Croatia where rotational EV parking lot equipped with 8 EV chargers is planned for installation. The overview of investment and maintenance costs for different equipment categories is provided in Table 1.

Table 1. Technical and financial parameters of the rotary parking lot, PV plant, and battery storage system considered in the analysis.

Rotary Parking Lot Parameters		
Technical parameters	*Unit*	*Value*
No. of EV chargers/lots	nb.	8
EV charger efficiency	p.u.	0.95
EV charger rated power	kW	22
Financial parameters	*Unit*	*Value*
Rotary parking investment costs	EUR/lot	1000
Rotary parking maintenance costs	% investment	3.0%
PV Plant Parameters		
Technical parameters	*Unit*	*Value*
PV plant max. inst. power	kW	60
Financial parameters	*Unit*	*Value*
PV plant investment costs	EUR/kW	1500
PV plant maintenance costs	% investment	2.0%
BSS Parameters		
Technical parameters	*Unit*	*Value*
Maximum capacity	kWh	500

Table 1. *Cont.*

Rotary Parking Lot Parameters		
Power-to-energy ratio	-	0.25
Charging efficiency	p.u.	0.95
Discharging efficiency	p.u.	0.95
DoD	p.u.	0.1
CC-CV mode switch limit	p.u.	0.90
Financial parameters	*Unit*	*Value*
BSS investment costs	EUR/kWh	200
BSS maintenance costs	% investment	2.0%
BSS battery replacement	year	10
Battery replacement costs	EUR/kWh	60

To ensure realistic PV plant production modeling, we acquire time series data from an actual PV plant situated in close proximity to the potential location near the rotary parking lot. These data are then normalized with respect to the installed capacity of the PV plant. The normalization process allows us to account for variations in production efficiency and capacity, providing a more accurate representation of the potential performance at the considered location.

In Figure 4, we present a comprehensive visualization of the normalized data. Figure 4a showcases a heatmap depicting the 15 min average relative PV plant production, offering a granular view of the temporal dynamics. This representation is crucial for capturing the intricacies of the PV system's output throughout the day.

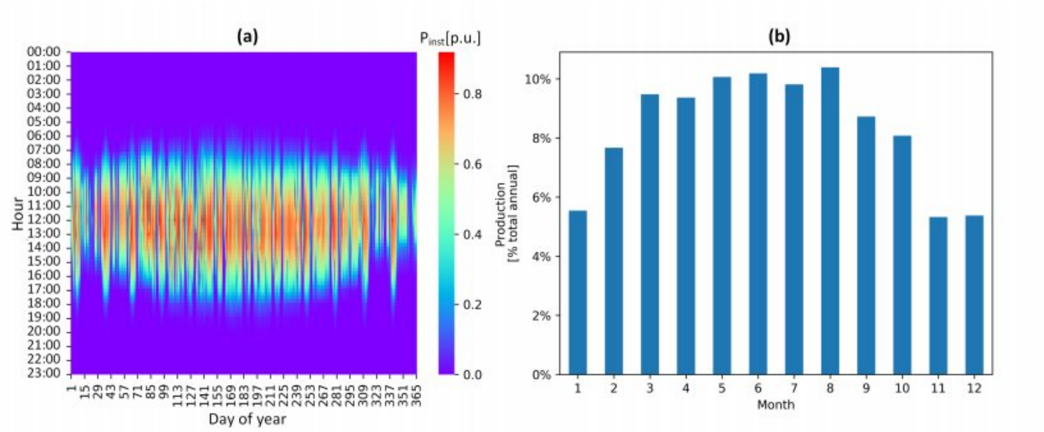

Figure 4. Heatmap of relative PV plant production (**a**) and monthly production relative to total annual production for PV plant (**b**).

Furthermore, Figure 4b provides insight into the relative monthly production expressed in relation to the overall annual production. This comparative analysis helps highlight seasonal variations and provides a nuanced understanding of how the PV plant's output fluctuates over the course of the year at the specified location.

By utilizing real-world data and normalization techniques, our modeling approach aims to enhance the accuracy and applicability of the results, contributing to a more robust assessment of the solar potential at the rotary parking lot site. The financial model assumes the PV module's lifetime is equal to the project lifetime (25 years) so there is no need for PV module replacement. The PV plant investment costs are considered in the amount of 1500 EUR/kWp and the operational costs are considered in the amount of 2% of total investment costs. The location has an area suitable for the construction of a maximum 60 kWp PV plant and the proposed method needs to determine the optimal PV plant capacity inside this limit.

The battery investment costs are taken to be 200 EUR/kWh with both charging and discharging efficiencies equal to 95%, which gives a battery round trip efficiency of 90%.

If the optimization model determines that the BSS should be included in the PL power supply, then it is necessary to include battery replacement costs, which are included in the amount significantly lower than the initial investment costs due to BSS cost reduction projections; see Table 1.

The parking lot demand characteristics are derived from time-dependent statistical distributions obtained from real measurements. Given that the test case investigates the model of a parking lot that is in service at an office building, typical patterns for this category are used. The EV arrival rate is typically higher in the early morning hours and lower during the afternoon hours. In some specific cases in which employers use company vehicles, the patterns could be different (departure in the early morning hours and arrival in the afternoon hours with overnight charging—lot 3 in Figure 5). Figure 5 displays the generated EV profile for each parking lot for the first day (arrival/departure time, energy requirement). Similar EV profiles are generated for all other days in the representative year.

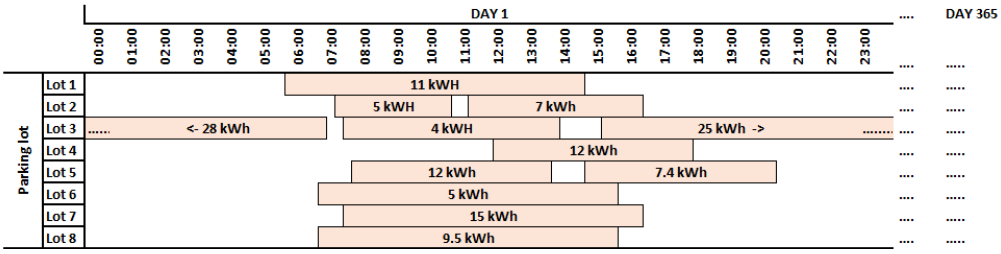

Figure 5. Example of parking lot utilization.

An overview of energy production, network usage, RES tax, peak power, and grid connection costs considered in the analysis for the Croatian test case is given in Table 2. In Croatia, the peak power costs are paid on a monthly basis, while grid connection costs are only paid once, at the time of PL grid connection, and are defined based on the expected annual peak power, which is contracted with the local distribution system operator. In the Croatian power system, the standard time interval for determining peak power is 15 min, so the model is run with a 15 min time resolution for a period of one representative year.

Table 2. Time-of- use tariff costs for industrial consumers in Croatia.

Time-of-Use Tariff Cost, Croatia		
Energy production cost (EPC)	*Unit*	*Value*
EPC—high tariff (07–21 h)	EUR/kWh	0.285
EPC—low tariff (21–07 h) [a]	EUR/kWh	0.168
Grid usage cost (GUC)	*Unit*	*Value*
GUC—high tariff (07–21 h) [a]	EUR/kWh	0.029
GUC—low tariff (21–07 h) [a]	EUR/kWh	0.013
Peak power cost (PPC)	EUR/kW	5.17
RES tax	EUR/kWh	0.014
Annual increase in EPC, GUC, PPC	%	2%
Grid connection cost	EUR/kW contract	225

[a] This time activation period is valid for the high-season period. For the low-season period, the high-cost tariff is active between 08 and 22 h while the low tariff is active between 22 and 08 h.

The general financial parameters used in the base model are given in Table 3. It is assumed that the total investment cost is partially financed through a loan with a loan equal to 30% of the total investment costs. The loan payback time is 10 years and the annual interest rate is 5%.

Table 3. Project financial parameters.

General Financial Parameters		
Project lifetime	years	25
Discount rate	%	7%
Loan/self-financing ratio	% invest.	30%/70%
Loan interest rate	%	5%
Loan payback time	years	10

3.2. Charging Station Power Supply Options

The proposed model has been assessed by examining the base case in addition to two other distinct case studies, each one focusing on the optimal power supply of electric vehicles (EVs) and power supply cost minimization at the charging station level with different power supply options. The case studies evaluated are as follows:

- **Case I** —The first case is centered around EV charging stations alone, exploring the impact of the EV smart charging strategy on the grid energy costs (energy costs, peak power costs, grid connection costs). In this simulation framework, the proposed model analyzes the benefits of increasing the grid connection power and associated costs in relation to the energy/peak power operation costs in the smart charging context.
- **Case II**—In the second case, the analysis was expanded to include the integration of photovoltaic (PV) plants alongside EV charging stations. This combination allowed for the utilization of solar energy to power the charging stations, reducing grid energy import costs. The lack of battery energy storage in this supply option limits the possibility of grid peak cost reduction together with grid connection cost reduction. In this test case, two subcases were considered in relation to the PV energy surplus reimbursement method:
  - **Case II-a**—In this case we assume that there is no financial reimbursement for energy surplus from the PV plant delivered to the distribution network in certain time instances.
  - **Case II-b**—In this case, the PV plant's energy surplus is reimbursed with a unit price equal to 80% of the energy supply price paid for EV charging from energy suppliers.
- **Case III**—The third and most comprehensive case examined the integration of EV charging stations, PV plants, and battery storage systems. This holistic approach, which combines solar power and battery energy storage systems, can help to mitigate peak power demand charges, reduce grid connection costs, and reduce EV energy supply costs. Integrating solar power and battery energy storage, charging stations can reduce their dependence on the grid and alleviate the need for expensive grid connection upgrades. This approach can save costs associated with grid infrastructure expansion and reduce strain on the existing electrical infrastructure. Similar to **Cases II-a** and **II-b**, two subcases were considered in relation to the PV energy surplus reimbursement method:
  - **Case III-a**—Excess energy from PV plant is not reimbursed;
  - **CASE III-b**—Excess energy from PV plant is reimbursed with unit price equal to 80% of energy supply price paid for EV charging from the energy supplier.

Each case provides valuable insights into the benefits, challenges, and potential synergies associated with integrating EV charging stations with renewable energy and energy storage technologies. The analysis aimed to inform decision-makers and stakeholders about the possibilities and considerations involved in creating sustainable and efficient charging infrastructure for electric vehicles as well as the influence of incentives for RES production on the levelized cost of charging (LCOC).

3.3. Results

The optimization model described in Section 2 determines the optimal investment decisions related to grid supply and contracted peak power, PV plant capacity, and battery storage capacity, together with optimal charging station operation while considering EV energy requirements, charging limits, and available charging time. The optimization model is formulated as a mixed-integer linear programming model and implemented in Python with the commercially available solver Gurobi [26].

The optimal grid supply and contracted peak power, PV plant capacity, and battery storage capacity, together with the net-present value of total investment and operation costs for different test cases, are shown in Table 4. The results from Table 4 show the highest energy supply costs in the amount of EUR 240.049 for case 1 which only includes smart EV charging. By including PV and a BSS, the net present value costs of charging stations can be significantly reduced. The NPV cost reduction depends on the charging station power supply solution but even more on how the PV plant's excess energy is reimbursed to the charging station owner. Due to the relatively low LCOE for PV plants, which is currently significantly lower than utility energy prices, in the case when the PV plant's excess energy is reimbursed the algorithm proposes the construction of the PV plant to its full available install capacity (60 kW), while in the case when there is no reimbursement for excess PV plant energy surplus the algorithm optimizes the PV plant's install capacity to minimize the value of the charging station's total NPV costs.

Table 4. Optimization results.

	Grid Connection Power (kW)	PV Plant Power (kW)	BSS Capacity (kWh)	NPV Total Costs (EUR)	Average Annual EV's Energy Demand (kWh)	LCOC (EUR/kWh)
CASE I	38.2	-	-	240.049		0.410
CASE II-a	35.4	28.6	-	174.712		0.299
CASE II-b	54.0	60.0	-	41.865	50.196	0.072
CASE III-a	20.7	30.7	80.0	158.824		0.272
CASE III-b	41.5	60.0	51.7	35.639		0.061

From the results, we can see that it is possible to contract lower charging station grid connection power in relation to the total PV install capacity given that a certain portion of the power is either used to charge the EV or to charge the BSS when the PV is operating with nominal power. Generally, the contracted grid connection power is lower in power supply combinations which include BSS. Also, for case I, which does not include a PV plant and BSS, the grid connection power is significantly lower than the sum of the total nominal power of all the EV chargers given that we can balance the charging process through smart charging. This level of reduction will depend on the EV charging coincidence, EV energy requirements, and maximum EV charging power, and as such will be location- and use-case-dependent.

Figure 6 shows the annual charging station operation for different system components and different power supply options. In case I, the EVs are supplied only from the grid and the proposed method optimizes the charging process to reduce the grid connection costs as well as the grid supply costs (energy and peak power costs). On a daily basis, EV charging is optimized to account for electricity tariff costs and peak power costs. As we can see from Figure 6, the higher EV charging rates are evident just before the morning low/high tariff change. In this test case example, we assume the charging patterns that are relevant for office buildings, so this is a time when employees start to arrive at the office. Throughout the office working hours which are mostly coincidental with time periods when the high tariff is active, the algorithm will determine the optimal charging profile in relation to the EV owner's energy needs and charging capabilities while limiting the total charging power below the determined monthly peak power.

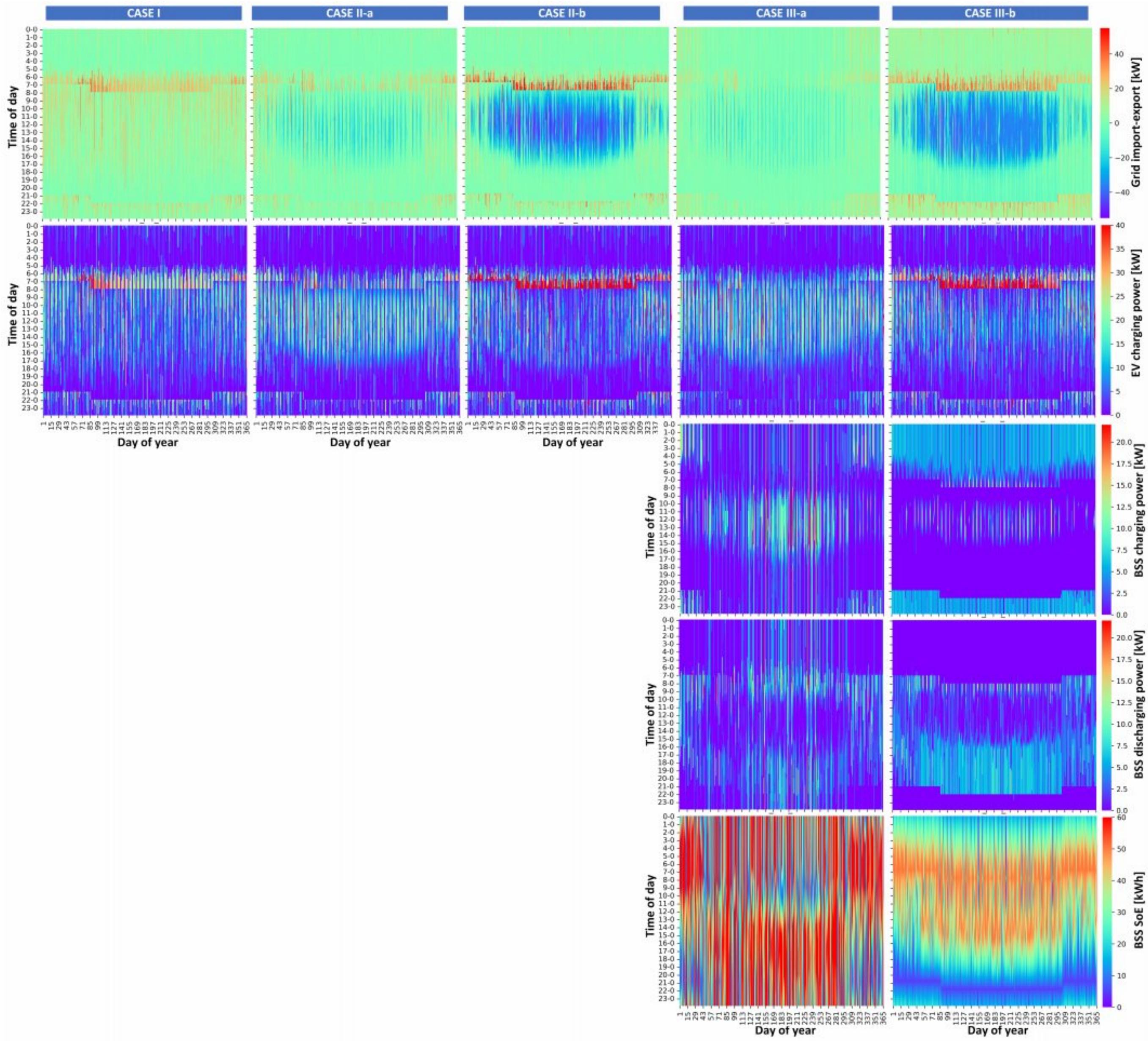

Figure 6. Charging station operation for different test cases.

Figure 7 shows the charging station operation for one day with relatively high energy demand. From Figure 7, we can see almost constant total EV charging power for the period between 7 and 20 h which was achieved through optimization on each charger level. For this specific day, the total charging power, which was constant for most of the day, (Figure 7—case I) is equal to the monthly peak power. Although in this period the charging power remained constant on the charging station level, we can see that charging rates on the level of individual chargers vary according to EV energy demand and available charging time. Charging station operations for other power supply options are significantly different.

In cases that assume a reimbursement of excess PV plant production, the grid connection power as well as monthly peak power are generally higher in relation to other cases—Figure 8. The reason for higher grid connection power and monthly peak power in cases II-b and III-b is the larger PV plant capacity, with high grid export in certain operating conditions. On the other hand, the higher values of monthly peak power allow for larger grid power draw in the early morning hours just before activation of the high energy tariff—

Figure 6 case II-b and case III-b. This, in addition to profit from excess PV production, reduces the total charging station net present costs. In case III-b, which includes a BSS, we can see that the BSS begins charging during periods when the low energy tariff is active, as well as during the daytime when PV production is high, to limit the increase in monthly peak power. The BSS starts discharging between 15 and 16 h (or even sooner in winter periods) to compensate for lower PV production and charge EVs using the energy stored during low-tariff periods—Figure 6, case III-b. Usually, the BSS state of charge reaches a lower DoD level by the end of the high energy tariff.

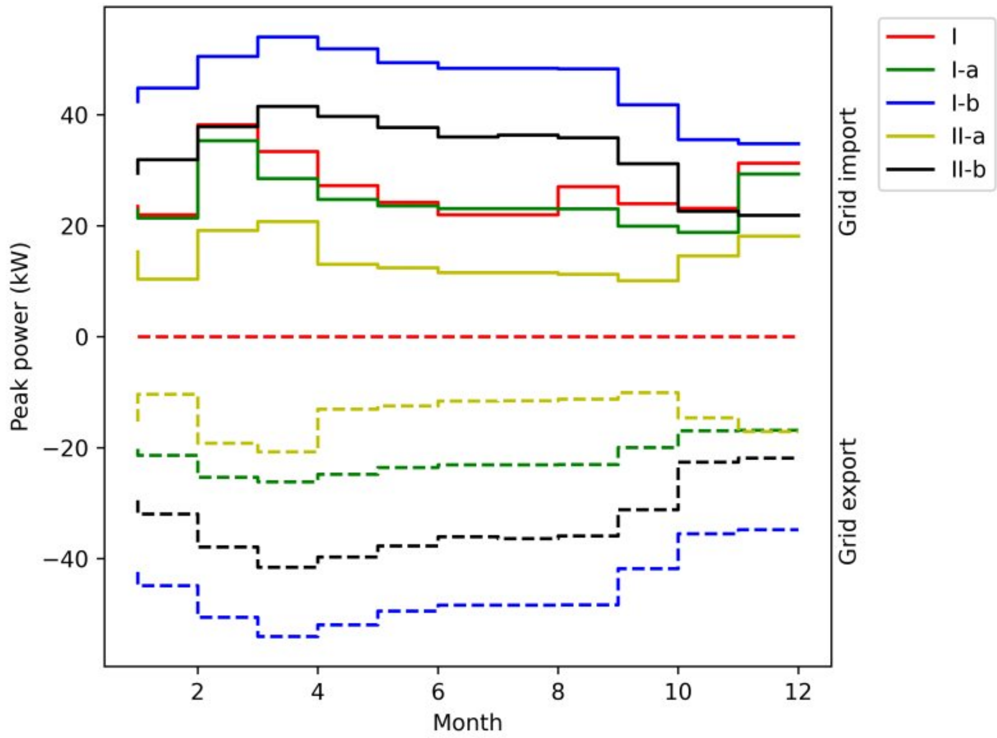

Figure 7. Monthly peak power values for different test cases.

In cases that assume that there is no financial reimbursement for energy surplus from the PV plant, charging station operation is different. Given that the nominal PV plant capacity is lower, PV plant energy export is lower, as well as the value of monthly peak power and associated costs at charging station level—Figure 7. Given that the energy surplus from the PV plant is not reimbursed, EV charging is optimized to use PV plant production as much as possible considering EV arrival/departure times, EV charging capabilities, and energy requirements. In these cases, we can also see a reduction in energy import from the grid in morning periods when the low energy tariff is active, as well as during the daytime when there is production from the PV plant—Figure 6 case II-a and case III-a. In relation to case III-b, in case III-a, BSS operation is significantly different. In winter periods, in which daily PV production is lower, the BSS is charged during low energy tariffs and optimally discharged during the day for EV charging needs in combination with grid supply and PV energy. In summer periods, with higher daily PV production, the BSS usually discharges in early morning and late afternoon periods. This ensures sufficient BSS capacity reserve for acceptance of PV energy surplus during midday periods, which reduces or completely eliminates grid energy export.

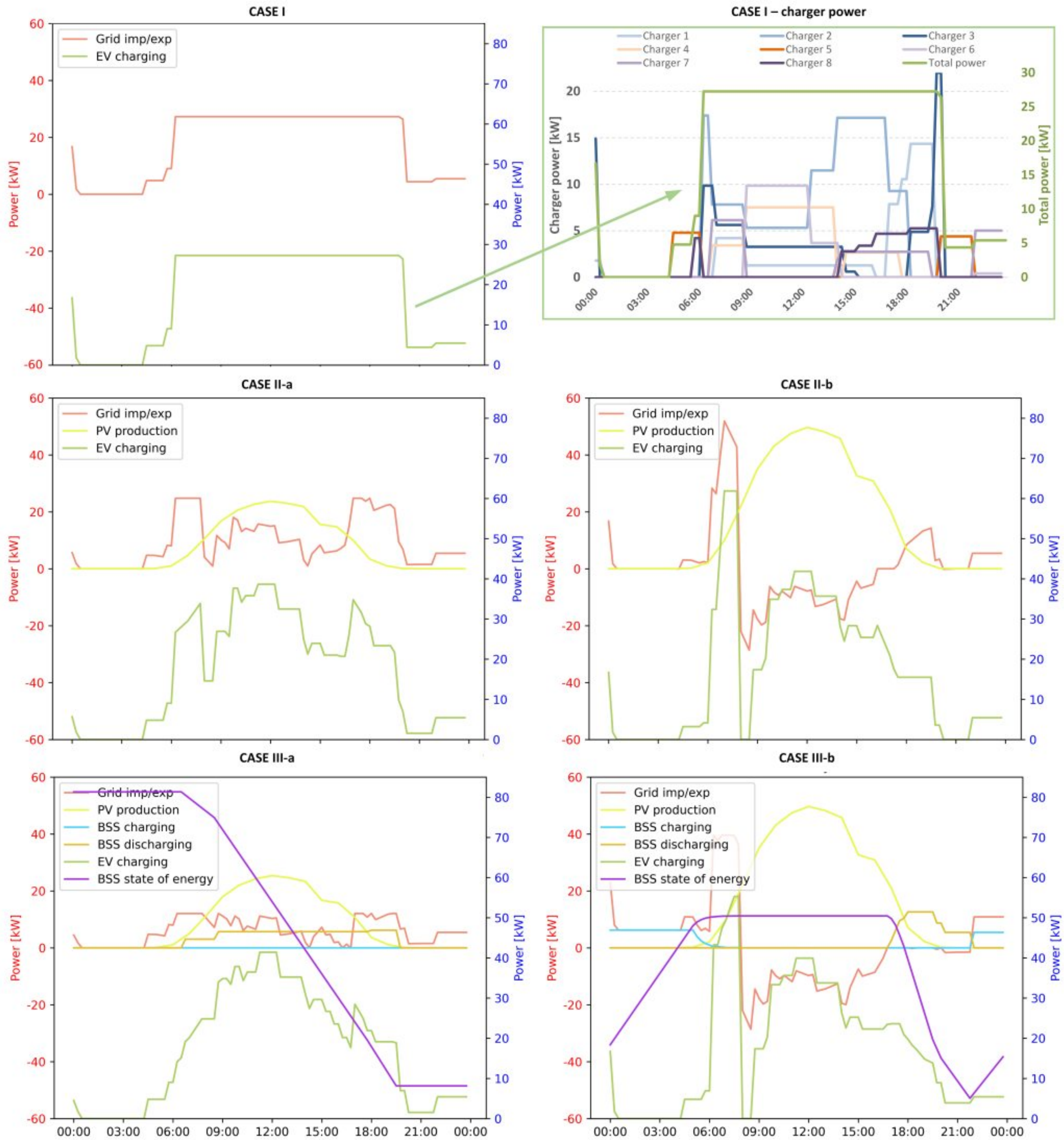

Figure 8. Charging station operation for different test cases: example day.

3.4. Parking Lot Levelized Cost of Charging

The commonly used metric to assess the economic viability and competitiveness of EV charging compared to traditional ICEVs is the LCOC. The LCOC represents the average cost of charging an electric vehicle (EV) over its lifetime, taking into account various factors such as the cost of electricity, upfront costs of charging infrastructure and energy supply equipment, equipment maintenance costs, and project financing costs. The LCOC for the different case studies is given in Table 4. In this paper, the LCOC is calculated considering the charging station investment and operation cost breakdown considered in the proposed optimization model.

$$LCOC = \frac{T^{PV}_{TOTAL}}{\sum_{n \in N} \frac{E^{annual}_{EV}}{(1+d)^n}} = \frac{T^{PV}_{inv} + T^{PV}_{main} + T^{PV}_{EE} + T^{PV}_{loan} + T^{PV}_{repl} - T^{PV}_{prof}}{\sum_{n \in N} \frac{\sum_{t \in T} \sum_{i \in PL} P^{EV}_{t,i} \cdot \Delta t}{(1+d)^n}} \tag{44}$$

Figure 9 shows the LCOC for different test cases considered in the analysis as well as the LCOC breakdown over different cost subcategories. All the energy and financial parameters used to calculate the LCOC are given in Tables 1–4. Based on typical investment horizons, and contractual arrangements, in the analysis, we consider a 25-year lifetime for all charging station equipment except for the BSS. For supply options that include a BSS, we consider a BSS replacement after 10 years of operation. All charging station costs are determined using the optimization model described in Section 2. The charging station infrastructure investment costs are divided into four subcategories: costs of charging equipment, PV plant installation, BSS installation, and grid connection costs. The total charging station infrastructure costs are additionally divided into self-financed investment costs and costs that are financed through loans, with a payback period of 10 years and a 5% interest rate. If we look at the LCOC we can see that the energy costs contribute the most to total LCOC. In the study, the EV charging behavior is modeled with the assumption that the charging takes place at a charging station located near the office buildings so the EV charging takes place during office working hours. This is also a period when high energy and grid usage tariffs are active, which increases energy costs. By including PV plants in the charging station energy supply mix, energy costs can be significantly reduced in relation to pure grid supply. It is interesting to note that in the case of excess energy reimbursement (cases II-b and III-b), although PV plants have generally higher optimal capacities in relation to cases (cases II-a and III-a) without financial reimbursement, the energy costs are higher. The reason for higher grid energy costs regardless of the higher participation of PV plant production in charging station energy supply is due to larger associated peak power costs due to the larger installation capacity of PV plants. Despite this cost increase, profit from excess PV energy supplied to the grid significantly reduces the LCOC of the charging station. In the test study, the charging station utility rate is relatively low given that the charging station is used primarily for employees working inside an office building. Also, many of today's plug-in-hybrid vehicles have low-charging-power capabilities (often up to 3.7 kW), which also reduces the charging station utility rate. The increase in charging station utility rate would reduce the equipment investment and maintenance cost components of LCOC while increasing the energy cost components.

3.5. Discussion

From the results provided in the previous analysis, we can see that investment in BSSs for EV charging stations offers a wide range of advantages, from charging station cost management and reduction, reduction in grid impact, to better utilization of available PV production for EV charging. Although the integration of BSSs in charging stations will always reduce the charging station's total energy costs, its overall impact on charging station net present costs can be negative in cases when investment costs in the BSS are high. In order to investigate the influence of BSS investment costs on total charging station LCOC, as well as the optimal system design, a sensitivity analysis was conducted for cases III-a and III-b, which consider BSS in the charging station energy supply mix. Figure 10 shows the charging station optimal power supply parameters for major components (PV plant install power, grid connection power, BSS capacity), as well as the LCOC for different values of BSS investment costs.

For case III-a, the BSS install capacity drops with an increase in the BSS investment costs. With BSS costs around 600 EUR/kWh the further increase in investment costs in a BSS outweighs the benefits of the energy cost reduction and it is not optimal to include a BSS in the charging station supply mix. The reduction in BSS capacity results in slightly higher grid connection power and associated costs, while the optimal PV plant power remains the same. The LCOC increases with the decrease in BSS capacity (increase in BSS investment costs), and this change is significant for BSS investment costs in a range 100–400 EUR/kWh, while additional BSS cost increases have a lower pronounced effect on the LCOC.

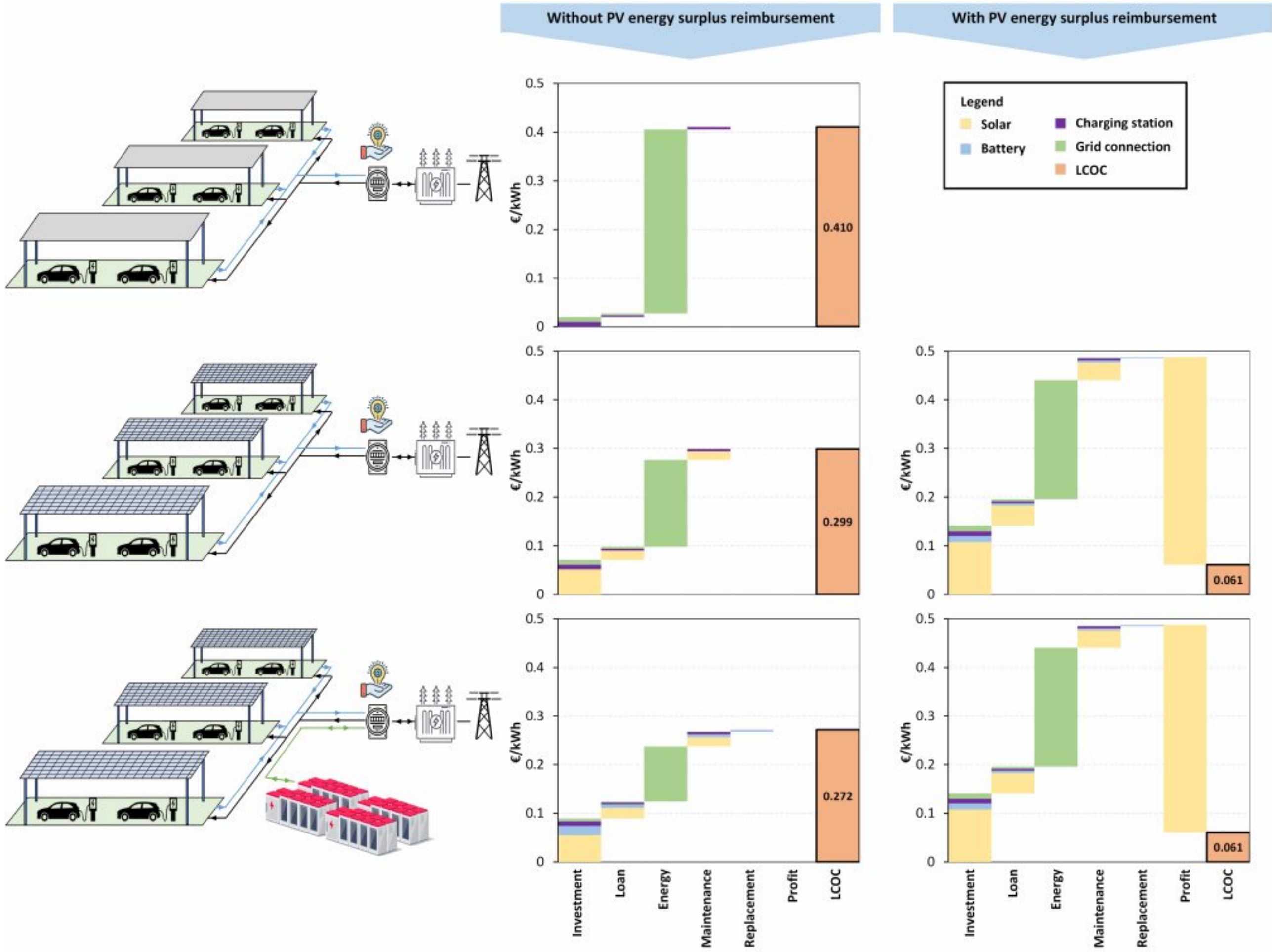

Figure 9. Contributions of different cost components to LCOC for different power supply options.

For case III-b, which considers reimbursement of PV surplus energy, the BSS is left out of the charging station optimal supply mix even at lower BSS investment costs (around 400 EUR/kWh). Similar to case III-a, the grid connection power and associated costs increase with a decrease in the BSS capacity. For BSS costs above 400 EUR/kWh, there is no further change in the charging station power supply system design, so there is no change in operation or LCOC either. These breakpoints for BSS investment decisions will vary from system to system so only project-specific conclusions can be made. In addition to BSS investment costs, investment decisions will depend on several factors such as grid tariff costs, PV plant investment costs and the energy surplus reimbursement mechanism, EV charging behaviors, grid connection costs, etc.

Integrating renewable energy and battery storage in EV charging stations offers numerous environmental and economic benefits. However, addressing challenges related to optimization modeling and uncertainties in long-term investments requires careful consideration and robust planning. Investment in PV production offsets electricity costs, and investment in a BSS allows for energy storage during periods of excess generation and low energy prices. This stored energy can be used during peak demand times, reducing reliance on the grid and potentially decreasing electricity costs. The combination of PV production and a BSS contributes to EVCSs' energy independence, making EV charging stations less susceptible to grid disruptions or price volatility. Making long-term decisions regarding investments in PV plants and BSSs as part of EVCSs power supply are complicated due to uncertainties related to technological advancements, regulatory changes, market dynamics, and the quality of the input data initially used in making such decisions. Gathering detailed and accurate data are crucial for optimizing the sizing of EVCS. This includes data on EV usage patterns, energy demand, and the performance of PV plants, as well as predictions related to future energy and technology cost trends. Participating in demand response programs, where EVCSs adjust their electricity consumption in response to grid conditions, can provide additional revenue streams and incentives. In addition to this, collaborating with energy service providers and participating in ancillary services, such as frequency regulation or grid support, can create additional revenue streams for EVCSs.

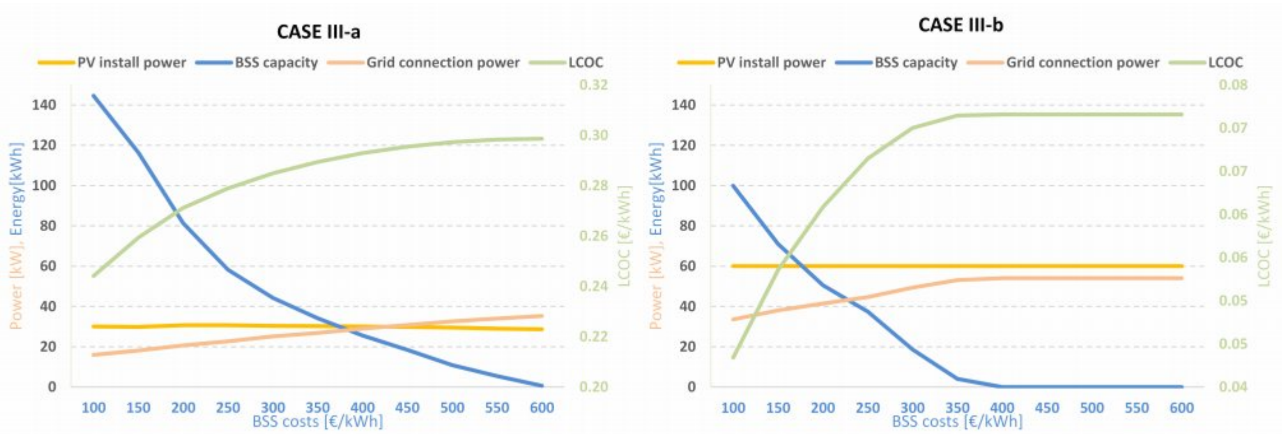

Figure 10. The influence of BSS investment costs.

4. Conclusions

This paper presents a comprehensive optimization model designed to address the complex and dynamic challenges associated with EV charging stations' power supply. The proposed model, formulated as a mixed-integer linear programming (MILP) problem, integrates multiple critical components, including grid supply, PV plant production, and a BSS, while accounting for the interplay between investment decisions and their influence on the efficient energy management of EV charging stations. By optimizing the use of grid supply, PV plant production, and battery storage, the model seeks to minimize the charging station's net present cost, which is calculated as the difference between the present value of all costs (investment, operational, equipment replacement, and financing costs) and profits over the project's lifetime.

The model is applied to three test cases that consider different charging station power supply options. In addition to this, for power options that include a PV plant power supply, two different subcases were considered in relation to the PV plant energy surplus financial reimbursement option.

The provided results show the benefits of combining different technologies for charging station power supply. In every scenario considered, the overall costs are less than those incurred when the charging station exclusively relies on grid power. In scenarios that consider financial reimbursement for PV energy surplus, the profit generated by the PV energy surplus significantly reduces the total costs as well as the LCOC. On the other hand, to increase profitability in this scenario PV plants are oversized in relation to EVs' energy needs, which leads to higher system peak powers. Adding the BSS reduces the grid peak power and associated costs but only up to a certain value of investment costs. For the test cases considered in this paper, the investment in a BSS is profitable for BSS investment costs up to 400 EUR/kWh when there is no reimbursement for PV energy surplus, and up to around 600 EUR/kWh when there is financial reimbursement. Investment in a BSS can become even more profitable if the charging station participates in the reserve and balancing market. Future research will focus on an extension of the optimization model in order to investigate the effect of a charging station's participation in the reserve and balancing market on system power supply decisions as well as operation.

Author Contributions: Conceptualization and methodology, D.J. (Damir Jakus) and J.V.; optimization modelling, D.J. (Damir Jakus); data curation, J.V. ; investigation, D.J. (Danijel Jolevski); validation, D.J. (Danijel Jolevski) and J.V.; writing—original draft, D.J. (Damir Jakus) and J.V.; writing—review and editing, D.J. (Danijel Jolevski); visualization, D.J. (Damir Jakus); resources, D.J. (Damir Jakus), supervision, D.J. (Damir Jakus), project administration, D.J. (Damir Jakus), funding acquisition, D.J. (Damir Jakus). All authors have read and agreed to the published version of the manuscript.

Funding: This work has been supported by the European Union through the European Regional Development Fund Operational program Competitiveness and Cohesion 2014–2020 of the Republic of Croatia under Grant KK. 01.2.1.02.0228 "Research and development of smart-grid charging station for electric vehicles within the construction of a rotary parking system.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

Sets

Ψ	Set of all optimization problem variables
L	Loan payback period year set
M	Month set
N	Project lifetime period set
PL	Set of parking lots
T	Time instances set
Δt	Time instance duration
η_{ch}	Charging efficiency
η_{ds}	Discharging efficiency
c^{BSS}	BSS variable cost
c^{BSS}_{repl}	Battery replacement costs
c^{conn}	Grid connection variable costs
c^{peak}	Grid peak power costs
c^{PL}	Fix investment cost per parking lot
c^{PV}	PV plant variable costs

Parameters

$c_t^{E_{H/L}}$	Energy production costs in high/low tariff at time step t
$c_t^{Grid_{H/L}}$	Grid usage costs in high/low tariff
$c_t^{RES_{H/L}}$	RES support tax price at time step t
d	Discount rate
DoD	BSS depth of discharge limit
$E_{cap}^{BSS.max}$	Maximum BSS energy capacity
E_{EV}^{annual}	Total EV energy demand on annual basis
E_{int}^{BSS}	Initial BSS state of charge
$E_i^{LOT.cap}$	Battery capacity of i^{th} EV
E_{limit}^{CC-CV}	BSS CC-CV mode switch limit
$E_{on_arrival}^{LOT_i}$	Energy state of the i^{th} EV on arrival at time t
f	Portion of total investment financed through a loan
k	Loan interest rate
M^{big}	Large-enough scalar
N^{PL}	Number of EV chargers/parking lots
$P_{inst}^{PV.max}$	PV plant maximum install power
$P_{max}^{ch\_ds}$	BSS maximum charging/discharging power

$P_t^{PV.pu}$	Relative PV plant production at time t
r	Fix annual growth rate
$req_{t,i}^{LOT}$	Requested energy requirement for i^{th} EV at departure time t
z	BSS battery replacement year
E_t^{BSS}	BSS energy state at time step t
$LCOC$	Levelized cost of charging
M^{BSS}	BSS maintenance costs
M^{PL}	Parking lot maintenance costs
M^{PV}	PV plant maintenance costs
$P^{contracted}$	Grid connection purchase power
P_{inst}^{ch}	EV installed charging power
P_{inst}^{PV}	Optimal PV plant install power
$P_{max,t}^{ch}$	BSS maximum charging power at time step t
P_{max}^{EV}	EV maximum charging power
$P_m^{grid_max}$	Monthly grid peak power at month m
$P_{t,i}^{EVmax}$	Maximum charging power for i^{th} EV at time step t
$P_{t,i}^{EV}$	Charging power for i^{th} EV at time step t
P_t^{ch}	BSS charging power at time t
P_t^{ds}	BSS discharging power at time t
$P_t^{grid_+}$	Power imported from grid at time step t
$P_t^{grid_-}$	Power exported to grid at time step t
P_t^{grid}	Total exported and imported grid power at time step t
P_t^{PV}	PV plant power production at time t
$SOE_{t,i}^{LOT}$	State of Energy of i^{th} EV at time step t
$T_{annuities}$	Annuity cost for loan
T_{EE}^{annual}	Total annual electric energy costs (energy + grid usage + peak power costs)
T_{EE}^{PV}	Present value of total electric energy costs (energy + grid usage + peak power costs)
Variables	
b^{BSS}	BSS binary investment decision variable
b_t^{grid}	Binary variable indicating power import from grid at time t
b^{PV}	PV plant binary investment decision variable
E_{cap}^{BSS}	Optimal BSS capacity
$E_{t,i}^{LOT}$	Energy state of i^{th} EV at time step t
T^{inv}	Investment costs
T_{loan}^{PV}	Present value of loan costs
T_{maint}^{PVs}	Annual PV plant maintenance cost
T_{main}^{BSS}	Annual BSS maintenance cost
T_{main}^{PL}	Annual charging station maintenance cost
T_{main}^{PV}	Present value of total equipment maintenance costs
T_{prof}^{annual}	Annual profit from excess PV energy export to the grid
T_{prof}^{PV}	Present value of total profit from excess PV energy export to the grid
T_{repl}^{BSS}	BSS system replacement costs
T_{repl}^{PV}	Present value of equipment replacement costs
T_{TOTAL}^{PV}	Total charging station net present cost
x_t	Binary variable indicating BSS charging at time t

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