Stationary Energy Storage System for Fast EV Charging Stations: Optimality Analysis and Results Validation

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Abstract: In order to minimize the peak load of electric vehicles (EVs) and enhance the resilience of fast EV charging stations, several sizing methods for deployment of the stationary energy storage system (ESS) have been proposed. However, methods for assessing the optimality of the obtained results and performance of the determined sizes under different conditions are missing. In order to address these issues, a two-step approach is proposed in this study, which comprises of optimality analysis and performance evaluation steps. In the case of optimality analysis, random sizes of battery and converter (scenarios) are generated using Monte Carlo simulations and their results are compared with the results of sizes obtained from sizing methods. In order to carry out this analysis, two performance analysis indices are proposed in this study, which are named the cost index and the power index. These indices respectively determine the performance of the determined sizes in terms of total network cost and performance ratio of power bought during peak intervals and investment cost of the ESS. During performance evaluation, the performance of the determined sizes (battery and converter) are analyzed for different seasons of the year and typical public holidays. Typical working days and holidays have been analyzed for each season of the year and suitability of the determined sizes is analyzed. Simulation results have proved that the proposed method is suitable for determining the optimality of results obtained by different sizing methods.

Keywords: electric vehicles; energy storage system; fast-charging station; optimality analysis; performance evaluation

1. Introduction

The penetration of electric vehicles (EVs) has increased in the last few years in the transportation sector due to the reduced cost of battery packs [1] and global drives for climate change, such as the Paris Climate Agreement [2] and Kyoto Protocol [3]. The enhanced penetration of EVs is beneficial in terms of reducing the dependence of the transportation sector on the fossil-fuels-based energy sources, which ultimately helps in reducing air pollution and the emission of greenhouse gasses. However, there are still several technical challenges that need to be addressed to facilitate the wide-spread adaptation of EVs. Among several other challenges, the challenges associated with the power grid are considered as the major challenges. The integration of EVs results in uncertain loads and the current power systems are not designed to handle major fluctuations [4,5]. This problem becomes more severe with increased penetration of renewables, which makes both the generation and load...
highly unpredictable [6]. EVs can cause peak loads in the system and the problem intensifies when several EVs start charging with fast EV charging infrastructure during system peak load hours. In order to address this issue, integration of an energy storage system (ESS) has been suggested as a potential solution in the fast EV charging stations [7–10].

An ESS has the potential to reduce the peak load by feeding EVs during the system peak intervals while charging during the system off-peak intervals. In addition, an ESS can also be utilized to support the grid during critical peak intervals by feeding power back to the grid [7]. However, the initial investment cost associated with the deployment of an ESS is still an obstacle and bigger size ESSs are not yet considered as a viable option [8]. Therefore, the size of the battery needs to be selected carefully after analyzing the grid conditions across the year and the expected penetration of EVs in the near future. This brings us to the optimal sizing of an ESS for fast EV charging stations, where the stochastic loads of EVs are estimated and year-round grid conditions are analyzed to determine the optimal size of the ESS. This problem becomes more challenging due to the difference in the lifetime of components of ESSs such as battery and the power electronic converters. Several studies are available in the literature on the optimal sizing of an ESS within the fast EV charging stations [11–16].

Simplified approaches based on established rules have been utilized in [11], and [12] for optimal sizing of the ESS in fast EV charging stations. The relationship between wait time and battery size has been analyzed in [11] and the optimal size of the ESS has been determined by analyzing several cases. The number of charging slots required for a charging station is determined first in [12] and then the size of the ESS has been determined by considering charging of EVs as a stochastic event. Rule-based approaches are easy to implement and are computationally less extensive. However, the major drawback of these techniques is dependence on the experience of the field experts. In addition, these techniques may not necessarily provide an optimal solution. Therefore, recently, model-based sizing techniques are suggested in the literature to overcome the limitations of the rule-based sizing techniques [13–16].

In [13], the integration of ESS with three different methods has been considered and the optimal size of the ESS for fast EV charging stations has been determined. The minimization of the annualized cost for deployment of an ESS in Stockholm in a fast-charging station has been considered in [14], where the optimal size has been determined by using mixed-integer linear programming. The minimization of the annualized cost for the ESS in a fast EV charging station has been proposed in [15], where both the ESS investment cost and cost for buying power from the grid are considered. However, in these studies, the sizing of the ESS and converter have been carried out separately or fixed-sized converters are considered. It results in over- or under-sizing of converters, which ultimately increases the cost and amount of power bought during system peak intervals. Therefore, simultaneous sizing of the ESS and converter has been considered in [16] and its superiority over other methods has been demonstrated.

In these studies, methods for determining optimal sizes of ESSs are proposed but methods for assessing the optimality of the determined sizes are not presented. Optimality analysis is necessary to analyze the performance of sizing algorithms, especially for rule-based methods. Specifically, optimality analysis indices based on the operation cost and other parameters are required to analyze the performance of different sizing approaches. In addition, the validation of determined sizes for different seasons of the year and different day types (working days and holidays) are also necessary to analyze the robustness and peculiarities under different cases. This analysis is also missing in the existing studies. A rigorous analysis of the applicability of the determined size of the ESS for different cases is required to validate the determined results.

In order to address these issues, as an extension of [16], a two-step approach is proposed in this study for optimality analysis and validation of results. In the first step, two optimality indices are proposed to analyze the performance of different sizing methods. These two indices are the cost index and the power index, where the former utilizes the information of total network cost for different scenarios. The latter utilizes the information of the amount of power bought during peak price intervals and the investment cost of the ESS for different scenarios. The scenarios are generated by using Monte
Carlo simulations in this study and the performance of the determined sizes through sizing algorithms is compared with all these scenarios. In the second step, the performance of the determined sizes for different seasons of the year and typical public holidays of the year are analyzed. The performance of the determined sizes for typical working days and holidays of different seasons of the year are analyzed. In this step, the amount of power traded with the utility grid and the operation of the ESS for different intervals of the day (peak and off-peak) is analyzed. In both steps, the sizes of the battery and converter determined in [16] are utilized as a test case.

2. Power Balancing in the Network

2.1. Network Configuration

The configuration of the system for assuring the power balance of the fast EV charging station with ESS is shown in Figure 1. It can be observed from the figure that, power transfer between the battery and the grid is two way, buying and selling. However, EVs can only buy from the grid to fulfill the load demand at each interval. In this article, only grid-to-vehicle (G2V) mode of EVs is considered due to the presence of a stationary ESS in the charging station, which can be utilized for peak-shaving. The objective of this configuration is to maintain the power balance in the network throughout the year. The power balance can be assured by making optimal decisions for power buying, power selling, battery charging, and battery discharging. Details about the functions of individual components are discussed in the following sections.

![Figure 1](image_url). Configuration for power balance for a fast electric vehicle (EV) charging station with an energy storage system (ESS).

2.2. Electric Vehicle (EV) Load

The load of individual EVs is determined by utilizing the information of daily commuting profiles of vehicles in Korea for the year 2018 [17]. The stochastic load of the charging station is determined by summing the load of individual EVs similar to [18,19]. The load profiles of the charging station for different days of the year are shown in Figure 2. It can be observed from Figure 2 that the load profiles of weekdays are different from the holidays due to the difference in the transit activities of the EV owners.
The proposed indices are explained in the following sections. The description of all the parameters and the power from the grid during off-peak price intervals. In addition, the ESS can also sell power back to the grid during critical peak price intervals. The variables used in this study are summarized at the end of the manuscript.

2.3. Energy Storage System (ESS)

The objective of the energy storage system in the network is to reduce the peak load introduced due to EV charging. The ESS can buy power from the grid during off-peak price intervals and store the energy. Similarly, the stored energy can be discharged to fulfill the load demand of EVs during peak price intervals. In addition, the ESS can also sell power back to the grid during critical peak price intervals to support the grid. However, the primary objective for the deployment of the ESS in the network is to shave the peak load introduced due to the charging of EVs during system intervals.

2.4. Utility Grid

The utility grid serves as a major power source as well as a power sink in the network. However, the objective of this scheme is to minimize the power buying from the grid during system peak load intervals, instead, utilize the ESS to charge the EVs in the charging station. However, ESS can buy power from the grid during off-peak intervals. Similarly, ESS can also sell back power to the grid during peak price intervals, if there is an excess of power remaining in the ESS after feeding the EVs in the charging station.

2.5. Power Conversion System (PCS)

The power conversion system is required to convert the AC power bought from the grid into DC power for storing. Similarly, the conversion system is also required to convert the DC power of the battery into AC before selling. Finally, the power bought by the EVs from the grid also needs to be converted before storing it in the EVs. However, the conversion from AC to DC or DC to AC is subjected to conversion losses, which depends on the efficiency of the converter.

3. Optimality Evaluation Indices

In order to analyze the optimality of the size of the battery and converter in an ESS, two optimality indices are proposed in this study. The sequence for computing the indices and analyzing the optimality of the determined sizes is shown in Figure 3. It can be observed from Figure 3 that, initially, N random samples of battery size and converter capacity are generated using Monte Carlo simulations. The optimization algorithm is run for each of these scenarios and results are stored. The optimization results of cost for each scenario are utilized to determine the cost index (CI). Similarly, the value of investment cost and amount of power bought during peak price intervals is utilized to determine the power index (PI). Finally, the indices are utilized to compare the results obtained from the sizing approach with the results from the generated scenarios. If the determined sizes perform better than all the scenarios, only then can they be called optimal. If even one of the scenarios performs better than the determined sizes, the determined sizes will be declared as suboptimal. Details about both the proposed indices are explained in the following sections. The description of all the parameters and the variables used in this study are summarized at the end of the manuscript.
3.1. Cost Index

In order to determine the cost index for evaluating the optimality of the determined sizes, the information of the yearly cost of charging station without battery \( \text{C}^{\text{WoESS}} \) is required. It can be determined by setting the ESS and converter size to zero in the optimization problem. The yearly cost for scenario \( s \) is termed as \( C_s \) and the yearly cost with determined ESS size is named as \( C^{\text{Opt}}_s \). This information is utilized to determine the cost ratio \( C^{\text{Rat}}_s \) for each scenario, as shown in Equation (1). The cost ratio can take both positive and negative values. Negative values imply that the scenario \( s \) is performing even worse than the without battery case, i.e., yearly operation cost is higher. A positive but less than 1 value indicate that the determined size is performing better than scenario \( s \) and values greater than 1 imply that scenario \( s \) is performing better than the determined size. Finally, the cost ratio of 1 implies that both scenario \( s \) and the determined size are giving the same results. Therefore, Equation (2) is utilized to evaluate the performance of individual scenarios against the determined sizes. Finally, Equation (3) can be utilized to determine the normalized CI values, where non-zero positive values indicate that at least one of the scenarios was performing better than the determined size. In other words, the value of CI needs to be zero, if the determined size is optimal.

\[
C^{\text{Rat}}_s = \frac{\text{C}^{\text{WoESS}} - C_s}{\text{C}^{\text{WoESS}} - C^{\text{Opt}}_s}; \; \forall s
\]  

\[
CI_s = \begin{cases} 
1 & \text{if } C^{\text{Rat}}_s \geq 1; \; \forall s \\
0 & \text{else}
\end{cases}
\]  

\[
CI = \sum_{s=1}^{S} \frac{CI_s}{S}; \; \forall s
\]

3.2. Power Index

Similar to the cost index, an additional index named as a power index is proposed to evaluate the performance of the generated scenarios and the determined size in terms of power bought during peak price intervals and the corresponding investment cost of the ESS. The ratio of power \( P^{\text{Rat}}_s \) and investment cost \( I^{\text{Rat}}_s \) are determined using Equations (4) and (5), respectively. Where, \( P^{\text{Opt}}_s \) and \( I^{\text{Opt}}_s \), respectively represent the amount of power bought and corresponding investment cost of the ESS for the optimal case (to be verified). Similarly, \( P_s \) and \( I_s \), respectively represent the power bought and the investment cost of the ESS for scenario \( s \). Negative values of \( I^{\text{Rat}}_s \) imply that scenario \( s \) is performing
better than the determined size in terms of power buying and vice versa. Same is the case for $I_{s}^{\text{Rat}}$ with respect to the investment cost. It is worth noting that a particular scenario could perform better in one of the two aspects but should not perform better in both aspects simultaneously. Otherwise, the determined size of the ESS will be declared as sub-optimal. Therefore, Equation (6) is utilized to determine the performance of scenario $s$ in comparison with the determined sizes, considering both power and investment cost. Finally, Equation (7) can be utilized to determine the normalized PI index, where positive values imply that the determined size is sub-optimal. PI needs to be zero to show that none of the scenarios was performing better than the determined size.

$$p_{s}^{\text{Rat}} = \frac{p_{s}^{\text{Opt}} - p_{s}}{p_{s}^{\text{Opt}}}; \forall s$$ (4)

$$I_{s}^{\text{Rat}} = \frac{I_{s}^{\text{Opt}} - I_{s}}{I_{s}^{\text{Opt}}}; \forall s$$ (5)

$$PI_{s} = \begin{cases} 1 & \text{if } p_{s}^{\text{Rat}} \geq 0 \text{ and } I_{s}^{\text{Rat}} \geq 0 \\ 0 & \text{else} \end{cases}; \forall s$$ (6)

$$PI = \sum_{s=1}^{S} \frac{PI_{s}}{S}; \forall s$$ (7)

4. Mathematical Modeling for Results Evaluation

An optimization problem is required to find the values of the yearly operation cost and the amount of power bought from the grid during peak price intervals. However, the investment cost can be computed by using the size of the battery and the capacity of the converter determined for each scenario. Similarly, the cost and amount of power bought in the case of the determined battery and converter size are also evaluated using the same operation model. In this section, the mathematical model utilized in this study is explained, which comprises of objective function and constraints related to the components of the network.

The mathematical problem is formulated to minimize the annualized cost of the charging station by making decisions for trading power with the utility grid, especially to avoid buying power during system peak price intervals. All the decision variables in the objective function are of a float type. The problem is subjected to several equality and inequality constraints. The total number of equality constraints is $4 \times 730$ and inequality constraints are $10 \times 730$ in the formulated problem.

4.1. Objective Function

The objective function comprises two main parts, i.e., a total cost for trading power during a year ($C_{\text{Grid}}$) and a total penalty price paid for buying power during system peak hours ($C_{\text{Peak}}$), as shown in Equation (8). The total price for trading power during a year can be obtained by utilizing the information of the amount of power bought and sold along with the corresponding prices, as shown in Equation (9). In Equation (9), $t$ and $d$, respectively represent the time of the day and day of the year. Similarly, $T$ represents the total intervals in a day and $D$ represents total days in a year. The yearly penalty cost can also be computed in a similar way by accumulating daily penalty costs, as shown in Equation (10). The total yearly cost can be computed by summing the value of the objective function (yearly cost for trading and penalty cost for buying) and the investment cost of the ESS, as given by Equation (11). The investment cost of ESS can be determined by using Equation (12), where $\gamma$ represents the cost recovery factor while $P_{\text{Conv}}^{\text{cap}}$ and $P_{\text{Bat}}^{\text{cap}}$, respectively represent the size of the converter and battery. Similarly, $C_{\text{PCS}}$ and $C_{\text{Bat}}$, respectively represent the unit cost of the power conversion system (PCS) and battery, respectively. Finally, $C_{\text{BOP}}$ and $C_{\text{O&M}}$ represent the cost for balance of the
plant (BOP) and operation and maintenance cost (O&M), respectively. The operation and maintenance cost is taken as annual cost; therefore, it is not multiplied with the cost recovery factor.

\[
\text{Min } C_{\text{Grid}} + C_{\text{Peak}}
\]

\[
C_{\text{Grid}} = \sum_{d=1}^{D} \sum_{t=1}^{T} (PR_{d,t} \cdot \text{Buy}_{d,t} - PR_{d,t} \cdot \text{Sell}_{d,t})
\]

\[
C_{\text{Peak}} = \sum_{d=1}^{D} \sum_{t=tb}^{T} C_{d,t} \cdot \text{Buy}_{d,t}
\]

\[
\text{Total cost} = \text{ObjValue} + C_{\text{ESS}}
\]

4.2. Power Balancing Constraints

Power balancing is considered as one of the major constraints for the power systems due to its impact on the system frequency. The equality constraint for the power balance of the fast EV charging station is given by Equation (13). It can be observed from Equation (13) that the demand of EVs can be fulfilled by either buying power from the grid or by discharging the ESS or both of them. The decision of choosing either of these two quantities or both of them depends on the objective function, i.e., minimization of the yearly cost. It can also be observed that the battery can only be charged by buying power from the grid. However, the battery can be discharged to either sell power to the grid or feed the EVs or both of them. Here also the decision of choosing either one or both of them is controlled by the value of the objective function. It has been noted in [20,21] that simultaneous buying and selling could occur during trading power with the utility grid. In order to avoid this situation, binary variables for buying \((b_t)\) and selling \((s_t)\) are introduced and Equation (14) assures that one of these actions is carried out at any time \(t\).

\[
p_{t}^{\text{Buy}} \cdot b_t + p_{t}^{\text{BD}} - p_{t}^{\text{Sell}} \cdot s_t - p_{t}^{\text{BC}} = p_{t}^{\text{EV}}
\]

\[
b_t + s_t = 1; \quad b_t, s_t \in \{0, 1\}
\]

4.3. ESS and Converter Constraints

In order to maximize the lifetime of the ESS, over-charging and deep discharging need to be avoided [22]. In this study also, limits are imposed on the maximum and minimum values of state-of-charge (SOC) of the ESS. In order to keep the test system the same, the same operation bounds have been used in this study which were utilized for the sizing of the ESS [16]. Equation (15) represents the constraint for the maximum bound of the SOC (SOC\(_{\text{max}}\)) during the charging of the ESS. Similarly, the constraint on the lower bound of the SOC is given by Equation (16). In these Equations, \(p_{t}^{\text{RC}}\) and \(p_{t}^{\text{BD}}\), respectively represent the amount of power charged to the ESS and the amount of power discharged from the ESS, respectively. Similarly, \(\eta_{c}\) and \(\eta_{d}\), respectively represent the charging and discharging efficiencies of the ESS. Similar to [23,24], the self-discharge/leakage effect of the ESS is not considered in the model. \(p_{t}^{\text{Bat}}\) represents the amount of energy conceded by the battery from the previous day and it can be computed using Equation (17). Finally, \(p_{\text{cap}}^{\text{Bat}}\) in these equations represent the capacity of the battery in kWh, which will be randomly generated for each scenario. The charging and discharging rates of the battery are constrained by the rating of the converter, as given by Equations (18) and (19), respectively. In these Equations, \(p_{\text{cap}}^{\text{Conv}}\) represents the capacity of the converter in kW, which is also randomly generated for each scenario. Equation (20) implies that the efficiency of the ESS can be between 0% to 100%. It has been noted in [20] that simultaneous charging and discharging could occur during the operation of the ESS. In order to avoid this situation, binary variables for charging \((c_t)\)
and discharging \((d_t)\) of the ESS are introduced and Equation (21) provides constraints that at any time \(t\) only charging or discharging of the ESS could occur.

\[
P_{\text{Bat}} + \sum_{t \leq t} \left( p_{t}^{BC} \cdot \eta_{C} \cdot c_t - \frac{p_{t}^{BD}}{\eta_{D}} \cdot d_t \right) \leq \frac{\text{SOC}_{\text{max}} \cdot P_{\text{Bat}}}{100}, \forall t
\]

(15)

\[
P_{\text{Bat}} + \sum_{t \leq t} \left( p_{t}^{BC} \cdot \eta_{C} \cdot c_t - \frac{p_{t}^{BD}}{\eta_{D}} \cdot d_t \right) \geq \frac{\text{SOC}_{\text{min}} \cdot P_{\text{Bat}}}{100}, \forall t
\]

(16)

\[
P_{\text{Bat}} = \sum_{t \leq t} \left( p_{t}^{BC} \cdot \eta_{C} \cdot c_t - \frac{p_{t}^{BD}}{\eta_{D}} \cdot d_t \right), t = T
\]

(17)

\[
0 \leq p_{t}^{BC} \leq P_{\text{Conv}}^{\text{cap}}, \forall t
\]

(18)

\[
0 \leq p_{t}^{BD} \leq P_{\text{Conv}}^{\text{cap}}, \forall t
\]

(19)

\[
0 \leq \eta_{C}, \eta_{D} \leq 1
\]

(20)

\[
c_t + d_t = 1; c_t, d_t \in \{0, 1\}
\]

(21)

The values of \(P_{\text{Bat}}^{\text{cap}}\) and \(P_{\text{Conv}}^{\text{cap}}\) are randomly generated for each scenario \(s\) and the above-mentioned optimization model is executed. Results for each scenario are stored and the same model is executed using the values of battery size and converter ratings determined by using optimization algorithms. Then, the optimality of the obtained results is evaluated by using the performance indices, explained in the previous section.

5. Simulation Results: Optimality Analysis

In this section, the optimality analysis of the determined battery and converter sizes is analyzed. In order to analyze the performance, two indices are utilized in this study, i.e., cost index and power index. In this study, a scheduling horizon of one year is considered by dividing days into working days and holidays. The time interval for each day is taken as 30-min, i.e., 48-time intervals. All the simulations in this study have been carried out in Java, NetBeans [25] environment by integrating with CPLEX 12.3 [26]. The optimal value of battery size and converter capacity for this system has been turned out to be 831 kWh and 68 kW, respectively. The aim of this section is to analyze the optimality of these results obtained in [16]. The proposed method is for the planning phase and it is an offline approach for assessing the optimality of the determined ESS size.

5.1. Input Data

The input data for this section comprises of 1000 random samples of battery size and converter size, generated using Monte Carlo simulations. However, any finite number of scenarios can be generated and any finite number of EVs can be considered. The maximum number of scenarios/EVs is constrained by the computational/storage capability of the machine solving the problem. The range for battery size has been taken as between one and two times of the determined value (1662) and the generated samples are shown in Figure 4a. Similarly, the range for samples of converter size is also set between one and two times of the determined value (136) and the generated samples are shown in Figure 4b. Each sample pair (battery size and converter size) has been fed to the operation algorithm at a time and the results (total cost, investment cost, and peak power buying) has been stored. The results of all the samples are compared with the determined sizes of battery and converter in [16], which will be discussed in the following sections.
5.2. Power Index Evaluation

In order to evaluate the optimality of the determined results in terms of peak power bought by the fast-charging station, two parameters need to be considered. These two parameters are the amount of power bought during peak price intervals and the corresponding investment cost for deployment of the ESS. The investment cost index for each scenario, computed by using (5), is shown in Figure 5a, where positives indicate that the particular scenario is performing better than the determined sizes. Similarly, the values of the power index for each scenario computed by using (4), are shown in Figure 5b, where positive values indicate that the particular scenario is performing better than the determined sizes. It can be observed that in both cases (investment cost and peak power), some of the scenarios have positive values. It is worth noting that in a particular scenario, a bigger size battery can be chosen which has reduced the power buying during peak intervals but it results in a higher investment cost. Contrarily, in some scenarios, smaller battery size has been chosen which has reduced the investment cost but it increases peak power buying. Therefore, these two parameters need to be considered simultaneously. By using Equation (6), the value of the power index has been computed and all the values turned out to be zero, i.e., none of the scenarios were at par or better than the determined sizes. For the sake of visualization, normalized indices of the first 100 scenarios are shown in Figure 6. It can be observed that both the indices are not positive for any scenario, although both were negative for some scenarios.
5.3. Cost Index Evaluation

The second index proposed in this study for evaluating the optimality of determined battery and converter sizes in a fast-charging EV station is the cost index. The cost index utilizes the information of the total yearly cost for each scenario and compares it with the cost for determined sizes of battery and the converter (optimal case). The values of cost for the generated scenarios, using Equation (2), are shown in Figure 7. In Figure 7, values less than one indicate that the determined sizes are performing better than that particular scenario. Similarly, the value of one indicates that the particular scenario is performing the same with that of the determined sizes. Finally, greater than one values indicate that the particular scenario is performing better than the determined sizes. It can be observed from Figure 7 that, in all the scenarios, the values of the cost index are less than one. For the sake of visualization, the values between 0.5 and 1 are zoomed out on the right side of Figure 7. It can be clearly seen from the right side of the figure that none of the scenarios have values equal to or greater than one. Since both price index (computed in the previous section) and the cost index for the determined sizes are performing better as compared to all the scenarios. It implies that the proposed sizes of battery and converter in [16] are optimal.

The optimality analysis has been carried out by taking a hundred scenarios at a time for ten times. The maximum and minimum values for each scenario group are tabulated in Table 1. It can be observed that the minimum value of total cost shows more deviations as compared to the maximum cost. The maximum value for the investment cost is one for all the cases while small deviations have been observed in the minimum values for different cases. Finally, small deviations have been observed in both maximum and minimum values for the peak power index.
Table 1. Comparison of optimality evaluation indices for different scenario groups.

| Scenarios   | Total Cost Index |  | Investment Cost Index |  | Peak Power Index |  |
|-------------|------------------|---|-----------------------|---|------------------|---|
|             | Maximum          | Minimum       | Maximum          | Minimum       | Maximum          | Minimum       |
| 1–100       | 0.938911         | −0.94318      | 1               | −17.3996      | 0.938911         | −0.94318      |
| 101–200     | 0.945434         | −1.05896      | 1               | −17.422       | 0.846379         | −0.96941      |
| 201–300     | 0.948319         | −0.84696      | 1               | −17.4505      | 0.855825         | −0.97841      |
| 301–400     | 0.950075         | −0.74837      | 1               | −17.419       | 0.856725         | −0.91341      |
| 401–500     | 0.948695         | −0.52358      | 1               | −17.4310      | 0.848403         | −0.97413      |
| 501–600     | 0.947316         | −0.96500      | 1               | −17.4378      | 0.840306         | −0.97593      |
| 601–700     | 0.951831         | −0.65404      | 1               | −17.0082      | 0.869996         | −0.97526      |
| 701–800     | 0.948946         | −0.71287      | 1               | −17.0412      | 0.867746         | −0.91588      |
| 801–900     | 0.951706         | −0.85499      | 1               | −17.4145      | 0.873594         | −0.97706      |
| 901–1000    | 0.946688         | −0.96851      | 1               | −16.9573      | 0.864148         | −0.95119      |
| Total       | 0.951831         | −1.05896      | 1               | −17.4505      | 0.938911         | −0.97841      |

6. Simulations Results: Results Verification

In order to verify the performance of the determined sizes of battery and converter, five different cases are considered in this section. These cases include the four seasons of the year (winter, spring, summer, and autumn), where both working days and holidays have been considered for each season. In the last case, two public holidays of a year in Korea (Chuseok and Seollal) are considered. In all the cases, the interval-wise balance of power in the fast charging station is analyzed, especially the usage of the battery is focused on.

6.1. Input Data

The input data of the fast-charging station, such as the number of vehicles, cost parameters of the ESS, and mileage pattern of vehicles is taken as the same with [16]. The market prices for selected days are shown in the following figures. Figure 8 shows the hourly market price for selected working days and holidays during the winter and spring seasons. Similarly, Figure 9 shows the corresponding data for the summer and autumn seasons. Finally, Figure 10 shows the market prices for the selected public holidays. The detailed analysis of results and contribution of different components of the network during different cases are discussed in the following sub-sections. In this study, the four seasons of the year are considered in the Korean climate and data of the year 2018 is utilized.

Figure 8. Hourly market price signals for different seasons: (a) winters; (b) spring.
6.2. Winter Season

January 14 and 15 are taken as the representative days for the winter season in this section, where January 14 is a holiday (Sunday) and January 15 is working day (Monday). The market prices shown in Figure 8a are used as input for this case. It can be observed from Figure 11a that during off-peak price intervals (5–8 a.m.), power is bought from the grid and the battery is charged and also the demand of EVs is fulfilled by buying power from the grid. During peak price intervals (11 a.m. to 11 p.m.), the battery is discharged to fulfill the load demand of the charging station. In the last intervals, the battery is charged again to save energy for the following day. In the case of the holiday, the ESS is charged during different hours of the day and is only discharged during the peak hours, 11 p.m. onwards. It is interesting to note that during the holiday, the ESS is not fully charged due to the smaller number of peak load intervals during the holidays. It implies that the size of the battery is sufficient for this particular case since the optimization algorithm has determined the size by considering different days of the year. In the winter season, none of the power was bought from the grid during peak intervals.

6.3. Spring Season

April 15 and 16 are taken as representative days for the spring season, where April 15 is a holiday (Sunday) and April 16 is a working day (Monday). The results of the selected day for the spring season are shown in Figure 12. The market price signals shown in Figure 8b are taken as input for this case. Similar to the previous case (winter season), power is bought from the grid during off-peak price
intervals and the ESS is charged. The ESS is utilized to feed the EVs in the fast charging station during the peak price intervals. It can be noticed that during intervals having higher market prices (higher than off-peak and lower than peak), the ESS is neither charged nor discharged, i.e., interval 10,11 a.m. in Figure 12a. During the holiday (Figure 12b), the ESS is utilized to fulfill the load demand during one of the off-peak intervals (4 p.m.) which was also due to the availability of energy and a reduced number of peak load intervals. In both cases (working day and holiday), the energy level of the ESS is maintained to the energy level at the beginning of the day.

![Figure 12. Fast charging station power balancing in spring season: (a) working day; (b) holiday.](image)

6.4. Summer Season

July 15 and 16 are taken as the representative days for the summer season in this section, where July 15 is Sunday and July 16 is Monday. The price signals shown in Figure 9a are used as input data for this case. It can be observed from market price signals data that the difference between off-peak and peak price intervals is highest for the summer season as compared to the remaining four seasons. The results for both the selected working day and the holiday, in this case, are shown in Figure 13. In contrary to the previous two cases, the ESS has been fully utilized during both the working day and the holiday. The pattern for charging and discharging of the ESS is the same as the previous cases, i.e., charging during off-peak price intervals and discharging during peak price intervals. It is worth noting that during the holiday, the ESS is discharged to feed the EVs even during some of the off-peak price intervals, i.e., 2 a.m. and 3 a.m. This is due to the larger difference in price signals between early morning (5 a.m. to 8 a.m.) off-peak price intervals and the late-night (2 a.m. to 4 a.m.) off-peak price intervals, which can be observed from Figure 9a. SOC at the end of the day is maintained to the same level at the beginning of the day in case of the working day. However, more energy has been charged to the ESS during the last intervals of the day in case of the holiday. This is due to higher market prices in the following day, i.e., working day.

![Figure 13. Fast charging station power balancing in summer season: (a) working day; (b) holiday.](image)

6.5. Autumn Season

The representative days for the autumn season considered in this case are October 14 and 15, where October 14 is a holiday (Sunday) and October 15 is a working day (Monday). The market price signals shown in Figure 9b are taken as input for this case. The power balancing for the selected weekday and holiday are shown in Figure 14a,b, respectively. It can be observed from Figure 14a that the ESS is fully utilized in the working day due to longer peak price intervals. It is worth noting that
during intervals 1 a.m. to 3 a.m., energy is bought from the grid despite being higher price intervals. This is due to the insufficient size of the ESS for this particular day. The optimization algorithm has chosen an optimal size of ESS to cover loads for different types of days. Similarly, due to the shorter number of peak load intervals on the holiday, the ESS is not fully utilized. The ESS is charged in this case randomly during the initial off-peak intervals due to the same market price values, Figure 9b.

![Figure 14](image1.png)

**Figure 14.** Fast charging station power balancing in autumn season: (a) working day; (b) holiday.

### 6.6. Representative National Holidays

The two major public holidays observed in Korea are known as Chuseok [27] and Seollal [28], where the former is generally observed in September and the latter is generally observed in February, following the lunar calendar. The input data for this case is shown in Figure 10 and the optimization results are shown in Figure 15. September 25 has been taken as the representative day for the Chuseok event and February 15 has been taken as the representative day for the Seollal event. It can be observed that the load profile of the charging station during these days is different from other holidays due to the difference in the activities of car owners. The overall ESS utilization pattern is the same as previous cases, i.e., charging during off-peak price intervals and discharging during peak price intervals. In both cases, power has not been bought from the grid during peak price intervals due to the sufficient size of the ESS and it has been fully utilized.

![Figure 15](image2.png)

**Figure 15.** Fast charging station power balancing during public holidays: (a) Chuseok; (b) Seollal.

### 6.7. Comparison of Different Cases

In order to compare the performance of the determined battery and converter sizes, the amount of power bought during peak price intervals and the amount of power discharged from the battery during off-peak intervals is analyzed in this section. A summary of results for different cases is tabulated in Table 2. It can be observed that during the working day in the autumn season, some amount of energy is bought from the grid during peak intervals. Similarly, during the summer holiday and public holidays, the ESS is discharged during off-peak intervals also. This is due to the consideration of different load patterns across the year. If the ESS is sized to cover all the peak loads for the entire year, huge size ESSs will be required which will not be fully utilized during most days of the year. Therefore, the optimization algorithm finds the tradeoff between the size of the ESS and the amount of energy buying during peak price intervals.
Table 2. Comparison among different cases considered for optimal results evaluation.

| Time of Year   | Day Type       | Energy Bought during Peak Price Intervals (kWh) | ESS Utilized during off-Peak Intervals (kWh) |
|---------------|----------------|-----------------------------------------------|---------------------------------------------|
| Winter season | Working day    | 0                                             | 0                                           |
|               | Holiday        | 0                                             | 0                                           |
| Spring season | Working day    | 0                                             | 0                                           |
|               | Holiday        | 0                                             | 0                                           |
| Summer season | Working day    | 0                                             | 0                                           |
|               | Holiday        | 0                                             | 95.89                                       |
| Autumn season | Working day    | 158.31                                        | 0                                           |
|               | Holiday        | 0                                             | 0                                           |
| Public holidays | Holiday (September) | 0         | 51.14                                       |
|               | Holiday (February) | 0         | 82.94                                       |

7. Conclusions

A methodology for analyzing the performance of different sizing techniques available in the literature on the sizing of battery and converters for fast EV charging stations is proposed in this study. The proposed performance analysis method is comprised of two phases, which are the optimality analysis phase and the results analysis phase. During the first phase, the optimality of the determined sizes of the battery and the converter is evaluated by using the proposed optimality analysis indices. Simulation results have proved that the two proposed optimality analysis indices are sufficient to evaluate the optimality of sizes of ESS in a fast EV charging station. In the second phase, the performance of the determined sizes is evaluated for different cases throughout the year. Simulation results have shown that the ESS is not sized to shave the peak load of EVs by 100% in all cases due to the requirement of huge size ESSs. Instead, the sizing algorithm finds a trade-off between buying a limited amount of power during peak hours and the size of the ESS. Therefore, it has been observed that in some cases (weekdays), a limited amount of power is bought from the utility grid. Similarly, it also has been observed that in some cases, especially holidays, the ESS is utilized to feed EVs during off-peak hours. This is due to the presence of sufficient size of the battery and a reduced number of peak intervals in holidays as compared to weekdays.

This article has utilized estimated values of load and real values of market price signals. However, these two parameters are subjected to uncertainties and consideration of these uncertainties during results evaluation could be a suitable extension to this article. These uncertainties can be incorporated by utilizing the methods suggested in [9,29,30].

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Nomenclature

Identifiers and Binary Variable

- \(d\): The identifier for a day, running from 1 to \(D\).
- \(t\): The identifier for a time interval, running from 1 to \(T\) (hour).
- \(t_{pb}, t_{pe}\): Identifiers for daily peak beginning and peak ending time intervals (hour).
- \(s\): An identifier for the number of scenarios, running from 1 to \(S\).
- \(b, s\): Binary variables for buying and selling power, respectively.
- \(c, d\): Binary variables for charging and discharging power to/from ESS, respectively.

Parameters and Variable

- \(C_{W\text{ESS}}\): The yearly cost of charging station without ESS (KRW).
- \(C_s, C_{Opt}\): The yearly cost of charging stations for scenario \(s\) and optimal cases, respectively (KRW).
- \(C_{Rats}\): Cost ratio for scenario \(s\) (KRW).
- \(C_{I}, C_{I\text{Opt}}\): Cost index for scenario \(s\) and normalized cost index, respectively.
- \(P_{s}, P_{Opt}\): Amount of power bought for scenario \(s\) and optimal case, respectively (kWh).
- \(I_{s}, I_{Opt}\): Yearly investment cost of ESS for scenario \(s\) and optimal case, respectively (KRW).
- \(P_{Rats}, I_{Rats}\): Power ratio and investment cost ratio for scenario \(s\).
- \(P_{I}, P_{Opt}\): The power demand for fast EV charging stations at time \(t\) (kW).
- \(C_{\text{Grid}}, C_{\text{Peak}}\): Cost for trading power and for buying power during peak period, respectively (KRW).
- \(P_{\text{Buy}}, P_{\text{Sell}}\): Price for buying and selling power during day \(d\) and time \(t\), respectively (KRW/kWh).
- \(P_{\text{Buy}d, t}, P_{\text{Sell}d, t}\): Amount of power bought and sold during day \(d\) and time \(t\), respectively (kW).
- \(P_{\text{Buy}d, t}, P_{\text{Sell}d, t}\): Power index for scenario \(s\) and normalized cost index, respectively.
- \(P_{I}, P_{Opt}\): The power demand for fast EV charging stations at time \(t\) (kW).
- \(C_{\text{Grid}}, C_{\text{Peak}}\): Cost of ESS (KRW) and penalty price for buying power from the grid during peak intervals (KRW/kWh), respectively.
- \(C_{\text{ESS}}, C_{\text{Opt}}\): Cost of ESS (KRW) and penalty price for buying power from the grid during peak intervals (KRW/kWh), respectively.
- \(P_{Rats}, I_{Rats}\): Power ratio and investment cost ratio for scenario \(s\).
- \(C_{\text{Conv}}, C_{\text{Bat}}\): Cost recovery factor for converter and battery, respectively.
- \(C_{\text{Conv}}, C_{\text{Bat}}\): Charging efficiency and discharging efficiency of the battery, respectively (%).
- \(C_{\text{Conv}}, C_{\text{Bat}}\): Initial SOC of battery at the beginning of the day (kWh).

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