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Risk Analysis Of Electricity Demand At Public Electric Vehicle Charging Stations (SPKLU): CVaR Model Approach

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Abstract

The electricity demand at Public Electric Vehicle Charging Stations (SPKLUs) exhibits significant volatility, which is driven by several aspects including electricity demand patterns at specific time intervals, load variability, SPKLU capacity, and other related factors. The variability of these swings can present hazards for SPKLU operators in relation to energy administration as well as operational and financial hazards. The objective of this study is to assess the risk associated with energy demand fluctuation at SPKLUs by employing the Conditional Value-at-Risk (CVaR) model technique. CVaR, or Conditional Value at Risk, is a quantitative measure of risk that calculates the predicted loss value in the most unfavorable situation. It is commonly employed to enhance the risk management approach of SPKLUs. The electricity demand at SPKLU exhibits significant volatility, with an average fluctuation of 10.15% and a standard deviation of 49.67%. The CVAR, calculated at -121.19% for a confidence interval of 1%, represents the maximum potential loss that could be experienced during worst-case electrical demand conditions, highlighting the substantial fluctuations in demand. The study initially implemented the CVaR model to analyze power demand at SPKLU, providing novel perspectives on risk reduction for critical infrastructure and proposing unique strategies for managing demand fluctuations in a reliable and efficient manner. The results also offer comprehensive insights into risk exposure and facilitate the formulation of well-informed and strategic risk management plans.

Keywords: SPKLU, Electricity Demand, Conditional Value at Risk (CVaR).

1. Introduction

Fossil-fueled cars provide a substantial contribution to the release of carbon emissions, environmental pollution, and public health issues (Adu-Gyamfi et al., 2022). The worldwide community has made it a top priority to create strategies for phasing out conventional fossil-fuel cars. This is because the transportation sector is responsible for consuming around 23% of the world's energy and generating an estimated 12% of global carbon emissions (OECD, 2016).

The adoption of electric cars is increasing in both Indonesia and worldwide. According to Canalys' most recent study, the sales of electric vehicles (EVs) worldwide are projected to increase by 29% and reach a total of 13.7 million units by 2023. This would represent a penetration rate of 17.1%. The worldwide electric vehicle (EV) market is projected to expand by 27.1% by the year 2024, reaching a total of 17.5 million units (canalys, 2024.)

In Indonesia, the upward trend in sales of electric vehicles (EVs) from manufacturers to distributors is evident. Based on Gaikindo data, the wholesale sales volume of battery-based electric automobiles, also known as battery electric vehicles (BEVs), is projected to reach 17,060 units in Indonesia by 2023. This statistic had a significant increase of 65.2% when compared to the previous year, 2022, and has reached a new peak. (katadata.co.id, 2024).

Expanding the number of charging stations will enhance the infrastructure's preparedness for the introduction of electric vehicles (EVs), hence alleviating concerns among potential adopters regarding the restricted driving range and their hesitancy to embrace EVs.(Setiawan et al., 2022). 842 SPKLU Charging units have been constructed in 488 public areas by PLN, a government-controlled entity, to promote EV ecosystems either independently or in partnership with PLN (Ministry of Energy and Mineral Resources, 2023).

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Indonesia, as a developing nation, is facing several challenges due to its growing demand for electricity, including concerns related to inadequate electrical quality. Indonesia faces a deficiency in its ability to store energy on a broad scale, which hampers its ability to efficiently handle variations in power demand and respond promptly. The utilization of electric cars for load balancing and frequency management is of utmost importance in Indonesia (Aziz & Huda, 2019).

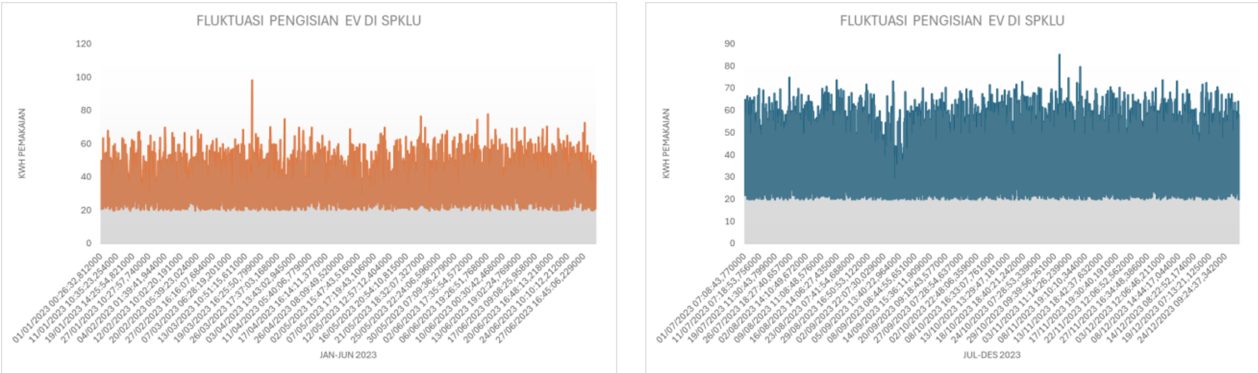

Figure 1. Example of fluctuation of SPKLU electricity demand in Jakarta (year 2023), Indonesia

The chart's fluctuations can be used to determine if the current capacity is adequate or needs to be raised. Understanding user behaviour can also be aided by the analysis of patterns in graphs. Predictive models that calculate future capacity needs based on present trends and growth projections for electric vehicles can be developed using historical data from this graph.

Comprehending the consequences of variations in energy demand on the effective operation of the electric power system is essential for guaranteeing stability in upcoming power generation. The dearth of pertinent knowledge underscores the significance of this work in the realm of literature. (Qiao et al., 2023). Charging stations can function as load aggregators in demand response by synchronizing the charging capacity of electric vehicles. Inadequate synchronization of charging load can lead to unfulfilled charging requirements, causing dissatisfaction among users (Jin et al., 2022).

Demand Response (DR) plays a vital role in the energy market by using load flexibility to balance supply and demand, instead of just adjusting generating levels (Jin et al., 2022). In order to maintain a balance between the demand and supply of electricity, it is necessary to have sufficient capacity for generation, transfer, and distribution to handle any anticipated peak demand. Nevertheless, there have been few investigations into the economic scheduling of charging stations that take into account resource ownership. Meanwhile, certain studies have specifically concentrated on the arrangement of charging electric vehicles (EVs) and the incorporation of Renewable Energy Sources (RES). Subsequent research can analyze the comprehensive conduct of electric vehicles (EVs), including their entry and exit times, as well as the distance they travel, in order to develop charging stations (shafiei & Ghasemi-Marzbali, 2023).

The uncertainties associated with electric vehicle (EV) charging have a significant effect on power dissipation and nodal voltage. The power generated by distributed generation (DG) in distribution networks is continually volatile, and its effect on power loss and nodal voltage is significant. The uncertainties associated with EV charging are determined by various factors, including battery characteristics, state of charge (SOC), driving distance, arrival and departure times, and charger ratings(Wu et al., 2024).

Integrated energy systems can enhance energy consumption efficiency and facilitate sustainable energy development, while also satisfying diverse energy demands. The CVaR method was incorporated into the system optimization model for risk management to address the operational risk arising from system uncertainty. However, the lack of clarity could increase the potential for operational risk, but this matter has not been extensively analyzed, especially in relation to risk management measures.

CVaR is a more advanced risk assessment technique that is derived from the value-at-risk (VaR) method. The CVaR method effectively overcomes the limitations of the VaR method in measuring loss and its lack of subadditivity (Fu et al., 2020). The implementation of the CVaR model is crucial in this scenario as it serves as a valuable instrument for quantifying and evaluating the operational and financial risks linked to the uncertainty in meeting the demand for SPKLU.

Despite existing research on the factors that impact electricity demand at EV charging stations and the associated risks, there is still a lack of understanding regarding how variables such as infrastructure, technology, weather conditions, and user behavior specifically influence the relationship between electricity requirement and financial risk at charging stations. This research seeks to address these deficiencies by further investigating the significance and impact of moderator variables within the setting of SPKLU.

Hence, the objective of the study is to examine the financial risks associated with meeting the demand in the SPKLU by employing the CVaR model technique. The purpose of this analysis is to offer strategic suggestions to stakeholders on how to optimize the functioning of the SPKLU, while reducing the financial risk caused by unpredictable changes in filling requirements.

2. Literature Review

2.1. Electricity Demand

When discussing electrical energy, it is important to understand two related but distinct measurement parameters: consumption and demand. Consumption is a term that is more commonly understood by the majority of individuals. In simple terms, it refers to the whole quantity of energy consumed. Demand refers to the instantaneous rate at which a product or service is being consumed.

Mathematically, the measurement unit used to represent energy consumption is kilowatt hours (kWh). The electric meter captures the readings as the dials rotate. The consumption rate is measured in kilowatt hours per hour, or simply kilowatts (kW). Residential users are usually not subject to power demand measurement. Nevertheless, commercial customers incur charges for both their energy use and the rate at which they consume it. The utility's ability to supply energy is directly proportional to the rate at which the aggregate customer base consumes energy. The capacity of a system refers to the amount of energy it needs to generate in order to fulfill the immediate load, even if it is only for a brief period of time. This notion is also employed in the design of systems or buildings to ensure that electrical distribution equipment is appropriately dimensioned. A utility's capacity must be sufficient to satisfy the demand, ensuring that no consumers experience a lack of electricity (Stonybrook.edu, 2024).

The growing proliferation of electric vehicles poses issues to the electrical infrastructure. Initially, the existing charging infrastructure is inadequate to meet the growing need for chargers. With the growing number of electric vehicles (EVs), there will be a corresponding rise in peak demand within the network. This has the potential to inflict harm on the network infrastructure (Wu et al., 2024).

The conversion of internal combustion engine (ICE) cars to electric vehicles (EVs) presents chances to decrease fossil fuel usage, emissions levels, and overall driving expenses. Nevertheless, the widespread use of electric vehicles increases the need for a variable and unpredictable power burden on the electrical grid. It is imperative to conduct a comprehensive investigation of the effect of electric vehicle charging demand on the functioning of the distribution network (Mozafar et al., 2018).

Shafiei & Ghasemi-Marzbali, 2023, are in a discussion about designing a fast charging station for electric vehicles. They are considering a probabilistic model that takes into account renewable energy sources and demand responses. The goal is to decrease the strain on the power grid by using renewable energy sources and an energy storage system. One of the models employed allows the station owner to regulate a portion of the electric load, thereby decreasing the peak load and subsequently reducing the required capacity of installed equipment, initial investment expenses, and operation and maintenance costs.

Implementing a well-designed strategy is crucial for effectively planning charging behaviour in order to increase the charging load on public EVCS (Electric Vehicle Charging Station) and decrease peak demand (Zhao et al., 2024). Within his research, he outlined a system for scheduling public electric vehicle charging stations that involved two stages. This strategy considered various demand patterns and non-linear charging profiles. This approach incorporates an internet-based reservation system and a regulated pricing system to allocate demand from high-demand periods to low-demand periods.

The unpredictable and heavy charging demands of electric vehicles provide an unavoidable difficulty that can cause grid overload. An effective strategy involves integrating charging stations into demand response systems as load aggregators, allowing them to coordinate the electric charging power of vehicles. Nevertheless, inadequate synchronisation of the charging load can result in an unfulfilled charging requirement, ultimately causing discontent among the consumers (Jin et al., 2022). To address these difficulties, it is necessary to implement efficient demand-side solutions. Hence, the utilisation of the demand response approach (DR) is crucial and significant in the strategic coordination and control of the supply and demand aspects (Sambasivam & Balachandra, 2023).

Electric vehicles often have a battery capacity ranging from 60 kilowatt-hours (kWh) to 100 kWh, and they may be charged at a rapid rate of 100 kWh. A power load of 100 kW per hour is utilised, which is about equivalent to the monthly electricity consumption of a single-person family. Consequently, the increasing popularity of electric vehicles is expected to drive up the demand for power charging, which in turn may cause significant fluctuations and reduced reliability in the electrical grid. Due to the necessity of maintaining a constant equilibrium between supply and demand, the system has challenges in promptly adapting to unexpected increases in workload. Predicting the demand for electric car charging is particularly challenging due to its strong dependence on the lifestyle and decision-making of electric vehicle users (Son et al., 2022).

Enhancing the security of power supply can be achieved more effectively by regulating the load on the demand side rather than by increasing the capacity of the power system. With the advancement of new technologies, demand response (DR) emerges as a promising method to tackle critical situations arising from EV charging. It involves modifying electricity rates or offering incentives to manage charging loads and alleviate strain on the power system (Albadi, 2008 ; Jin et al., 2022)

2.2. Charging Station Selection Factor for EV

The primary issue for electric vehicle (EV) owners is the apprehension caused by the limited driving range dictated by the battery capacity, also known as range anxiety. Currently, battery technologies have not reached a state of maturity. Several batteries exhibit a finite lifespan and substantial initial expense, while also lacking adaptability to fluctuating temperatures. From an economic standpoint, the cost is a significant factor that limits the adoption of electric vehicles in the market. The expenses associated with the individual charging point, battery replacement, communication, and charger are substantial, making them unsuitable for a household with typical income (Savari et al., 2023).

The presence of charging infrastructure is crucial for the widespread adoption of electric vehicles (EVs), since it alleviates consumer concerns about limited driving range, which is often lower for EVs compared to internal combustion engine vehicles (ICEVs). The issue of range limitation is particularly pertinent for E2W ride hailing drivers, as the majority of E2Ws have a charging cycle that only allows for 50-60 km, which is inadequate for their daily coverage (Padhilah et al., 2023). The majority of customers tend to leave their electric vehicles at charging stations for a longer duration than required, so enabling the charging station to modify the load profile based on this actual data. The purpose of the EV charging problem can be categorized into three primary areas: optimizing grid advantages, enhancing customer service satisfaction, and lowering charging costs while ensuring battery health (Jin et al., 2022).

The most efficient approach to address the growing need for charging is to construct additional Electric Vehicle Charging Stations (EVCSs). The expansion of the charging infrastructure requires a substantial amount of energy for charging, which might lead to sudden increases in peak demand and potentially overload the system. Utilizing efficient methods to efficiently organize charging behavior is crucial in order to provide a balanced charging load at public Electric Vehicle Charging Stations (EVCSs) and reduce peak demand.

The rapid proliferation of electric vehicles presents challenges to the reliable operation of the electrical infrastructure. Electric vehicles, particularly at peak periods, have substantial power demands that might impact the stability of the electrical grid, increase load fluctuations, and potentially lead to disruptions in specific areas of the grid. Thoroughly strategizing the charging demand schedule is crucial to ensure the secure operation of the power system. Electric vehicle (EV) users can minimize their waiting time in the queue by uniformly dividing the charging load. This not only increases customer happiness but also encourages the adoption and expansion of EVs (Zhao et al., 2024).

2.3. CVaR (Conditional Value at Risk) Method

This research will employ the CVaR approach to evaluate and measure the risk of load fluctuations at the charging station, specifically SPKLU, caused by the power usage of electric vehicle (EV) customers.

Value at Risk (VaR) is a commonly employed method for evaluating the risk associated with electrical grids. It may also be utilized to determine the highest potential loss of a decision or grid design within a specific timeframe. However, it fails to consider the significant tail incident, which greatly impacts the accuracy of the risk calculation. Furthermore, due to its failure to meet the criteria of second additivity, VaR is not an ideal tool for quantifying risk. CVaR was introduced following enhancements to the conventional VaR approach. Conditional Value at Risk (CVaR) is a measure used to assess the portion of the loss distribution that exceeds the Value at Risk (VaR). It provides a more comprehensive evaluation of the risk beyond a specific threshold, allowing for a more effective assessment of the potential risk associated with an event. This addresses the limitation of the VaR method in estimating the tail risk. In addition, CVaR is extensively employed in diverse risk evaluations due to its consistent risk measurement (Wu et al., 2018).

Assume that f(x,y) be a loss function depending on a decision vector X = (x1, x2, ..., xn), x in R^n and a stochastic vector Y = (y1, y2, ..., ym), y in R^m. According to Eq. (1), VaR has the lowest loss rate for the confidence interval beta in a given time interval with the probability of (1 - β) (Ghasemi et al., 2021).

$$\text{VaR}\_\beta = \min\{\alpha \in R : P(f(x, y) \leq \alpha) \geq \beta\} \quad (1)$$

$$\text{for } 0 \leq \beta \leq 1$$

The main goal of the problem is to find the optimal value of x that minimizes the cost function, taking into account the random character of y. Var is a risk metric employed in economic contexts, however it can have non-convex properties. The CVaR risk rating index, sometimes referred to as average value at risk and mean deficit, is employed to mitigate this problem. CVaR is determined by the confidence level β.

$$\beta \text{ - CVaR} = EY[f(x, y)|f(x, y) \geq \beta \text{ - VaR}] \quad (2)$$

Equation (2) represents the expected value of the cost function, conditioned on it being bigger than the β-percentile. CVaR minimization serves as the objective function in optimization principles. The performance of the optimization problem is enhanced when the consideration of uncertainty in parameter y is incorporated. This improvement leads to retail pricing that are more closely aligned with the actual conditions of the optimization problem in a microgrid.

Minimizing the Conditional Value at Risk (CVaR) mitigates the potential for a system to experience substantial financial losses. To address optimization problems related to a linear cost function, the objective function can be linearly reduced by focusing on the Conditional Value at Risk (CVaR). Equation (3) estimates the Conditional Value at Risk (CVaR) by using samples obtained from the probability distribution of the stochastic parameter y.

$$\text{CVaR}\_\beta = \min(\alpha + [1/(M \times (1 - \beta))],\ \Sigma\,[n=1 \text{ to } M]\,[Z^+], \quad Z = f(x, y) - \alpha) \quad (3)$$

Z+ represents positive values of Z. M denotes the number of pathways generated by the scenario generation process to calculate the expected value in β - CVaR within the cost function. Yn represents the nth trajectory of the created stochastic variable, with the value [0+] commonly used as a constraint to solve the problem. Therefore, the fundamental equation for minimizing Conditional Value at Risk (CVaR) can be written as:

$$\text{CvaR}_\beta = \min\left(\alpha + \frac{1}{\text{M x }(1-\beta)} \sum_{n=1}^{M}[Zn]\right), \text{Zn} \geq 0, Zn \geq f(x,y) - \propto \quad (4)$$

Based on the prior theoretical explanation, the conceptual framework can be summarized as follows.

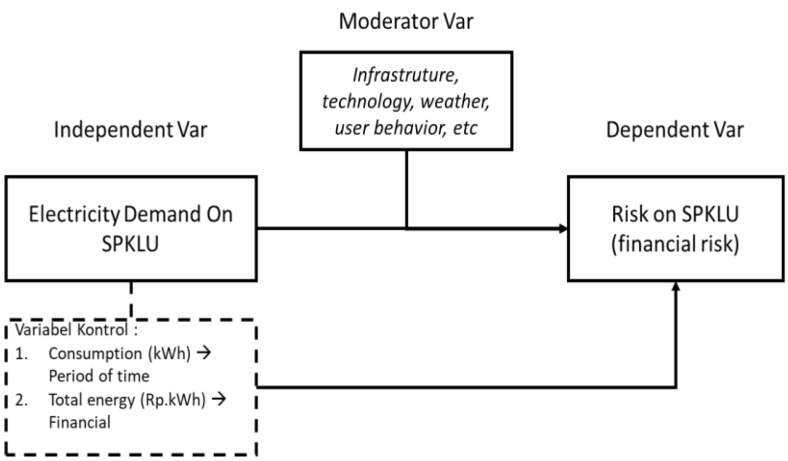

Figure 2. Conceptual Framework

2.4. Dataset

This study utilizes secondary data acquired from PT. XYZ, an institution (state-owned) that operates in the sector of electrical energy in Indonesia. The provided data represents a transaction log for SPKLU (Public Electric Vehicle Charging Station) spanning from 2020 to February 2024. After applying a filtering process, the dataset has a total of 162,100 data observations from January 31, 2023 to January 31, 2024. This dataset contains the hourly electricity use data for a period of 366 days. The range is chosen to observe more accurate patterns in the utilization of electricity on SPKLU. The primary objective of this data processing is to examine the electricity usage at the SPKLU in order to detect variations in load based on electricity demand and associated financial hazards.

The study aims to analyze datasets over a four-year period (March 2020) to examine the fluctuations and reactions in SPKLU's electricity consumption patterns, both on a daily basis and in terms of long-term trends. The study also examines the financial consequences of the disparity between SPKLU capacity and power demand, a crucial factor that may lead to financial losses.

The study will employ the CVaR approach to quantify and examine the most significant level of risk in historical datasets. CVaR is a useful tool for evaluating the expected losses that may occur over a specific loss value, known as VaR. It provides valuable information about the potential extreme risks. This method aims to enhance comprehension of the operational and financial risks encountered by SPKLU and offer strategic suggestions for efficiently managing these risks.

3. Research Method and Materials

To measure the load fluctuations of SPKLUs using the CVaR you first have to calculate the Value at Risk (VaR) which is then used to determine the CVaR. Here are commonly used basic steps and formulas:

3.1. VaR Calculation

Determine the β confidence level, which is often set to 95% or 99%. Then, use historical data to compute the VaR with the formula according to the chosen approach. (historis, varian-kovarian, atau simulasi Monte Carlo).

a) Historical approach:

   VaR = Quantile (1- β,Losses)

b) Varian-Kovarian Approach

   VaR= Z_β × σ × Portfolio Value

   Where Z_β is the Z value for β trusts and σ is the standard deviation of portfolio returns

c) Monte Carlo Simulation

   Simulate various asset price movements scenarios and calculate VaRs based on the distribution of losses on the simulation.

3.2. CVaR Calculation:

After obtaining the VaR, count the CVAR which represents the expectation of average losses outside the VAR for the same level of confidence.

$$\text{CVaR} = \left(\frac{1}{(1-\beta)} \int_{VaR}^{\infty} x \ f(x) dx \right)$$

3.3. Application to SPKLU Load Fluctuations:

For SPKLU, load fluctuations will be measured as variability in electricity consumption. In this context, VaR and CVaR will be calculated on the basis of the distribution of financial losses resulting from operating costs fluctuating as a result of such electricity load variability.

Kerugian=biaya per unit ×(beban aktual-beban prediksi)

The following formula is to calculate losses based on load fluctuations in the SPKLU:

1. Cost Per Unit:

   This is the cost per power unit. In the context of the SPKLU, this can mean the costs per kilowatt-hour (kWh) to operate the charging station.

2. Actual load:

   It is the actual amount of eSlectricity consumed during a given period. In a context of SPKLÜ, this will be measured in kWh.

3. Forecast load:

   This will be the amount of electrical power expected or estimated to be used during the same period, also measureed in kWh.

This formula quantifies the discrepancy between the observed electric charge and the anticipated charge, resulting in a measure of loss. If the current electricity consumption exceeds the expected amount, it suggests excessive usage and leads to financial losses as more energy needs to be supplied than first planned. If the actual load is lower, there may be losses due to the failure to achieve the planned revenue from power sales. The losses computed using this technique can be further examined to approximate the Conditional Value at Risk (CVaR), which offers an assessment of the anticipated financial loss risk at a specific confidence level above the maximum loss threshold determined by the Value at Risk (VaR)

3.4. Analysis and Interpretation

Upon computing the CVaR, the data are examined to identify the time with the greatest peak load risk, where the anticipated average loss beyond the risk threshold accepted by the SPKLU.

TANGGAL	SPKLU	DAYA_CHARGEBOX	KWH	RPKWH
01/01/2023 00:26:32,812000	SPKLU POOL DAMRI KEMAYORAN	180 kW	40.53	99978.5934
01/01/2023 08:05:02,805000	Rest Area KM 10.6 Tol Jagorawi	60 kW	22.709	56018.10702
01/01/2023 08:16:59,119000	SPKLU PLN UID JAKARTA RAYA	50 kW	29.773	73443.44094
01/01/2023 09:42:15,475000	SPKLU POOL DAMRI KEMAYORAN	180 kW	38.03	93811.6434
01/01/2023 09:57:36,339000	Rest Area KM 10.6 Tol Jagorawi	60 kW	26.046	64249.75188
01/01/2023 10:46:59,794000	SPKLU POOL DAMRI KEMAYORAN	180 kW	41.63	102692.0514
01/01/2023 12:31:14,070000	SPKLU PLN UID JAKARTA RAYA	50 kW	21.001	51804.84678
01/01/2023 12:44:35,051000	SPKLU POOL DAMRI KEMAYORAN	180 kW	26.43	65196.9954
01/01/2023 14:00:31,522000	SPKLU PLN UP3 KEBUN JERUK	60 kW	49.7	122598.966
01/01/2023 14:04:24,757000	SPKLU PLN UP3 BANDENGAN	60 kW	27.2	67096.416
01/01/2023 16:12:49,123000	SPKLU POOL DAMRI KEMAYORAN	180 kW	44.73	110339.0694
01/01/2023 16:43:12,689000	SPKLU POOL DAMRI KEMAYORAN	180 kW	40.9	100891.302
01/01/2023 17:49:47,295000	SPKLU PLN UID JAKARTA RAYA	50 kW	33.556	82775.26968
01/01/2023 20:17:41,646000	Rest Area KM 10.6 Tol Jagorawi	60 kW	24.298	59937.82044
01/01/2023 20:25:22,234000	SPKLU PLN UP3 CEMPAKA PUTIH	60 kW	49.3	121612.254
01/01/2023 21:31:16,307000	SPKLU PLN UP3 BANDENGAN	60 kW	35.7	88064.046

Figure 3. SPKLU Data Transaction

The "filter" dataset concentrates data processing into multiple required categories, including transaction date (transaction time), area or regional code (Jakarta is the focus area), charge-box power or capacity and type of SPKLU, energy or charging amount, and rupiah value of the electricity use transactions on EV charging. Considering the extensive volume of data (consisting of hundreds of thousands of rows), only the data pertaining to the time period from 2023 to January 2024 is chosen. This selection specifically focuses on the category of SPKLU ultra fast charging, which refers to charging stations with a minimum power output of 50 kW. The electricity demand value is determined by averaging the daily transactions of both energy and economic value. This results in a figure of 19.519 kWh or 47743.318 RpkWh (1 kWh = Rp2446). The value that exceeds this average, specifically $\geqslant$20 kWh, is selected to observe the fluctuation of demand.

4. Results and Discussion

4.1. Electricity Demand Fluctuation (kW)

Here are the results of the processing of SPKLU transaction data using the CVaR method against electricity usage:

Tanggal	kWh	Fluktuasi kWh	confidence interval	VaR (VCV)	CVaR(VCV)	# simulation	random X	random Y	VaR (X)	within?
01/01/2023 00:26:32,812000	40.53		0.1%	-143.34%	-143.34%	1	0.61%	-117.54%	-114.26%	0
01/01/2023 08:05:02,805000	22.709	-0.43969899	0.2%	-132.80%	-138.07%	2	0.77%	-95.27%	-110.30%	1
01/01/2023 08:16:59,119000	29.773	0.311066097	0.3%	-126.33%	-134.15%	3	0.64%	-66.83%	-113.41%	1
01/01/2023 09:42:15,475000	38.03	0.277331811	0.4%	-121.57%	-131.01%	4	0.61%	-36.24%	-114.22%	1
01/01/2023 09:57:36,339000	26.046	-0.31511964	0.5%	-117.79%	-128.36%	5	0.67%	-119.82%	-112.73%	0
01/01/2023 10:46:59,794000	41.63	0.598326039	0.6%	-114.62%	-126.07%	6	0.39%	-74.01%	-121.88%	1
01/01/2023 12:31:14,070000	21.001	-0.49553207	0.7%	-111.90%	-124.05%	7	0.64%	-69.07%	-113.41%	1
01/01/2023 12:44:35,051000	26.43	0.258511499	0.8%	-109.50%	-122.23%	8	0.61%	-1.32%	-114.35%	1
01/01/2023 14:00:31,522000	49.7	0.880438895	0.9%	-107.35%	-120.58%	9	0.82%	-85.46%	-109.06%	1
01/01/2023 14:04:24,757000	27.2	-0.4527163	1.0%	-105.40%	-119.06%	10	0.04%	-119.14%	-155.90%	1
01/01/2023 16:12:49,123000	44.73	0.644485294	1.1%	-103.61%	-117.65%	11	0.51%	-141.32%	-117.50%	0
01/01/2023 16:43:12,689000	40.9	-0.08562486	1.2%	-101.96%	-116.35%	12	0.61%	-115.13%	-114.38%	0
01/01/2023 17:49:47,295000	33.556	-0.1795599	1.3%	-100.42%	-115.12%	13	0.31%	-137.04%	-126.02%	0

Figure 4. Fluctuation Data Calculation of SPKLU

The VaR is computed to assess the extent of tail risk surpassed by the CVaR, as the CVaR considers risk or loss that surpasses the VaR value as the metric for measuring a loss. Given a confidence level of 99%, utilize historical data to compute Value at Risk (VaR) using the selected methodology (historical, variance-covariance, or Monte Carlo simulation).

Table 1. Calculation Result

Metrik	Nilai
Mean	10.15%
Standar Deviation	49.67%
Confidence Interval	1%
Minimum	-150%
CVaR	**-121.19%**

Based on the available computations, the distribution of losses or losses resulting from load fluctuations in SPKLU can be visualized using a graph in Excel.

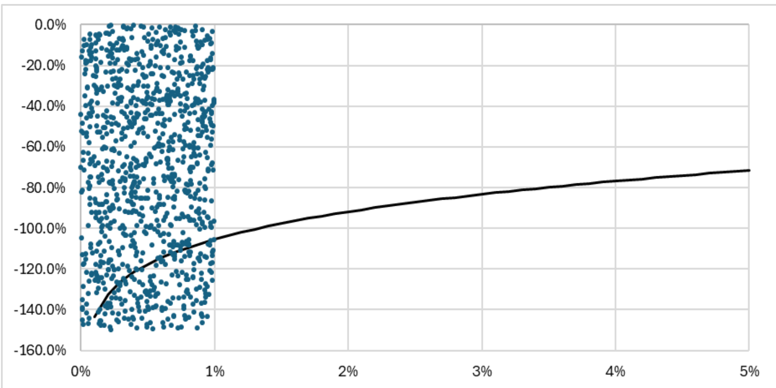

Figure 5. CVaR Chart Fluctuation of Electricity Demand

The provided graphic displays the variations in kilowatt-hour (kWh) prices represented as a loss percentage (CVaR) in relation to the likelihood of experiencing such a loss. The Y axis, which is vertical, displays the percentage of loss. It starts from 0% and decreases to around ± -150%. These charts depict the decrease in Conditional Value at Risk (CVaR) at either a 1% or 99% confidence level. The nadir of the trend line signifies that at the furthest level of confidence in the sample or simulation, the projected loss can approach -150%, while the X-axis (horizontal) represents the relative probability or frequency of the risk event taking place. The axis ranges from 0% to around 5% and shows the cumulative likelihood of loss happening. The starting point is represented by 0% and the highest probability measured or simulated is represented by 5%.

The graph above clearly demonstrates that when the likelihood increases, the predicted loss likewise increases. Each data point represents a certain probability value on the x-axis and its related CVaR loss level on the y-axis. The dispersion of these data points illustrates the range of possible outcomes in the simulation or historical data, indicating the presence of numerous distinct results across the analysis period. Within the realm of risk management, these numerical values can be utilized to ascertain the probability and magnitude of potential losses that may be incurred.

Additionally, the R Studio application is utilized to conduct a simulation that provides a visual representation of the comparison between the VaR and CvaR approaches. This serves as a fundamental approach to see the range of the loss distribution of a variable. This is the CVaR distribution chart created using the Variance-Covariance (VCV) approach, along with a comparison to the VaR method as part of the CvAR calculation.

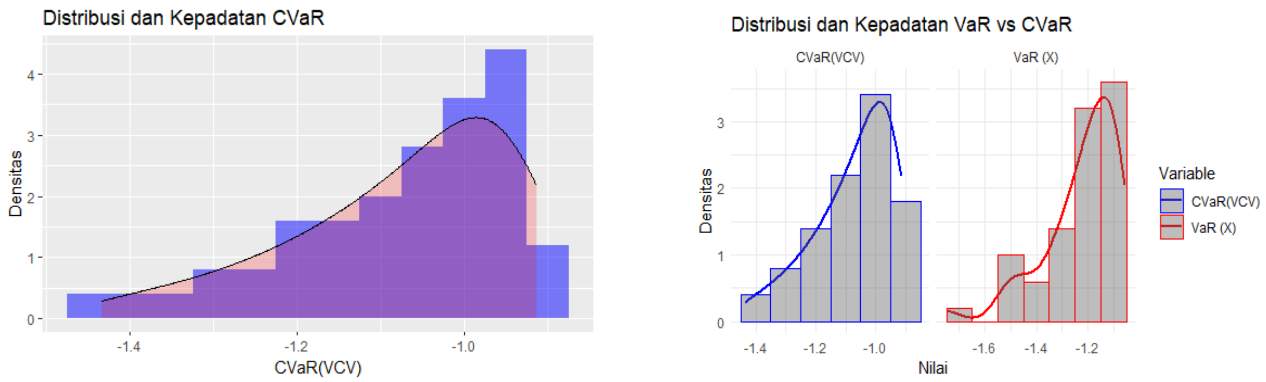

Figure 6. CVaR distribution,CVaR vs. VaR

The displayed figure is a composite plot featuring a histogram and a density curve. It is utilized for the examination of the distribution of CVaR, which is calculated using the Variance-Covariance method. A vowel-consonant-vowel (VCV) pattern. In graph (a), the density distribution starts from the left side with a CVaR value of approximately -0.13. It then increases and reaches its highest point at -0.11 before progressively falling towards the right side, where it reaches a CVaR value of around -0.09. This indicates that the majority of losses tend to cluster around the CVAR value of -0.11. The occurrence of losses decreases as it moves towards lower or higher CVaR values. In graph (b), the red curve (VaR) has a wider range and a closer peak to the right than the CVaR. This indicates a broader variation in risk assessment with the VaR, which does not take into account extreme losses such as the CVAR. It indicates that the CVAR, that includes averages of losses exceeding VaR values at a certain confidence level, gives a heavier estimate for potential losses.

4.2. Return (Financial) of SPKLU Electricity Usage (RpkWh)

The displayed table represents the results of a financial risk simulation that incorporates Value at Risk (VaR) and Conditional Value at Risk (CVaR) using the Monte Carlo approach. The column labeled "RpKWh" displays the cost per kilowatt-hour, while the "Return" column indicates the percentage change in value or fluctuation in power return.

With the same step to perform the calculation from the transaction data SPKLU owns, obtained the results as well as the distribution spread graph (scatter plot) as shown on Table 2.

Tanggal	RpkWh	Return	confidence interval	VaR (VCV)	CVaR(VCV)	# simulation	random X	random Y	VaR (X)	within?
01/01/2023 00:26:32,812000	99978.6		0.1%	-143.34%	-143.34%	1	0.66%	-18.97%	-112.85%	1
01/01/2023 08:05:02,805000	56018.1	-43.97%	0.2%	-132.80%	-138.07%	2	0.68%	-109.21%	-112.35%	1
01/01/2023 08:16:59,119000	73443.4	31.11%	0.3%	-126.33%	-134.15%	3	0.48%	-34.34%	-118.63%	1
01/01/2023 09:42:15,475000	93811.6	27.73%	0.4%	-121.57%	-131.01%	4	0.68%	-110.77%	-112.30%	1
01/01/2023 09:57:36,339000	64249.8	-31.51%	0.5%	-117.79%	-128.36%	5	0.19%	-0.18%	-133.42%	1
01/01/2023 10:46:59,794000	102692	59.83%	0.6%	-114.62%	-126.07%	6	0.92%	-70.40%	-107.01%	1
01/01/2023 12:31:14,070000	51804.8	-49.55%	0.7%	-111.90%	-124.05%	7	0.91%	-21.00%	-107.13%	1
01/01/2023 12:44:35,051000	65197	25.85%	0.8%	-109.50%	-122.23%	8	0.81%	-57.96%	-109.23%	1
01/01/2023 14:00:31,522000	122599	88.04%	0.9%	-107.35%	-120.58%	9	0.92%	-30.43%	-106.99%	1
01/01/2023 14:04:24,757000	67096.4	-45.27%	1.0%	-105.40%	-119.06%	10	0.04%	-1.12%	-155.28%	1
01/01/2023 16:12:49,123000	110339	64.45%	1.1%	-103.61%	-117.65%	11	0.44%	-2.27%	-119.89%	1
01/01/2023 16:43:12,689000	100891	-8.56%	1.2%	-101.96%	-116.35%	12	0.70%	-126.46%	-111.81%	0

Figure 7. Return Calculation Result (RpkWh)

Table 2. Calculation Result

Metrik	Nilai
Mean	10.15%
Standar Deviation	49.67%
Confidence Interval	1%
Minimum	-150%
CVaR	**-121.19%**

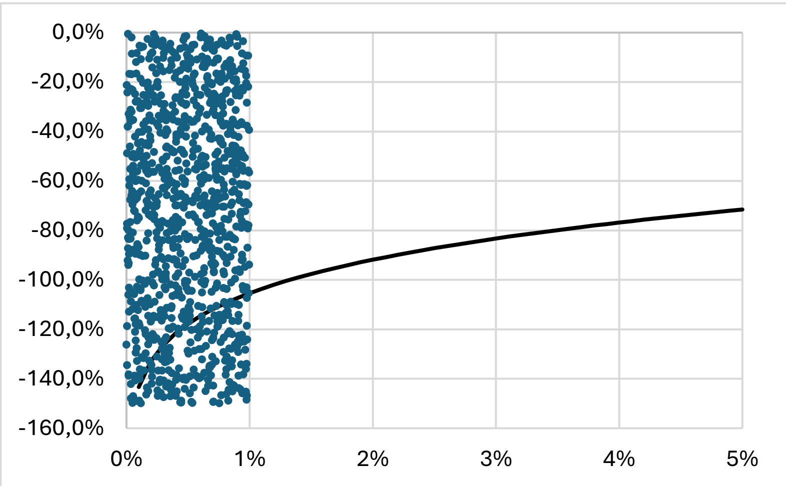

Figure 8. CVaR Return (RpkWh)

To get an overview of the comparison of the VaR and CvaR methods also done using R Studio which then obtained the figure 9.

The figure 9 demonstrate that possible losses can vary considerably, as indicated by the analysis and calculations conducted. VaR and CVaR, at a specific level of confidence, identify distinct losses. Within the framework of SPKLU, this refers to a time period in which there is a substantial decrease in the demand for energy (such as during unfavorable weather conditions or shifts in consumer habits), resulting in a notable reduction in revenue. Having a clear understanding of the magnitude of these variations enables SPKLU to effectively plan and implement appropriate financial safeguards or management strategies.

Examining the influence of fluctuations in demand on SPKLUs is a vital factor in comprehending the operational patterns of this infrastructure. The first image displays statistical metrics that reveal the central tendency and variability of demand data. This information, derived from average values and standard deviations, enables the identification of demand trends and patterns of fluctuation. The significance of the CVaR value suggests the level of prospective losses that should be taken into account. It provides insight into how demand fluctuation can potentially impact the primary risk factors of SPKLU financial risk.

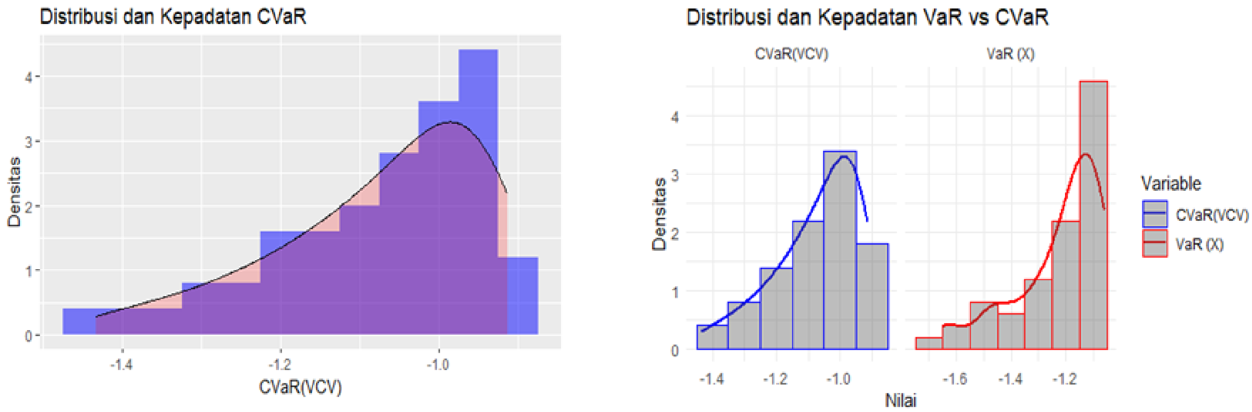

Figure 9. CVaR distribution,CVaR vs. VaR

Operational risks and challenges arise from load fluctuations on SPKLUs with a capacity above 50 kW (Ultra Fast Charging). Initially, the presence of idle capacity results in suboptimal utilization of infrastructure, hence diminishing the return on investment and escalating operating expenses. Moreover, substantial variations in power consumption might disrupt the reliability of the power network, potentially leading to power quality issues that impact other interconnected devices. Charging durations may be uncertain when loads near their maximum capacity. This uncertainty can lead to longer car charging periods, which in turn decreases customer satisfaction and raises the likelihood of equipment failure. Frequent variations at high frequencies further expedite the deterioration of SPKLU infrastructure, hence intensifying the requirement for prompt maintenance and replacement of components. To tackle these issues, it is necessary to have a well-designed system, regular maintenance, and efficient load control. Including the use of demand management techniques or energy storage devices to balance peak loads

5. Conclusion

With a high rate of fluctuation and significant potential losses as demonstrated by the CVaR of -121.19% at the 1% confidence interval, this study emphasizes the importance of having a strong risk management strategy. Furthermore, the study successfully evaluated the effectiveness of CVaR in measuring and mitigating the risks associated with demand fluctuations. The results supported the development of mitigation strategies based on the results of the CVaR analysis, which not only reduce the potential financial losses but also improve the operational resilience and stability of SPKLU. This strategy should be proactive and adaptive, integrating advanced forecasting and monitoring technologies to manage energy demand in real time. These measures may include the establishment of a financial buffer, implementation of dynamic pricing, and adoption of responsive capacity management. Implementing such strategies will enable SPKLU to effectively address swings in demand, efficiently manage capacity, and mitigate financial risks.

This research is still limited to the SPKLU data that exists in Jakarta only with Ultra Fast Charging capacity. In the future, it is expected that similar research can be carried out with more in-depth research such as:

a) Opposed to SPKLU throughout Indonesia

b) Suitable for all SPKLU kinds and capacities—low, medium, fast, and ultra fast charging

c) In addition, take into account technical issues of EV charging, such as rush hours, weather, seasons, and so on, as well as variables of parameters like driving distance, battery capacity, and EV user behaviour.

Further research on the aforementioned topics is anticipated to help establish strategies and plans for future SPKLUs and SPKLUs that can handle load fluctuations when charging electric vehicles (EVs), hence reducing operational and financial risks.

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References

Adu-Gyamfi, G., Song, H., Obuobi, B., Nketiah, E., Wang, H., & Cudjoe, D. (2022). Who will adopt? Investigating the adoption intention for battery swap technology for electric vehicles. *Renewable and Sustainable Energy Reviews*, *156*(November 2021), 111979. https://doi.org/10.1016/j.rser.2021.111979

Albadi, M. H. (2008). *A summary of demand response in electricity markets*. *78*, 1989–1996. https://doi.org/10.1016/j.epsr.2008.04.002

Aziz, M., & Huda, M. (2019). ScienceDirect ScienceDirect ScienceDirect Application opportunity of vehicles-to-grid in Indonesian electrical The Heating Application opportunity of Symposium Indonesian electrical grid grid Assessing the Muhammad feasibility. *Energy Procedia*, *160*(2018), 621–626. https://doi.org/10.1016/j.egypro.2019.02.214

Canalys, 2024. (n.d.). *global-ev-market-2024 @ www.canalys.com*. https://www.canalys.com/newsroom/global-ev-market-2024

Fu, Y., Sun, Q., & Wennersten, R. (2020). Effectiveness of the CVaR method in risk management in an integrated energy system. *Energy Reports*, *6*, 1010–1015. https://doi.org/10.1016/j.egyr.2020.11.084

Ghasemi, A., Jamshidi Monfared, H., Loni, A., & Marzband, M. (2021). CVaR-based retail electricity pricing in day-ahead scheduling of microgrids. *Energy*, *227*, 120529. https://doi.org/10.1016/j.energy.2021.120529

Jin, R., Zhou, Y., Lu, C., & Song, J. (2022). Deep reinforcement learning-based strategy for charging station participating in demand response. *Applied Energy*, *328*(September 2021), 120140. https://doi.org/10.1016/j.apenergy.2022.120140

Katadata.co.id. (2024). *Tren Mobil Listrik di Indonesia Kian Menguat pada 2023 Volume Penjualan Wholesale Tahunan Mobil Listrik BEV di Indonesia*. 2022–2023.

Ministry of Energy and Mineral Resources. (2023). *Regulasi Penyediaan Infrastruktur Pengisian Kendaraan Bermotor Listrik Berbasis Baterai (KBLBB) Upaya Percepatan Pengembangan Infrastruktur KBLBB*. https://gatrik.esdm.go.id/assets/uploads/download_index/files/f0294-bahan-dirbinus.pdf

Mozafar, M. R., Amini, M. H., & Moradi, M. H. (2018). Innovative appraisement of smart grid operation considering large-scale integration of electric vehicles enabling V2G and G2V systems. *Electric Power Systems Research*, *154*, 245–256. https://doi.org/10.1016/j.epsr.2017.08.024

OECD. (2016). OECD Factbook 2015-2016. In *OECD Publishing*. http://www.oecd-ilibrary.org/economics/oecd-factbook-2015-2016_factbook-2015-en

Padhilah, F. A., Surya, I. R. F., & Aji, P. (2023). *Indonesia Electric Vehicle Outlook 2023 Electrifying Transport Sector: Tracking Indonesia EV Industries and Ecosystem Readiness*. https://iesr.or.id/en/pustaka/indonesia-electric-vehicle-outlook-2023

Qiao, Q., Zhang, Z., & Lin, B. (2023). Environmental temperature variation and electricity demand instability: A comprehensive assessment based on high-frequency load situation. *Environmental Impact Assessment Review*, *103*(June), 107281. https://doi.org/10.1016/j.eiar.2023.107281

Sambasivam, B., & Balachandra, P. (2023). Demand response an effective solution for dynamic balancing of variable supply with variable demand: Evidence from Indian electricity system. *Energy and Environment*. https://doi.org/10.1177/0958305X231179908

Savari, G. F., Sathik, M. J., Raman, L. A., El-Shahat, A., Hasanien, H. M., Almakhles, D., Abdel Aleem, S. H. E., & Omar, A. I. (2023). Assessment of charging technologies, infrastructure and charging station recommendation schemes of electric vehicles: A review. *Ain Shams Engineering Journal*, *14*(4), 101938. https://doi.org/10.1016/j.asej.2022.101938

shafiei, M., & Ghasemi-Marzbali, A. (2023). Electric vehicle fast charging station design by considering probabilistic model of renewable energy source and demand response. *Energy*, *267*(July 2022), 126545. https://doi.org/10.1016/j.energy.2022.126545

Son, Y., Woo, H., & Choi, S. (2022). A Study on the Application of Game Theory for Optimal Operation of Electric Vehicle Charging Station. *International Conference on ICT Convergence*, *2022-Octob*, 338–340. https://doi.org/10.1109/ICTC55196.2022.9952489

Stonybrook.edu. (n.d.). *demand @ energy.stonybrook.edu*. https://energy.stonybrook.edu/facts/demand

Wu, J., Powell, S., Xu, Y., Rajagopal, R., & Gonzalez, M. C. (2024). Planning charging stations for 2050 to support flexible electric vehicle demand considering individual mobility patterns. *Cell Reports Sustainability*, *1*(1), 100006. https://doi.org/10.1016/j.crsus.2023.100006

Wu, J., Wu, Z., Wu, F., Tang, H., & Mao, X. (2018). CVaR risk-based optimization framework for renewable energy management in distribution systems with DGs and EVs. *Energy*, *143*, 323–336. https://doi.org/10.1016/j.energy.2017.10.083

Zhao, Z., Lee, C. K. M., & Ren, J. (2024). A two-level charging scheduling method for public electric vehicle charging stations considering heterogeneous demand and nonlinear charging profile. *Applied Energy*, *355*(May 2023), 122278. https://doi.org/10.1016/j.apenergy.2023.122278