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Assessing Economic Performance of An Energy Microgrid: A Conditional Value-at-Risk Optimization Approach

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Abstract. Distributed generation resources integration within the energy system not only ensures efficient power penetration and reliable electricity supply but also empowers consumers to optimize energy consumption, leading to a more flexible and customer-centric energy landscape. To enhance the economic performance of distributed energy resources (DERs), this work utilizes a hybrid fuel cell power generation system utilizing energy storage.
This research aims to address uncertainty in electricity and gas prices, a crucial parameter influencing economic feasibility. To achieve this, we adopt the conditional value-at-risk (CVaR) optimization method, enabling effective management and mitigation of potential risks associated with volatile electricity and gas prices. This approach seeks to ensure the optimal economic performance of the hybrid energy system under varying market conditions. This integration is aimed at optimizing energy supply and demand, thereby maximizing the economic benefits of the distributed generation system. Through economic modeling, we give a particular focus on the fuel cell's pivotal role in achieving benefits. The findings offer valuable insights for policymakers and stakeholders in the energy sector, paving the way for a more sustainable and efficient energy future.

Keywords: Conditional Value-at-risk, Energy Storage System, Energy Microgrid, Optimization, Uncertainty Management.

1 Introduction

Distributed energy resources (DERs) have gained significant prominence in power systems in recent years due to their ability to effectively mitigate greenhouse gas emissions while simultaneously offering power with a favorable penetration coefficient and exceptional reliability [1]. These sources play a pivotal role in reducing environmental pollution by minimizing the release of harmful gases, and they contribute to the overall sustainability of power generation. Moreover, their notable penetration coefficient ensures efficient utilization of power, while their remarkable reliability guarantees a consistent and uninterrupted electricity supply. The incorporation of distributed generation sources revolutionizes the transmission of energy across the power grid and enables consumers to exercise greater flexibility in their energy usage. This adaptation of decentralized production sources fundamentally alters the dynamics of energy distribution, facilitating a more efficient and adaptable system. Consequently, consumers are empowered to optimize their energy consumption patterns, making the most of the available resources while responding to their specific needs and preferences. This shift towards a more flexible and consumer-centric energy landscape enhances overall energy utilization and promotes a more sustainable and customer-driven approach. A novel hybrid fuel cell power generation system with high efficiency is proposed in [2]. The economic feasibility of MWe-scale systems using different fuels was assessed through economic modeling. The goal of this work was to develop the technology roadmap for this type of clean power system.

This research article presents a pioneering contribution that introduces an optimal energy management strategy, focusing on identifying and utilizing the maximum efficiency range (MER) for a hybrid car equipped with both a fuel cell and a battery, as outlined in reference [3]. The primary objective of this study is to address the challenges associated with energy management in such hybrid systems, aiming to optimize overall performance and efficiency. By strategically leveraging the MER, the proposed strategy aims to effectively manage power flow and utilization between the fuel cell and the battery, ensuring optimal utilization of both energy sources. This innovative approach contributes to the advancement of energy management strategies for hybrid cars, aligning with the broader objective of achieving sustainable transportation systems with enhanced energy efficiency. The authors in [4] focused on the design of an off-grid wind power generator with a hydrogen energy storage system. The authors propose a biological-inspired optimization algorithm that considers the total cost and load loss as objective functions. The algorithm, based on artificial bee colony optimization, outperforms the particle swarm optimization algorithm.

The reviewed studies highlight the significant advancements in the design, optimization, and integration of hybrid renewable energy systems for various applications. The findings demonstrate the potential of these systems in achieving cost-effective and sustainable energy generation, reducing carbon emissions, enhancing reliability, and improving the utilization of renewable resources. By considering the insights gained from these studies, future research can further advance the development and implementation of hybrid renewable energy systems, contributing to a cleaner and more resilient energy future.

In this paper, we are studying an energy system that includes several DERs and planning to minimize the total cost of the energy system. The uncertainty posed by the electricity and gas prices is addressed using the CVaR method.

2 The Studied Model

The studied model including its components is illustrated in Fig. 1 [5]. The objective of the model is to minimize the overall cost of the energy system through the application of CVaR method. This cost encompasses the expenses associated with electricity procurement from the upstream network and gas procurement from the gas network, while also considering the revenue from selling power to the upstream network. The objective function is expressed in Eq. (1). By minimizing the total cost of the system, the model aims to optimize the utilization of available resources. This objective function serves as a guide for decision-making processes in determining the optimal configuration and operation of the hybrid system. To achieve this objective, various factors are considered, including the prevailing electricity and gas prices, the power output of the system, and the amount of gas consumed. Also, stochastic programming using the CVaR method is applied in this formulation [6].

$$Min\ (1-\beta)\left(\sum_{t=1}^{NT}\left[\sum_{sc=1}^{SC}\pi(sc)\left(P_t^{Net}\lambda_{t,sc}^{Net}+G_t^{Net}\lambda_{t,sc}^{Gas}\right)\right]-P_t^{Exp}\lambda_t^{Net,sell}\right) - \beta\left(\eta+\frac{1}{1-\alpha}\sum_{sc=1}^{SC}\pi(sc)\xi_{sc}\right) \tag{1}$$

The probability of the scenarios is shown by $\pi(sc)$. β is the risk level of the risk measure. It can be a value between 0 and 1. The higher values of β make the system more risk-averse. The variable P_t^{Net} in the context of this study represents the quantity of electrical power procured from the upstream network. By accurately quantifying the power purchased from the upstream network, the optimization process aims to minimize expenses and optimize the system's energy procurement. The parameter $\lambda_{t,sc}^{Net}$ represents the price or cost associated with the power purchased from the upstream network at time *t* and scenario *sc*. The variable represents G_t^{Net} represents the amount of gas purchased from the gas network. Similarly, $\lambda_{t,sc}^{Gas}$ represents the price of gas purchased from the gas network at time *t* and scenario *sc*. Furthermore, P_t^{Exp} introduced as an amount of power sold back to the upstream network. This variable accounts for any excess power generated by the system that can be supplied back to the upstream network. Finally, $\lambda_t^{Net,sell}$ *is* the selling electricity price to the network.

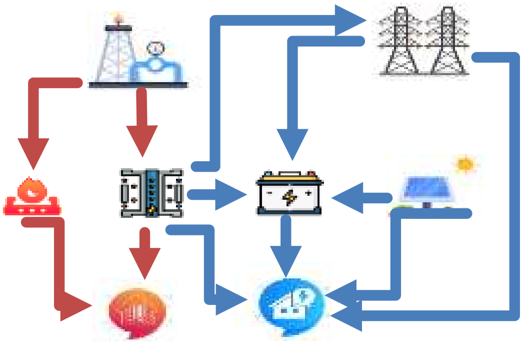

Fig. 1. The components of the studied energy system.

By balancing the power production and demand, the model aims to maximize the utilization of renewable energy sources while effectively meeting the energy needs of the system.

$$P_t^D+P_t^{Exp}+P_t^{ESS,C}=P_t^{Net}+P_t^{DER}+P_t^{ESS,D} \tag{2}$$

where variable P_t^D is the electric load. variable $P_t^{ESS,C}$ quantifies the charging power of the storage. Additionally, P_t^{DER} encompasses the combined power generated by the fuel cell and solar cells, representing the local renewable energy production. $P_t^{ESS,D}$ represents the power discharged from the storage system.

In order to determine the power generated by the solar system and fuel cell, the following formulations are utilized.

$$P_t^{DER} = \begin{cases} P_t^{PV} = S\eta^{pv}R_t \\ P_t^{FU} = G_t^{FU}\eta^{FU,E} \end{cases} \tag{3}$$

P_t^{PV} is the production power of the solar unit. S is the area required to install the solar unit. η^{PV} is the efficiency of the solar unit quantifies the conversion efficiency of solar radiation into electrical energy. R_t is the amount of solar radiation representing the intensity of sunlight available for power generation. P_t^{FU} is the production power of the fuel cell unit. G_t^{FU} is the amount of gas required for the operation of a fuel cell, typically hydrogen or a hydrogen-rich fuel and $\eta^{FU,E}$ is the efficiency of the fuel cells.

In addition, it is essential to address the thermal aspect of the system, particularly the heat generated by local sources such as the fuel cell and backup boiler system, in order to meet the thermal load requirements.

$$H_t^D = H_t^{DER} \tag{4}$$

The thermal load of the system is denoted as H_t^D. On the other hand, the heat produced by local sources such as fuel cell and backup boiler are represented by H_t^{DER}.

To accurately capture and model the heat generation from these sources, an equation is proposed, which describes the relationship between the produced heat and the operational parameters of the fuel cell and backup boiler system.

$$H_t^{DER} = \begin{cases} H_t^B = G_t^B\eta^B \\ H_t^{FU} = G_t^{FU}\eta^{FU,H} \end{cases} \tag{5}$$

The production heat of the backup unit which is denoted by H_t^B. Similarly, the production heat of the fuel cell is shown by H_t^{FU}.

The limits of energy production by local sources, which are crucial in understanding the system's capabilities and constraints, are detailed below. These limits represent the upper bounds of energy generation that can be achieved using the available local resources and technologies, providing valuable insights into the system's potential and operational limitations and ensure optimal energy production and utilization.

$$E_{Min}^{DER} \leq E_t^{DER} \leq E_{Max}^{DER} \tag{6}$$

The power limit exchanged between the energy system and the upstream network are defined as follows:

$$P_{Min}^{Net} \leq P_t^{Net} \leq P_{Max}^{Net} \tag{7}$$

$$P_{Min}^{Exp} \leq P_t^{Exp} \leq P_{Max}^{Exp} \tag{8}$$

The battery storage model is formulated as follow:

$$W_t^{ESS} = W_{t-1}^{ESS} + P_t^{ch}\eta^{ch} - P_t^{dis}\eta^{dis} \tag{9}$$

$$W^{Min} \leq W_t^{ESS} \leq W^{Max} \tag{10}$$

$$P_{Min}^{ch}I_t^{ch} \leq P_t^{ch} \leq P_{Max}^{ch}I_t^{ch} \tag{11}$$

$$P_{Min}^{dis}I_t^{dis} \leq P_t^{dis} \leq P_{Max}^{dis}I_t^{dis} \tag{12}$$

$$I_t^{ch} + I_t^{dis} \leq 1 \tag{13}$$

W_t^{ESS} is the energy stored in the battery. W_t^{ESS} represents the amount of energy that is currently stored in the battery. η^{ch} and η^{dis} are the charging and discharging efficiencies, respectively. $W^{Min}$and W^{Max} are the minimum and maximum energy stored in the battery, respectively. I_t^{ch} and I_t^{dis} are binary variables of the charging and discharging models.

$$\sum_{t=1}^{NT}\left[\left(P_t^{Net}\lambda_{t,sc}^{Net}+G_t^{Net}\lambda_{t,sc}^{Gas}\right)-P_t^{Exp}\lambda_t^{Net,sell}\right]-\eta\leq\xi_{sc} \tag{14}$$

$$\xi_{sc}\geq 0 \tag{15}$$

Constraints (14) and (15) represent the obligatory conditions for incorporating CVaR calculations within the stochastic programming model. As previously indicated, the application of the CVaR approach is proposed to evaluate the effect of the uncertain parameter. The electricity and gas purchased from the upstream network, i.e., $\lambda_{t,sc}^{Net}$ and $\lambda_{t,sc}^{Gas}$ are the uncertain parameters. α is a level of assurance, η is VaR, ξ_{sc} is the positive variable.

3 Result Discussions

In this section, a system has been employed for simulating the presented model, as depicted in Fig. 1. The daily operational cost of the energy system is $44. This cost reduction is attributed to the optimal utilization of local systems such as fuel cells in energy production and their efficient use.

Fig. 2 presents a visual representation of the expected total cost changes across various values of CVaR. In this study, α is set to 0.95, and β ranges from 0 to 1, with increments of 0.2. When β equals 0, the operator exhibits a risk-averse behavior, leading to the highest possible CVaR. As β increases, the decision-maker becomes more accepting of increased risk when dealing with uncertain parameters. Additionally, raising the value of β leads to a decrease in CVaR, implying that as risk tolerance increases, operational costs are minimized.

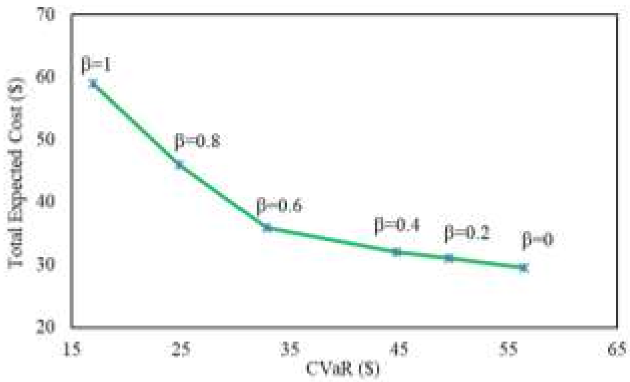

Fig. 2. The impact of the risk parameter on the total expected cost and CVaR.

The level of power generation by the solar unit is illustrated in Fig. 3. As observed, solar panel power generation commences at 5 AM and continues until 5 PM. The generated power is distributed to three units separately: battery, grid, and load. The highest solar panel power generation occurs in the afternoon, and this excess power is either sold back to the grid upstream or stored in the battery unit.

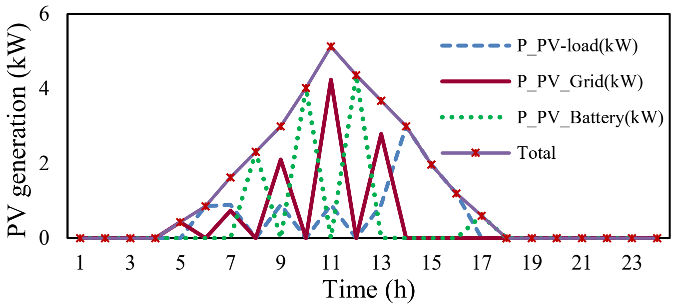

Fig. 3. Power produced by the photovoltaic system.

4 Conclusions

In this paper, the problem of optimal operation of an energy system is examined through application of CVaR as the risk management method. The goal of the proposed model is to optimize the utilization of local resources for energy supply and achieve economic benefits, resulting in minimizing the operational costs of the system. According to the results, it is shown that as the risk level increases, the operator becomes more accepting of increased risk when dealing with uncertain parameters. In future work, the possibility of considering electrical and gas network models can be explored.

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