Multi-Objective Optimization of a Photovoltaic-Based Energy System for Residential Power Supply

S. Hossein Shirazian[1] - Zahra Piryaei[2], Maryam Karami[1*], Parsa Fathi[1]
[1] Dept. of Mechanical Engineering, Kharazmi University
[2] Dept. of Renewable Energy Engineering, Shahid Beheshti University

ABSTRACT

Photovoltaic-based energy systems are increasingly recognized as sustainable options for decentralized power generation, particularly in high-irradiation regions such as Iran. However, the intermittent nature of solar energy poses challenges for continuous power supply. Hydrogen energy storage has been recently proposed as a promising alternative to traditional batteries for mitigating power shortages caused by fluctuating photovoltaic output. Despite the technological advancements in industrial solar-driven hydrogen production systems, robust sizing strategies for energy management in small-scale applications, such as residential buildings, remain scarce. This study presents a novel multi-objective optimization framework for sizing a photovoltaic–hydrogen energy system capable of fully supplying the energy demands of a residential building in Yazd, Iran. The system is dynamically modeled in TRNSYS, and optimization is carried out using an artificial neural network combined with genetic algorithms. Cost of energy, energy efficiency, and reliability are defined as key performance indicators and the objective is to find the best combination of them. The optimal system configuration consists of an 11-kW photovoltaic array, a 9.2-kW electrolyzer, a 3.7-kW fuel cell, and a 6.5-m³ hydrogen storage tank, resulting in a levelized cost of energy of $0.40/kWh and an overall energy efficiency of 8.53%. These findings highlight the potential of hydrogen energy storage to provide a reliable, efficient, and cost-competitive pathway toward sustainable residential energy supply.

Keywords: **Photovoltaic-based energy system, Hydrogen energy storage, Energy management, Optimization, Optimal sizing**

1. INTRODUCTION

The growing challenges posed by climate change, along with increasing concerns over energy security, have accelerated the global shift toward renewable energy technologies. Among the various options, solar energy, particularly photovoltaic (PV) systems, has emerged as one of the most promising solutions due to its widespread availability, declining cost, and technological maturity [1]. Despite these advantages, PV systems suffer from inherent intermittency, which makes energy storage indispensable for ensuring a reliable and continuous supply of power.

Traditionally, battery storage has been the dominant solution in renewable energy systems, offering well-established performance and integration frameworks. However, alternative storage technologies, such as hydrogen energy storage (HES), remain comparatively underexplored despite their significant potential. HES provides unique advantages, including long-term storage capability and scalability [2,3]. Nevertheless, the integration of HES into renewable energy systems introduces considerable complexity, necessitating systematic approaches for proper system design and component sizing.

A typical HES system consists of four key elements: (i) an electrolyzer that converts excess renewable electricity into hydrogen via water electrolysis, (ii) a compressor that pressurizes the hydrogen for storage, (iii) a storage tank that allows long-duration preservation of the gas, and (iv) a fuel cell that reconverts hydrogen into electricity during periods of energy deficit [4]. The technical and economic viability of such systems depends heavily on the appropriate sizing of each component.

Numerous optimization approaches have been proposed so far for renewable energy systems. However, the majority of these studies have focused predominantly on economic metrics, such as minimizing net present cost or levelized cost of energy (LCOE), while largely overlooking energetic performance [5]. This one-dimensional approach can result in designs that are financially appealing but energetically suboptimal, risking resource overuse and missing opportunities for performance improvements.

In this context, the present study proposes a novel optimization framework that simultaneously addresses cost-effectiveness, energy efficiency, and technical feasibility for a solar energy system integrating HES. The framework leverages the predictive capability of the artificial neural network (ANN) in combination with the global search ability of genetic algorithm (GA) to deliver a robust, multi-objective optimization tool. By considering both economic and energetic criteria, the proposed approach aims to advance the design of reliable and sustainable renewable–hydrogen hybrid systems capable of meeting future energy demands under uncertainty.

2. MATERIALS AND METHODS

2.1 System Description

A PV-HES system has been designed to meet the electricity demand of a residential building in Yazd, Iran, a location distinguished by high solar irradiation and significant temperature fluctuations. The building's electrical load is primarily driven by space heating and cooling, supplied through an air conditioning unit, and household appliances. The monthly electricity consumption profile is presented in Figure 1. As illustrated, space cooling is the most energy-intensive service, with demand peaking at around 1129 kWh/month in July. For this reason, the maximum electrical energy consumption (1139 kWh) is observed in this month. In contrast, the minimum consumption of 402 kWh occurs in April, when mild weather reduces the need for both heating and cooling.

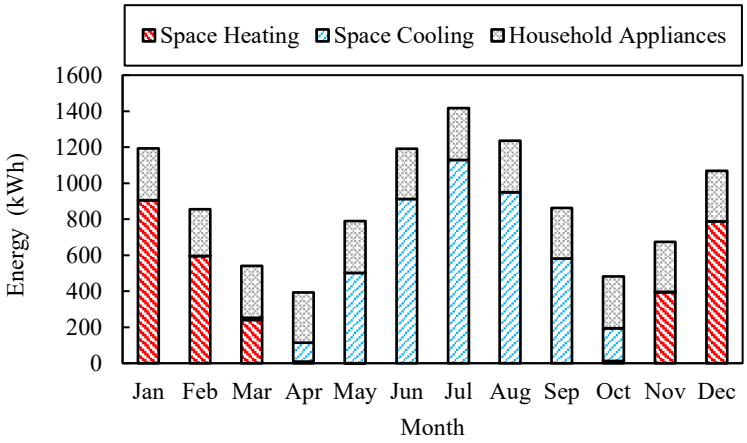


Fig. 1. *Monthly electrical energy consumption in the case study*

The proposed PV-HES system consists of a PV array and an HES unit as illustrated in Figure 2. A control unit monitors both the electrical load and the power output of the PV system, and accordingly activates or deactivates the HES unit by switching between the electrolyzer and the fuel cell. In this study, an alkaline electrolyzer is employed, while the fuel cell is of the proton exchange membrane (PEM) type. The PV array consists of multiple 455-W panels.

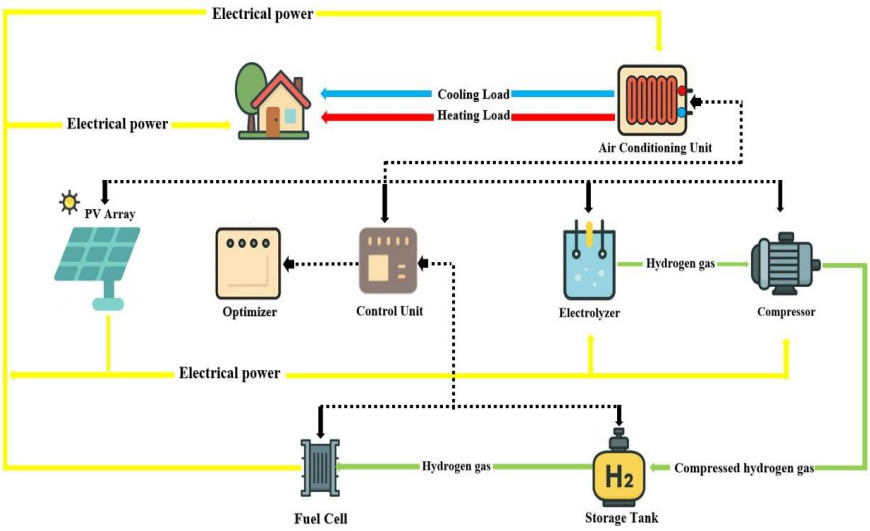


Fig. 2. *Schematic representation of the proposed PV-HES system*

2.2 Performance Indicators

In all energy systems, performance indicators play a crucial role in operational adjustments. As this study seeks to evaluate the energetic and economic performance of the proposed PV-HES system, along with its reliability, three key performance indicators are defined as follows:

- **Loss of Load Probability (LOLP):** This is a critical metric for evaluating the reliability of energy systems. It represents the probability that the system will be unable to meet the energy demand over a defined time interval. In the context of renewable energy systems, LOLP is particularly significant, as ensuring uninterrupted power supply takes precedence over considerations of cost or efficiency. The annual LOLP is calculated as [6]:

$$LOLP = \sum_{t=1}^{8760} D(t) \Big/ \sum_{t=1}^{8760} L(t) \qquad (1)$$

Where $L(t)$ is the electrical load (kWh) at hour t, and $D(t)$ the corresponding power deficit during that hour (kWh).

- **Energy Efficiency:** This metric quantifies the proportion of useful energy output relative to the total input energy over a defined period. In solar energy systems, solar irradiation is the primary input, while the total energy delivered is regarded as the output:

$$\eta = \sum_{t=1}^{8760} E_{out}(t) \Big/ \sum_{t=1}^{8760} A \times G(t) \qquad (2)$$

Where $E_{out}(t)$ is the energy delivered at hour t, $G(t)$ the solar irradiation, and A the area of the PV array.

- **LCOE:** This is a widely adopted economic metric for evaluating the cost-effectiveness of various energy generation technologies. LCOE is determined by dividing the total system cost (including capital investment as well as operation and maintenance expenses) by the total energy delivered:

$$LCOE = \left(\sum_{t=0}^{20} \frac{C_t + O_t}{(1+d)^t}\right) \Big/ \left(\sum_{t=0}^{20} \frac{E_{out_t}}{(1+d)^t}\right) \qquad (3)$$

Where, C_t is the total capital investment, O_t the operation and maintenance costs in year t, d the discount rate, which is assumed to be 10% in this study, and E_{out_t} the annual amount of energy supplied to the user. Moreover, the lifetime of the proposed energy system is considered to be 20 years.

2.3 Sizing Optimization

In this study, the best system configuration is determined through an optimization process. Before optimization can be performed, the system must first be modeled in a dynamic simulation environment to accurately capture its operational behavior. For this purpose, TRNSYS software is employed. The optimization procedure begins with data generation, where the operating conditions of the TRNSYS model are systematically varied across different component sizes to produce a comprehensive dataset of performance indicators over a wide design space. Next, configurations with an LOLP higher than 1% are excluded to ensure reliable power supply.

Subsequently, the generated dataset is used to train a two-stage neural network framework. In the first stage, a four-layer classification model (ReLU–ReLU–Tanh–Sigmoid activation functions with 128–256–128–1 neurons, respectively) is trained to identify stable configurations (those that do not fail during TRNSYS simulation), achieving an accuracy of 99.5%. In the second stage, a three-layer regression model (ReLU–ELU–Linear activation functions with 128–128–2 neurons, respectively) is trained to predict both LCOE and energy efficiency, with an R^2 score of 99.9%.

The two models are then embedded into an optimization framework using GA. This approach efficiently searches the design space and identifies the configuration with the lowest cost function, which is defined as:

$$Cost\ Function = LCOE/\eta \qquad (4)$$

3. RESULTS AND DISCUSSION

The optimal configuration obtained by the optimization process is presented in Table I. This configuration successfully meets all the electrical energy demand without any shortfall. It achieves an LCOE of $0.4/kWh and an energy efficiency of 8.53%. The optimal number of PV panels is also found to be 24.

Table 1. *Components' size in the optimal configuration*

Nominal PV power (kW)	Electrolyzer rated power (kW)	Fuel cell rated power (kW)	Storage tank volume (m^3)
11	9.2	3.7	6.5

Figure 3 illustrates how the PV system and the fuel cell contribute to energy supply in the optimal configuration. On average, the PV system provides about 42% of the total demand, with its maximum contribution of 62% occurring in April and its minimum of 22% in December. The remaining demand is covered by the fuel cell. The share of each source is strongly influenced by operating conditions. Solar irradiation plays a primary role, as the PV output is directly proportional to the available solar resource; thus,

reduced irradiation lowers the PV share. Another key factor is the temporal distribution of the load. When electricity consumption during nighttime or low-irradiation hours is reduced, the share of PV increases. Consequently, in months with lower 24-hour space heating or cooling requirements, the PV contribution becomes more significant.

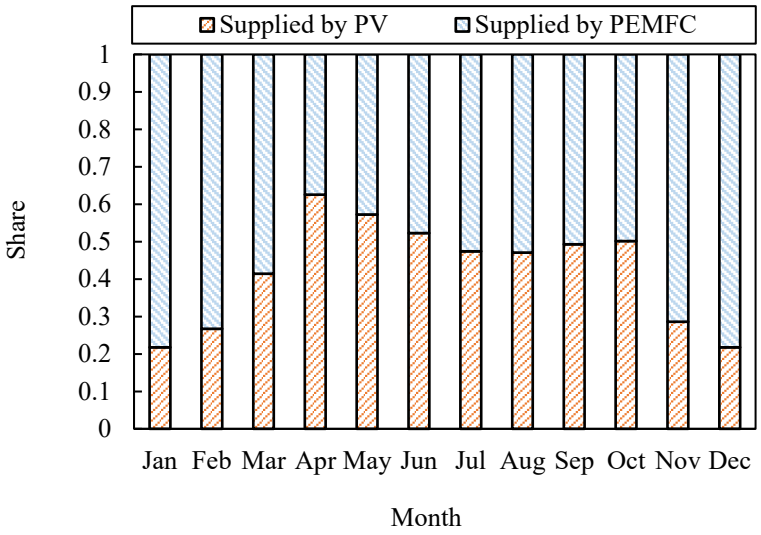


Fig. 3. *The contribution of the PV system and the fuel cell to energy supply*

The PV system capacity and the storage volume are two critical parameters that significantly impact energy efficiency, LCOE, and LOLP. As the most expensive component in PV-HES systems, the storage tank plays a major role in determining LCOE. Selecting the right storage volume not only influences system cost but also ensures a continuous fuel supply to the fuel cell and provides adequate capacity for the hydrogen produced by the electrolyzer. Likewise, PV capacity is directly related to the number of installed modules and, consequently, the solar collection area. A larger PV area leads to higher solar energy absorption, which directly impacts the input energy and thereby affects the overall energy efficiency. Figure 4 illustrates the influence of PV capacity and storage volume on LCOE. As shown, increasing the number of PV panels leads to only a marginal rise in LCOE, whereas enlarging the storage volume results in a pronounced linear increase. In contrast, Figure 5 shows that energy efficiency decreases exponentially with the addition of PV panels, while storage volume has only a minor effect on it.

Figure 6 indicates the monthly value of energy efficiency for the optimal configuration. It fluctuates significantly over the year, reaching a maximum of 17.8% in December and a minimum of 4% in April. These variations are governed by both the availability of solar energy and the degree of alignment between the consumption profile and PV power generation. The decline in efficiency under high solar radiation conditions is attributed to the fact that the increase in usable power does not scale proportionally with the rise in radiation. Similarly, when peak demand occurs during off-solar hours, a larger share of the load must be supplied through storage, which reduces efficiency. The localized increase in efficiency observed from May to July highlights the beneficial overlap between peak cooling demand and peak solar availability, enabling more direct utilization of PV output. It should also be noted that the integration of storage inherently reduces overall efficiency due to additional energy conversion steps and associated losses.

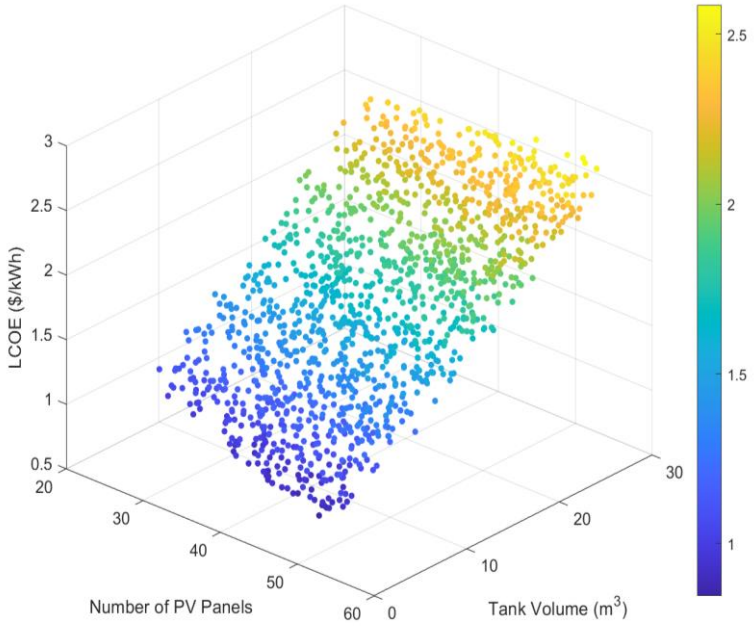


Fig. 4. *Effect of PV capacity and storage volume on LCOE*

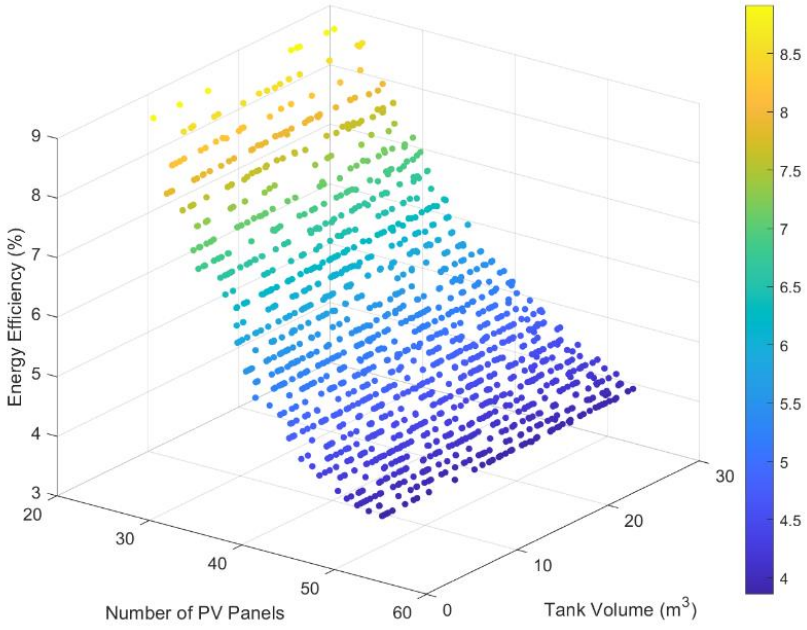


Fig. 5. *Effect of PV capacity and storage volume on system energy efficiency*

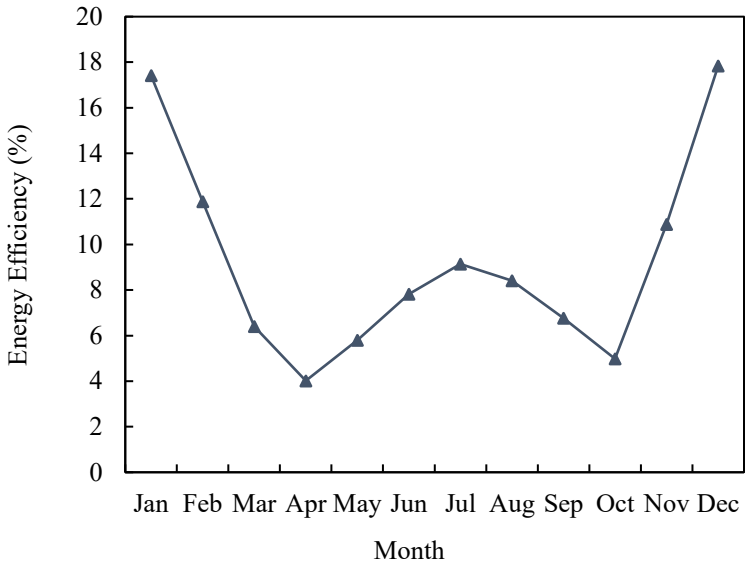


Fig. 6. *Monthly energy efficiency profile*

4. CONCLUSIONS

This study presented a multi-objective optimization framework for a photovoltaic–hydrogen energy storage system designed to supply residential electricity demand in Yazd, Iran. By combining dynamic simulations in TRNSYS with surrogate neural network models and a genetic algorithm, the framework identified an optimal configuration that achieves full load coverage with an LCOE of $0.40/kWh and an overall energy efficiency of 8.53%. The results revealed critical trade-offs: while increasing storage volume sharply raises system cost, oversizing the PV array reduces energy efficiency.

These findings demonstrate that cost-optimal solutions are not necessarily energetically optimal, underscoring the need for multi-objective approaches in renewable energy systems design. Future research should explore hybrid approaches combining HES with short-term battery storage or demand-side management to improve system performance. Expanding the framework to consider environmental impacts and sector coupling could further enhance the role of HES in sustainable energy transitions.

REFERENCES

[1] *M. Gandomzadeh* et al., *Dust mitigation methods and multi-criteria decision-making cleaning strategies for photovoltaic systems: Advances, challenges, and future directions,* Energy Strategy Reviews, *Vol. 57, p. 101629, 2025.*

[2] *M. Karami, Z. Piryaei, H. Abdolmaleki, and S. H. Shirazian, Application of Photovoltaic-Thermal Collectors in Energy Management Systems Integrated with Hydrogen Production, Storage, and Utilization, in* The Role of Exergy and Energy in Sustainability, *M. Z. Sogut, Ed. Cham: Springer Nature Switzerland, 2025, pp. 163–215.*

[3] *S. Akbarnejad, Z. Piryaei, Y. Alvari, P. Shahidi, G. Lavasani, and M. Zandi, A Comparative Study on Different Energy Storage Scenarios in an Off-Grid Dark Vertical Greenhouse, in* 2025 10th International Conference on Technology and Energy Management (ICTEM), *2025, pp. 1–6.*

[4] *Z. Piryaei, A. Gholami, and M. Zandi, 4E performance evaluation of renewable microgrids: Comparing hydrogen and battery storage for nearly net zero energy buildings,* Energy Conversion and Management*, Vol. 332, p. 119711, 2025.*

[5] *M. Karami, M. M. Asghari, and Z. Piryaei, Energy and exergy-based sizing optimization of a stand-alone hybrid renewable energy system. Zenodo, Dec-2024.*

[6] *M. Kharrich, O. Hazem Mohammed, M. Y. Suliman, and M. Akherraz, A review on recent sizing methodologies for hybrid microgrid systems,* International Journal on Energy Conversion*, Vol. 7, No. 6, pp. 230–240, 2019.*