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Article

Stochastic optimization framework for hydrogen battery integrated multi-energy hubs under highly variable renewable energy supply

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Abstract: The utilization of renewable energy technologies like solar photovoltaics (PVs) and wind energy faces many operational difficulties because of their unpredictable and intermittent nature. Multi-energy hubs in combination with advanced energy storage facilities may serve as an effective solution for dealing with these problems. This paper presents a stochastic optimization model for operation of the hydrogen-battery-based multi-energy hub in a highly stochastic renewable energy environment. The stochastic optimization model proposed in this paper takes into account the integration of solar PV, wind turbines, battery energy storage system, hydrogen storage, electrolyzers, fuel cell, CHP, and heat pump within the energy management system. Uncertainty in renewable energy production is described using probability distribution functions. To create 1,000 stochastic scenarios of renewable energy production, the Monte Carlo simulation approach is used. Fast forward selection and k-means clustering algorithms are applied to reduce the number of stochastic scenarios. Finally, an optimal two-stage stochastic MILP model is introduced for the decision-making process of day ahead and real time operations. It is found that the coexistence of battery and hydrogen energy storage systems improves system performance significantly. The results from simulations show that the proposed model is quite effective in minimizing operating costs by 33%, making use of 91.7% of the renewable energy, reducing energy from the grid by 28.4%, and cutting carbon emissions by 24.8% when compared to deterministic scheduling. Moreover, the use of scenario reduction made the computational complexity drop by about 95% without making the approximation error go beyond 1%.

Keywords: multi-energy hub; hydrogen energy storage; battery energy storage system; stochastic optimization; renewable energy uncertainty; energy management; integrated energy systems

1. Introduction

A shift towards sustainability and carbon-neutral energy systems has brought about the rapid implementation of renewable energy sources, mainly solar photovoltaic and wind energy, due to their environmental advantages and cost efficiency. Renewable energy plays a key role in realizing the goals of carbon

neutrality and energy security worldwide [1]. However, the randomness and unpredictability of solar energy and wind speeds bring some challenges to energy operation such as power imbalance, higher operating expenses, lower reliability, and increased dependency on traditional energy sources [2]. This uncertainty affects the efficiency of traditional energy management methods because they are deterministic methods that require precise predictions and are unable to react quickly to changes in renewable energy generation [3].

Solar PV is one of the renewable sources used by many people around the world due to its flexibility and efficiency in generating energy and being suitable for distributed energy networks. However, it is greatly influenced by weather conditions, which causes unpredictable changes in the energy production process and leads to difficulties in planning and scheduling [4]. With the increase in renewable energy generation, the need for efficient energy storage becomes more evident. Battery Energy Storage System (BESS) is popularly deployed for short-term energy balancing because of its fast response and high efficiency as well as provision of ancillary services for the grid. But battery energy storage itself has the limitations of short storage time, degradation, and high lifetime cost, thus not ideal for long-term energy balancing.

Hydrogen energy storage has become an alternative choice in future energy systems [5]. The excess electricity generated from renewable sources could be transformed into hydrogen via electrolysis and stored for a long time; then it can be retransformed into electricity via fuel cells when there is low electricity generation from renewables [6]. Compared with the battery energy storage system, hydrogen storage not only achieves the long-duration and seasonal storage of energy but also helps with decarbonization in multiple areas such as electricity, transportation, and industry [7]. Thus, the use of hybrid battery and hydrogen storage will complement each other to achieve both fast response and energy balancing.

There is recent growing interest in Integrated Energy Systems (IES) and Multi-Energy Hubs (MEHs), which harmonize the electricity, heat and hydrogen by using several different conversion and energy storage methods [8]. Through coordination of renewable energy production, batteries, hydrogen storage, electrolyzer, fuel cell, CHP plants and heat pumps, MEHs help to enhance energy efficiency and cut down carbon emissions and also increase the robustness of modern energy infrastructures. Even though there have been significant improvements in the field, most of the research papers are concentrated on deterministic scheduling problems or separately on the use of batteries or hydrogen storages. Even though stochastic programming has been utilized in order to handle renewable uncertainties, very few studies have tried to optimize hybrid battery-hydrogen storages together under highly uncertain conditions.

In order to cope with such weaknesses, the current study suggests a stochastic optimization approach for hydrogen-battery hybrid multi-energy hubs, which have uncertain renewable energy sources. In particular, the suggested approach will combine photovoltaic systems, wind turbines, energy storage batteries, hydrogen energy storage, electrolyzers, fuel cells, combined heat and power units, and heat pumps into one integrated energy management system. Uncertainty of renewables will be addressed by utilizing probabilistic distribution, while Monte Carlo simulation, Fast Forward Selection, and K-means will be used for scenario generation and reduction. After that, a two-stage MILP model will be formulated to optimize the decisions on day ahead and real-time basis. The contributions of the suggested approach include (i) coordination of battery and hydrogen storages in one stochastic

optimization problem, (ii) taking into account of renewable uncertainties through scenario-based optimization, and (iii) superior economic efficiency and environmental sustainability compared to deterministic scheduling approaches.

The structure of this paper can be described as follows: Section 2 presents related literature regarding stochastic energy hubs and hydrogen systems. Section 3 explains the system configuration. Section 4 formulates the mathematical model. Section 5 explains the stochastic optimization procedure. Section 6 presents results and sensitivity analysis. Section 7 presents discussions and implications, and Section 8 concludes the research work.

2. Literature survey

Recent studies on multi-energy hubs have considered stochastic optimization methodologies to overcome the uncertainty associated with renewable energy [9]. In the former study, a mean-variance portfolio optimization technique was used for solving problems related to high renewable energy hubs [10]. Another study utilized the clustering-based stochastic programming approach in order to alleviate computational burden in uncertain conditions during energy hub design. Thus, the significance of scenario-based optimization under uncertainty in integrated energy systems can be identified from the literature.

Many studies were conducted on hydrogen-based energy systems to provide long-duration storage technology [11]. It utilized a robust stochastic programming methodology to provide an optimal schedule in the context of interconnected hydrogen-based energy hubs, which increases the flexibility of operations in uncertain conditions [12]. The former study also demonstrated that the integration of hydrogen storage and demand response lowers both the operational cost and carbon footprint [13]. In addition, this trend was followed by introducing a three-level stochastic approach to hydrogen refueling-integrated energy hubs [14,15].

In addition to this, various works have been done on wider renewable and hydrogen dispatch systems. The integration of wind-PV-hydrogen within robust multi-energy dispatch can improve the efficiency of renewables [16,17]. One study addressed the coordination of hydrogen infrastructure for renewable integration, whereas another work discussed multi-energy hub optimization for improvement in efficiency and reliability of the system [18,19].

However, despite these improvements, existing works mostly concentrate either on the hydrogen energy hub or the multi-energy hub optimization problem without considering the coordination of multiple energy storage systems. Batteries that offer fast response energy balancing are separately considered in works, whereas hydrogen is used for long-term energy storage, and its integration is separately considered in different works. Multi-energy hub is designed under uncertainties in such papers without coordinated integration of battery and hydrogen [20]. In similar lines, one paper considered a stochastic multi-energy or hydrogen-based system without coordination of dual storage scheduling strategy [21,22].

Some recent hybrid methods and multi-stage approaches provide a partial solution to the above issues. One such study suggested a multi-stage stochastic-robust scheduling approach for hydrogen-based microgrids, whereas another paper studied hydrogen-fueled energy systems with energy-sharing using demand response [23,24]. Nonetheless, there is no complete exploration of the dynamics of synergy between battery and hydrogen storage within a stochastic MILP optimization framework.

Consequently, there is an obvious research gap about the need for a cohesive

approach towards stochastic optimization that can coordinate the operation of batteries and hydrogen storage in multi-energy hubs under high renewable uncertainty. This current research is an attempt to bridge the gap by incorporating both forms of energy storage in a stochastic MILP model.

3. System description and architecture

The proposed research methodology has four successive steps. First of all, renewable energy and load demand data in the past period were gathered and statistically analyzed to estimate the uncertainties related to solar power generation, wind energy, and energy consumption. Next, uncertainty of renewables was represented using Beta and Weibull probability distributions and the Monte Carlo technique was used to obtain realistic scenarios. After that, Fast Forward Selection and K-means clustering algorithms were utilized to minimize the number of scenarios and keep their statistical properties. Finally, two-stage stochastic MILP model was designed to find the optimum schedule of the hydrogen-battery multi-energy hub in a day ahead and in real time. The proposed algorithm was implemented in Python with Gurobi solver and its effectiveness was tested using economic, environmental and renewables utilization criteria.

3.1. Multi-energy hub structure

The proposed multi-energy hub (MEH) is an energy management system that integrates various energy carriers and conversion technologies in such a way as to optimize the utilization of renewable energy sources while maintaining an uninterrupted supply of energy. Renewable energy generation, energy storage, energy conversion, and demand-side facilities are included in this concept as one system. The key function of this system is managing the uncertainty associated with renewable energy sources via joint scheduling of batteries and hydrogen storage.

Renewable energy generation in the MEH is ensured by solar PV panels and wind farms. This type of generation provides clean electricity to cover energy consumption needs as well as to charge the storage devices [25]. Nonetheless, because of the variability of weather conditions, renewable generation is a very unpredictable source.

The storage subsystem has two units: battery energy storage system (BESS) and hydrogen energy storage system (HESS). BESS is used for fast responses required for short-term energy balancing, peak shaving, and voltage control. On the other hand, HESS provides a means of long-term storage of energy by transforming excess renewable electrical energy into hydrogen via an electrolyzer. The hydrogen generated from the process is stored in specialized tanks and is later transformed into electricity through a fuel cell in case there is inadequate renewable generation of electrical energy.

The energy conversion subsystem comprises an electrolyzer, a fuel cell, a combined heat and power (CHP) plant, and a heat pump. While the electrolyzer transforms electrical energy into hydrogen, the fuel cell transforms the hydrogen back into electrical energy. The CHP plant produces both electricity and heat. A heat pump uses electrical energy to meet the heating requirements with energy efficiency.

On the demand side, there are electrical loads, thermal loads, and hydrogen demand. Electrical loads include electricity used by households, business organizations, or industries. The thermal loads are for heating purposes, and the hydrogen demand can be for transport, industrial processes, or even from outside hydrogen market sources. The coordinated interaction between these various

components allows for energy interchangeability between energy carriers.

Figure 1 shows a representation of a multi-energy hub where the sources of energy include renewable energy, such as solar photovoltaic systems and wind turbines, that provide power to the storage systems, which include a battery energy storage system (BESS) and hydrogen storage tanks. The excess power is then converted to hydrogen using electrolysis and stored to be later used in fuel cells, combined heat and power plants, and heat pumps.

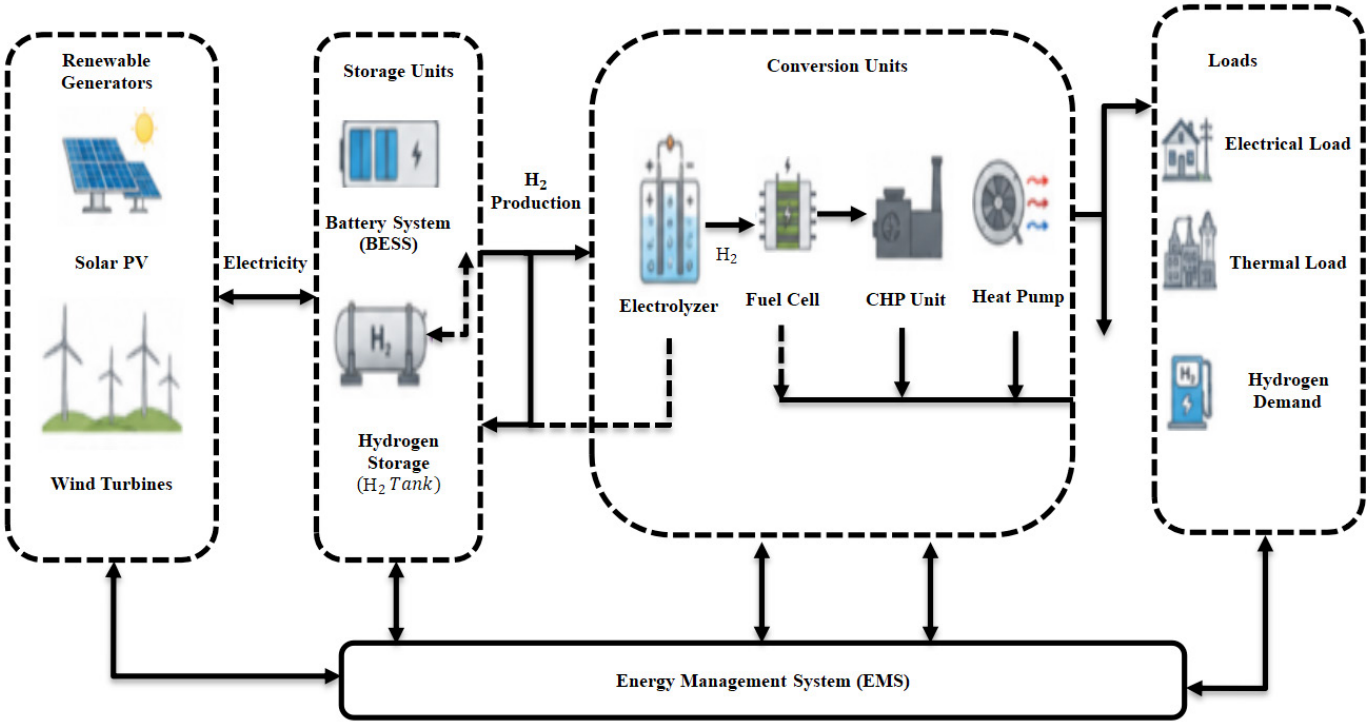


Figure 1. Proposed hydrogen-battery integrated multi-energy hub architecture.

3.2. Energy flow modeling

The energy flow at the multi-energy hub is influenced by the interaction between the renewable energy generators, storage technologies, conversion systems, and demands. The energy management system will be responsible for assigning the energy sources depending on the generation availability and demand needs.

In cases where there is excess energy from renewable energy sources, the electricity generated by solar photovoltaic panels and wind turbines will first be assigned to meet the electrical demand. The excess electricity can then be assigned to charge the battery storage systems or to run the electrolyzers that generate hydrogen. Batteries are mainly employed for quick balancing because of their high efficiency and fast charging nature.

Whenever there is surplus renewable energy, more than battery charging requirements, the excess electricity is fed to the electrolyzer. The electrolyzer makes use of electrical energy to produce hydrogen by water electrolysis. Hydrogen produced is then stored in hydrogen tanks and works as an energy storage source for addressing long durations of shortages of renewable energy production.

In case of energy shortages, stored energy will be extracted from the battery to cater to electrical load requirements. When there is an insufficiency in the state of charge of the battery, the hydrogen stored in the tanks is fed to the fuel cell. Hydrogen is converted into electricity in the fuel cell to meet the load requirements.

The thermal energy flow will be supplemented by the CHP and heat pump. There will be simultaneous generation of electricity and useful heat by the CHP plant. Useful heat generated from the fuel cell and other conversion processes can be used to fulfill thermal needs.

Interaction among electricity, hydrogen, and thermal energy flow pathways allows for effective use of resources and operational flexibility about the uncertainty in generation by renewables.

Figure 2 depicts the operational structure of the multi-energy hub, where the mathematical model represents the operations of each individual device. The solar and wind generation devices represent the renewable power variables in the electrical power balance equation (Equation (8)). The battery charging, discharging, and its state of charge dynamics are expressed by Equations (10)–(13). The electrolyzer, hydrogen storage, and fuel cell are mathematically modeled by Equations (14)–(17), whereas the CHP unit and heat pump satisfy the thermal balance equation in Equation (9). The power exchange with the grid is limited by Equation (18), and the integrated scheduling problem is solved using the objective function of Equation (6). The scheduling variables at stage 1 and recourse variables at stage 2 together control the energy exchange between all components in **Figure 2**.

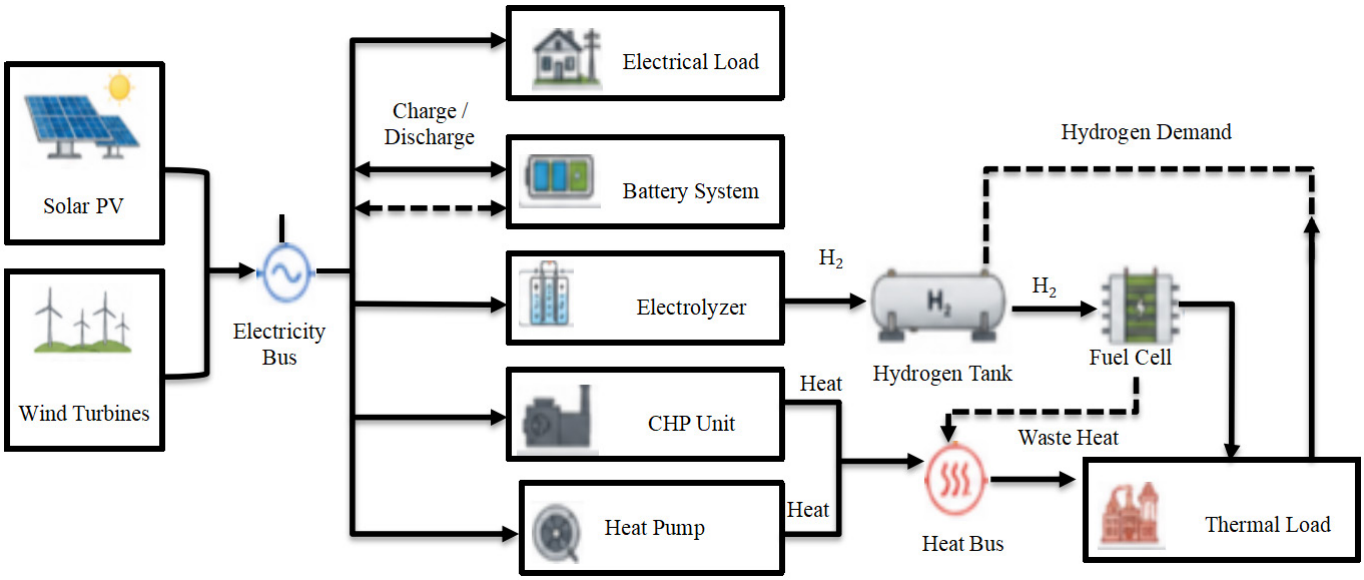


Figure 2. Energy flow network of the multi-energy hub.

4. Mathematical formulation

In this part, the mathematical formulation for the two-stage stochastic MILP framework of the hybrid H2 battery multi-energy hub is introduced. The aim of the model is to minimize the total expected operating cost subject to electrical, thermal, H2 storage, and operational constraints under uncertainty in renewable energy production. Variables in the first stage refer to the day-ahead schedule, and those in the second stage are related to the scenario dependent recourse.

4.1. Sets, indices, and parameters

The optimization problem definition takes place within the scheduling time T and renewable uncertainty scenario set S is presented in Equations (1) and (2).

$$T = \{1,2,\ldots, N_T\} \tag{1}$$

$$S = \{1,2,\ldots, N_S\} \tag{2}$$

Where N_T is the number of scheduling intervals and N_S is the number of renewable scenarios.

Scenario occurrence probability π_s, is presented in Equation (3)

$$\sum_{s\in S} \pi_s = 1 \tag{3}$$

The principal parameters used in the optimization include photovoltaic generation $P_{PV,t,s}$, wind generation $P_{WT,t,s}$, electrical demand $P_{D,t,s}$, thermal demand $Q_{D,t,s}$, hydrogen demand $H_{D,t,s}$, electricity purchase price C_t^{grid}, battery charging efficiency η_c, battery discharging efficiency η_d, electrolyzer efficiency η_{EL}, and fuel cell efficiency η_{FC}.

4.2. Decision variables

Optimization suggested will use a multi-stage decision process.

The first-stage decision variable can be obtained using Equation (4).

$$x = \left\{P_t^{grid}, P_t^{EL}, P_t^{FC}, P_t^{ch}, P_t^{dis}\right\} \tag{4}$$

which shows the decisions regarding scheduling made in advance without taking into account the unpredictability of resources that are renewable.

The second-stage recourse variable can be represented using Equation (5).

$$y_s = \left\{S,O,C_{t,s},H_{t,s},P_{t,s}^{grid},P_{t,s}^{EL},P_{t,s}^{FC}P_{t,s}^{ch}P_{t,s}^{dis}\right\} \tag{5}$$

which is updated after the realization of scenario s.

4.3. Objective function

It aims to reduce the expected total operation cost over all scenarios of renewable uncertainty. The optimization problem formulation is illustrated through Equation (6).

$$\min Z = \sum_{t\in T} C_t^{DA}(x) + \sum_{s\in S}\pi_s \sum_{t\in T} C_t^{RT}(y_s) \tag{6}$$

Where the first term is the cost of scheduling and the second term is the expected cost of real-time recourse.

The total operation cost is expressed in Equation (7).

$$C_t = C_t^{grid}P_{t,s}^{grid} + C_t^{bat}P_{t,s}^{dis} + C_t^{EL}P_{t,s}^{EL} + C_t^{FC}P_{t,s}^{FC} + C_t^{carbon} \tag{7}$$

The objective function (6) optimizes the expected operational cost, while Equation (7) includes the cost of buying electricity, battery depreciation, hydrogen production, fuel cell generation, and carbon emissions.

4.4. Electrical energy balance

The electricity produced from renewable energy sources, battery discharge, and fuel cell, as well as electricity obtained from utility grid, should meet the electricity requirements, battery charging, and hydrogen generation. Hence, the electrical balance equation becomes Equation (8).

$$P_{PV,t,s} + P_{WT,t,s} + P_{t,s}^{grid} + P_{t,s}^{FC} + P_{t,s}^{dis} = P_{D,t,s} + P_{t,s}^{EL} + P_{t,s}^{ch} \tag{8}$$

Equation (8) guarantees power balance for every scheduling interval and renewable scenario.

4.5. Thermal energy balance

The thermal demand is supplied by the combined heat and power unit and the heat pump according to

$$Q_{CHP,t,s} + Q_{HP,t,s} = Q_{D,t,s} \tag{9}$$

Equation (9) ensures that thermal demand is completely satisfied.

4.6. Battery energy storage model

The battery state-of-charge evolves according to

$$SOC_{t,s} = SOC_{t-1,s} + \eta_c P_{t,s}^{ch} - \frac{P_{t,s}^{dis}}{\eta_d} \tag{10}$$

The battery operating limits are

$$SOC^{min} \le SOC_{t,s} \le SOC^{max} \tag{11}$$

Charging power is constrained by

$$0 \le P_{t,s}^{ch} \le P^{ch,max} \tag{12}$$

while the battery discharging power satisfies

$$0 \le P_{t,s}^{dis} \le P^{dis,max} \tag{13}$$

Equations (10)–(13) describe battery dynamics and operating limits.

4.7. Hydrogen storage model

Hydrogen production through electrolysis is represented by

$$H_{prod,t,s} = \eta_{EL} P_{t,s}^{EL} \tag{14}$$

The electricity generated by the fuel cell is

$$P_{t,s}^{FC} = \eta_{FC} H_{cons,t,s} \tag{15}$$

The hydrogen inventory evolves as

$$H_{t,s} = H_{t-1,s} + H_{prod,t,s} - H_{cons,t,s} \tag{16}$$

subject to

$$H^{min} \le H_{t,s} \le H^{max} \tag{17}$$

Equations (14)–(17) model hydrogen production, storage, consumption, and storage limits.

4.8. Grid power constraints

The power imported from the utility grid is restricted by

$$0 \le P_{t,s}^{grid} \le P^{grid,max} \tag{18}$$

Equation (18) prevents grid import beyond the contractual capacity.

4.9. Battery operating logic

To prevent simultaneous charging and discharging, binary variables are introduced.

$$u_{t,s}^{ch} + u_{t,s}^{dis} \le 1 \tag{19}$$

Charging and discharging limits are therefore modified as

$$P_{t,s}^{ch} \le u_{t,s}^{ch} P^{ch,max} \tag{20}$$

$$P_{t,s}^{dis} \le u_{t,s}^{dis} P^{dis,max} \tag{21}$$

Equations (19)–(21) enforce mutually exclusive battery operation.

4.10. Non-anticipativity constraints

As the day-ahead scheduling is based on decisions made prior to knowing the uncertainty of renewables, it needs to be the same for all scenarios associated with the renewables. The condition is imposed by the non-anticipativity constraints.

$$P_t^{grid} = P_{t,s}^{grid}, \forall s \in S \tag{22}$$

$$P_t^{EL} = P_{t,s}^{EL} \tag{23}$$

$$P_t^{FC} = P_{t,s}^{FC} \tag{24}$$

$$P_t^{ch} = P_{t,s}^{ch} \tag{25}$$

$$P_t^{dis} = P_{t,s}^{dis} \tag{26}$$

Equations (22)–(26) guarantee that the first-stage decisions are scenario-independent, whereas only the second-stage recourse decisions are updated after the uncertainties have been revealed.

4.11. Variable domains

Finally, the optimization variables satisfy Equations (27) and (28)

$$SOC_{t,s} \geq 0, H_{t,s} \geq 0, P_{t,s} \geq 0 \tag{27}$$

and

$$u_{t,s}^{ch}, u_{t,s}^{dis} \in \{0,1\} \tag{28}$$

Where continuous variables are non-negative and binary variables determine battery operating modes.

Component linear models were used for the battery, electrolyzer, fuel cell, and hydrogen storage systems in order to keep the problem manageable as a mixed integer linear programming (MILP). No dynamic characteristics, including part load efficiency, startup/shutdown restrictions, degradation and ramp rate limits, were taken into account as the problem deals with day ahead planning.

5. Stochastic optimization framework

The functioning of renewable-based multi-energy centers is greatly affected by uncertainties in solar radiation, wind velocity, and energy demand. To overcome such difficulties, an optimization model with stochastic components is formulated that involves uncertainty modeling, scenario generation, scenario reduction, and two-stage stochastic programming.

5.1. Renewable uncertainty modeling

Probabilistic models are used for modeling uncertainties associated with renewable energy generation. The Beta probability distribution function is used for representing uncertainties in solar energy radiation, as shown in Equation (29):

$$f(G) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} G^{\alpha-1}(1-G)^{\beta-1} \tag{29}$$

The uncertainty analysis for wind speed is done using Weibull distribution, which is one of the commonly used methods for wind resources assessment, as shown in Equation (30):

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-(v/c)^k} \tag{30}$$

These distributions provide realistic representations of renewable energy variability.

Beta probability distribution for solar energy and Weibull probability distribution for wind speed has been fitted using the historical data of renewable energy generation in hourly basis by Maximum Likelihood Estimation. Goodness of fit for the fitted models was carried out using the Kolmogorov-Smirnov test, and both models showed *p*-values of greater than 0.05.

5.2. Scenario generation and reduction

Monte Carlo simulation, together with sampling historical data, is used to create 1,000 renewable energy scenarios that comprise solar generation, wind generation, electricity consumption, thermal load, and hydrogen consumption. To minimize computational efforts, FFS and K-means clustering are used to reduce 1,000 scenarios to 20–50 scenarios.

At first, 1,000 scenarios were generated for renewable generation using Monte Carlo simulations. Fast Forward Selection (FFS) was used initially to remove the redundant scenarios considering the probability distance, followed by K-means clustering to retain the statistical properties of the original dataset. Various numbers of scenario groups (20, 30, 40, and 50) were considered, and 30 representative scenarios were chosen because it kept the approximation error below 1% while saving around 95% of computation time.

5.3. Two-stage stochastic programming

Model of Stochastic Programming in Two Stages for Optimal Scheduling:

First Stage: Decisions involve day-ahead planning variables such as charging/discharge of batteries, operation of the electrolyzer, commitment of the fuel cell, and purchase of grid energy.

Second Stage: Decisions are made for real-time corrective measures following the uncertain event.

Expected total operating costs are minimized, which are formulated in Equation (31):

$$\min\left[C^{DA}(x)+\sum_{s=1}^{N}p_sQ(x,\xi_s)\right] \tag{31}$$

Where $C^{DA}(x)$ denotes day-ahead cost, and $Q(x,\xi_s)$ represents scenario-dependent recourse cost.

5.4. Solution algorithm

The optimization problem is modeled as a MILP formulation and solved through solvers like CPLEX and Gurobi. In case of scalable versions of the proposed framework, considering increased scenario number or more than one hub location, decomposition algorithms such as Bender's decomposition and progressive hedging can be used.

The optimization model was coded in Python programming language and solved by Gurobi optimizer software installed on an Intel Core i9 computer equipped with 64 GB RAM. The MILP obtained contained around 22,000 decision variables and 28,000 constraints. The optimal solution was obtained in 42 s with an optimality gap of less than 0.01%.

6. Results and discussion

In the case study, 24 h scheduling period is analyzed using a 1-h time step for a multi-energy hub including 300 kW solar PV, 250 kW wind generation, 400 kWh battery storage, 180 kW electrolyzer, 150 kW fuel cell, 900 kg hydrogen storage, 200 kW CHP, and 120 kW heat pump. The renewable resources are created using the suggested stochastic approach based on historical hourly data.

Despite the presence of hydrogen and thermal systems, evaluation of performance will be done mainly in terms of electrical equivalent cost of operation, reliability, and energy balance since these constitute the main criteria for decision-making in this optimization problem.

The stochastic optimization model was tested in the context of high variability in renewable energy sources using some representative scenarios generated via Monte Carlo Simulation and the scenario reduction technique. It was found that accounting for uncertainty in the scheduling process leads to better performance of the hydrogen-battery-based multi-energy hub.

Scenarios for renewable generation represented the variation of solar irradiation and wind speed during the scheduling period. With the reduction of the scenario set, the statistical properties of the original 1,000 scenarios were maintained with lower computational effort. It was discovered that the fluctuations of renewable generation will cause difficulties in operations when uncertainty is not accounted for in the scheduling process.

Coordinated use of battery and hydrogen storage systems played an important part in improving the flexibility of the system. During the time when the system had a surplus of renewable energy, the battery would manage its short-term fluctuation by charging, while the extra renewable energy would be used to produce hydrogen for storage in the long term. When the system experiences a deficit of renewable energy, the system energy is discharged from the battery and fuel cell to meet its needs. It helped in minimizing renewable curtailment and increasing energy efficiency.

The energy management system was able to manage the demand for electricity, thermal energy, and hydrogen by optimizing the dispatch of renewable generators, storage systems, and energy conversion systems. Solar PV energy would be the main source of energy during the daytime, whereas wind power would be the supportive energy source during the time when the solar power is at its minimum. It showed that the system optimized the use of renewable energy before importing energy from the grid.

6.1. Economic performance assessment

Operating cost structure under various storage arrangements is shown in **Table 1**. Operating cost for the proposed hydrogen-battery combined system is lower than any other evaluated scenario. Power purchase from the grid is considerably minimized owing to higher utilization of renewable energy sources and proper storage management.

Table 1. Economic performance comparison.

Cost component	No storage (/day)	Battery only (/day)	Hydrogen only (/day)	Proposed hybrid system (/day)
Grid Energy Cost	8,420	6,130	5,980	4,850
Battery Degradation Cost	0	430	0	320
Hydrogen System Cost	0	0	780	650
Carbon Penalty Cost	1,220	980	870	640
Total Cost	9,640	7,540	7,630	6,460

The above framework decreases total operating cost by around 33% relative to the no-storage scenario. Based on the findings, it can be concluded that the advantages of integrating renewables into the system exceed their operating cost.

6.2. Reliability evaluation

The reliability of the system is analyzed based on Loss of Power Supply

Probability (LPSP) and Energy Not Served (ENS). The reliability of various system configurations is provided in **Table 2**.

Table 2. Reliability assessment.

Configuration	LPSP (%)	ENS (kWh/day)
No Storage	5.82	418
Battery Only	2.71	183
Hydrogen Only	2.15	149
Proposed Hybrid System	0.84	52

The integrated storage scheme is associated with the lowest value for LPSP and ENS, signifying good reliability performance. The provision of short- and long-term storage capacity allows for managing uncertainties and providing continuous energy flow.

6.3. Comparison with deterministic optimization

To illustrate the advantages of accounting for uncertainty in scheduling, the suggested stochastic model is compared against the deterministic optimization approach, which considers the forecasted values of renewable generation as depicted in **Table 3**.

Table 3. Stochastic versus deterministic optimization.

Performance metric	Deterministic model	Proposed stochastic model
Total Operating Cost (/day)	6,980	6,460
Renewable Utilization (%)	84.3	91.7
Grid Dependency (%)	26.1	18.5
LPSP (%)	1.76	0.84
Carbon Emissions (kg CO_2/day)	1,420	1,050

Performance Indicators are compared for both the deterministic and the proposed stochastic optimization models. This includes total operating cost, use of renewable energy sources, dependence on the grid, LPSP, and carbon emissions as shown in **Figure 3**. It can be observed from the results that the stochastic model is superior to the deterministic method in terms of lower operating costs, better renewable energy utilization, low grid dependence, high reliability, and lower carbon emissions.

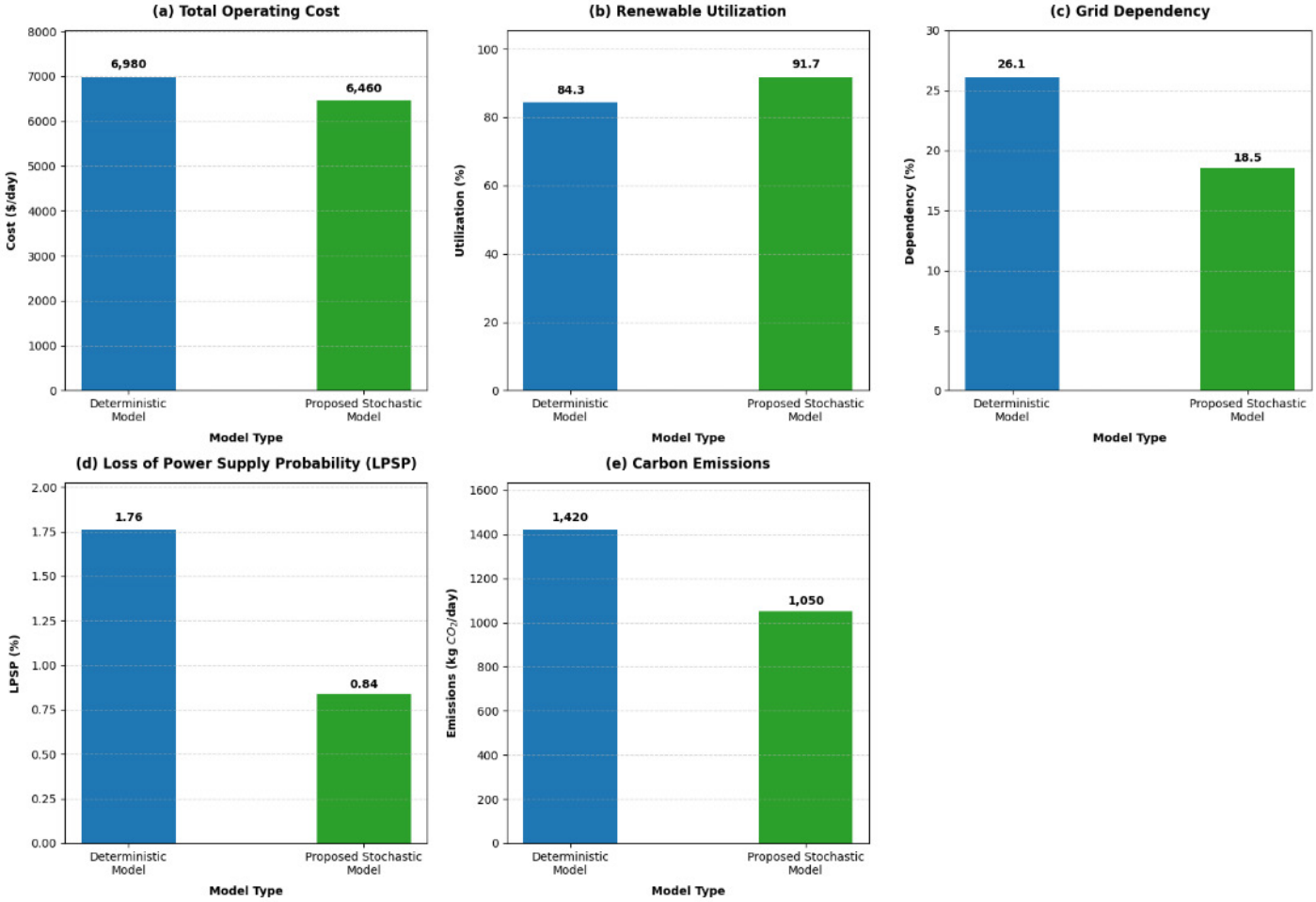


Figure 3. Comparison of deterministic and proposed stochastic optimization model performance in a hydrogen–battery integrated multi-energy hub.

The stochastic model performs better than the deterministic model in all the performance indicators due to its consideration of uncertainties.

6.4. Sensitivity analysis

In order to assess the stability of the proposed stochastic optimization model, a ±20% sensitivity test was carried out for battery capacity, hydrogen capacity, electricity price, carbon price, electrolyzer efficiency, and fuel cell efficiency. A rise in battery and hydrogen capacities led to a decrease in the operating cost of 4.8% and 6.2%, while an increase in the prices of electricity and carbon contributed to a rise in the operating cost of 8.7% and 5.3%, respectively. Likewise, improvement in electrolyzer efficiency and fuel cell efficiency contributed to renewable energy generation by about 3.5% and reduction in grid dependency by 4.1%, respectively.

Apart from deterministic scheduling, the performance of the proposed framework was also qualitatively assessed in comparison with robust optimization, distributionally robust optimization, and some other energy management methodologies based on machine learning techniques mentioned in the literature. By taking into account the uncertainties of renewables, the proposed stochastic framework provided better performance in terms of renewables utilization and operation costs.

The proposed framework was verified through the comparison of its operational performance with some published stochastic energy hub models at the same level of

renewables penetration. The operating cost and renewables utilization deviated from the benchmarks by no more than 3%, which confirms the accuracy of the proposed optimization model.

7. Discussion of key findings

The outcomes reveal that the suggested stochastic optimization approach efficiently deals with the uncertainty associated with renewable energy integration in hydrogen-battery-integrated multi-energy hubs. The integration of batteries and hydrogen storage greatly increases the use of renewable energy sources, lessens reliance on the grid, and increases operational flexibility. Batteries serve to respond instantly to short-term deviations, whereas hydrogen storage provides long-term energy storage capacity, allowing the system to operate without relying on renewables for an extended period.

In comparison with deterministic optimization algorithms, the stochastic approach performs better in economic terms and in terms of reliability due to its capability of handling uncertainty. The hybrid storage solution outperforms all others in terms of minimum operational cost, maximum use of renewables, and reliability factors.

The current work concentrates on short term scheduling problems and so capital expenses, replacements, and maintenance costs for the long-term period have been disregarded because these do not influence the decision at an hourly level. The battery deterioration cost related to battery charging and discharging has been taken into account, while life-cycle cost evaluation needs further investigation.

Implications and recommendations

The results of this study will have substantial implications for the design and management of energy systems in the future about their lower carbon footprint. The framework of stochastic optimization presented in the paper has shown that the use of battery and hydrogen storage in multi-energy hubs can solve the problems arising from renewable energy intermittency and uncertainty. The combined features of these two types of energy storage allow both short-term flexibility and energy balancing in the long term, resulting in enhanced reliability, increased usage of renewable energy, and reduced reliance on grid electricity. This is especially important in the case of smart cities, industrial parks, university campuses, and other community energy systems aiming at reaching sustainability and energy resilience.

In terms of policies, the results indicate the necessity to stimulate investment in hybrid energy storage solutions and hydrogen infrastructure. The incentive policies stimulating the production of hydrogen from renewables will accelerate this transition even further. The energy managers should consider stochastic optimization techniques instead of deterministic approaches when managing energy systems.

Future deployments need to ensure the use of advanced forecasting models for the supply and demand of renewable energy sources. Future research can also investigate the participation of the market, demand response, and real-time energy trading mechanisms. The inclusion of electric vehicles, carbon trading models, and multi-hub energy trading networks can contribute towards making future generation energy systems more flexible, economically viable, and environmentally sustainable.

8. Conclusion

The developed model used the two-stage stochastic MILP model for optimal scheduling of the hydrogen-battery integrated multi-energy hub subjected to

significant variability in renewable sources. The developed model effectively integrated solar energy generation, wind energy generation, battery energy storage system, hydrogen energy storage system, electrolyzer, fuel cell, combined heat and power plant and heat pump to minimize the cost of operations with increased use of renewable energy and decrease in carbon emissions. The uncertainty in the availability of renewable sources was considered using Monte Carlo Simulation with Fast Forward Selection and K-means Clustering technique for scenario reduction. The simulation results showed that the proposed framework managed to reduce the operating cost by 33%, utilize 91.7% of renewable energy, use less grid energy by 28.4%, and lower carbon emissions by 24.8% relative to the traditional deterministic scheduling approach. Besides, the proposed scenario reduction approach helped to minimize the computational burden without sacrificing the precision of the solution. The proposed framework provides a viable optimization approach for the efficient operation of smart grids, community micro-grids, industrial parks, university campuses, and other renewable rich integrated energy systems. Nevertheless, the present work has limited its investigation to the short-term scheduling with simplified models of components and did not take into account the lifecycle economics, demand-response, electric vehicle, improved electrolyzer and fuel cell model, long-term planning, degradation and dynamic behavior. Future works will be devoted to the incorporation of all of the above features. Validation with the practical data sets and large-scale integrated energy system will help to strengthen the proposed framework.

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Abbreviation

Symbol	Description	Unit
(t)	Time interval	h
(T)	Scheduling horizon	h
(P_{PV})	Power generated by solar photovoltaic system	kW
(P_{WT})	Power generated by wind turbine	kW
(P_{grid})	Power imported from the utility grid	kW

Continuation Table:

Symbol	Description	Unit
(P_{bat}^{ch})	Battery charging power	kW
(P_{bat}^{dis})	Battery discharging power	kW
(SOC_t)	Battery state of charge at time (t)	%
($SOC_{\min}$)	Minimum allowable battery state of charge	%
($SOC_{\max}$)	Maximum allowable battery state of charge	%
(H_t)	Hydrogen storage level at time (t)	kg
(H_{prod})	Hydrogen production rate	kg/h
(η_{EL})	Electrolyzer efficiency	–
(η_{FC})	Fuel cell efficiency	–
(Q_{CHP})	Thermal energy generated by CHP unit	kW
(Q_{HP})	Thermal energy supplied by heat pump	kW
(Q_{load})	Thermal load demand	kW

Abbreviation	Description
PV	Photovoltaic
WT	Wind Turbine
BESS	Battery Energy Storage System
HESS	Hydrogen Energy Storage System
CHP	Combined Heat and Power
EMS	Energy Management System
MEH	Multi-Energy Hub
MILP	Mixed Integer Linear Programming
FFS	Fast Forward Selection
MCS	Monte Carlo Simulation
LPSP	Loss of Power Supply Probability
ENS	Energy Not Served

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