Enhanced Distribution Network Operation with Hydrogen Storage and Network Reconfiguration

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ABSTRACT-In this study, we address the optimal operation problem in electrical systems powered by renewable energy with hydrogen storage, utilizing smart reconfiguration technologies. Our aim is to minimize a multi-objective function that balances techno-economic and environmental factors while considering uncertainties in load, irradiation, wind speed, temperature, and electricity prices. To manage these uncertainties, we employ Monte Carlo simulation, the Scenario Reduction Algorithm, and Probability Density Functions. Furthermore, we enhance the standard Golf Optimization Algorithm by integrating the Fitness-Distance Balance mechanism, a prairie dog-inspired strategy, and a combination of quasi- and opposite-based learning, improving both efficiency and accuracy. The effectiveness of the modified algorithm is validated through the IEEE 33 distribution system (DS).

Keywords—Renewable Energy Sources, Distribution Network, Optimal Operation, Modified Golf Optimization Algorithm, Hydrogen Storage System, Smart Reconfiguration.

1. INTRODUCTION

The increasing reliance on fossil fuels for power generation has led to severe environmental problems, primarily due to the emissions of greenhouse gas, which lead to air pollutions and climatic variations. As a result, there is a growing global emphasis on integrating renewable energy sources (RESs), such as wind turbine (WT) and photovoltaic (PV) systems, into power distribution networks (DNs) to achieve a cleaner and more sustainable energy future. However, the integration of RESs presents several challenges, particularly due to their intermittent and unpredictable nature, which can lead to significant mismatches between energy supply and demand. If not properly managed, these fluctuations can disrupt the DN's performance involving power instability, voltage deviations, and increased power losses, ultimately affecting the total efficiency of the power system and its economy. Furthermore, improper sizing and placement of RESs within the DN can significantly impact the network performance and its cost, making it essential to develop optimization strategies to ensure their effective utilization. To mitigate these issues, energy storage systems (ESSs) have become a crucial component of modern power grids, allowing excess renewable energy to be absorbed and later discharged when required. Among the various ESS technologies, the hydrogen (H2) storage system represents a promising solution, as it enables the conversion of surplus electricity into hydrogen through electrolysis , which can then be absorbed and later converted back into electricity using fuel cells (FCs) when demand rises. Hydrogen offers multiple advantages, including zero emissions and long-term energy storage, making it a key enabler for sustainable energy transitions. By integrating hydrogen systems into power DNs, it becomes possible to minimize dependence on fossil fuels, enhance energy security, and improve grid stability while effectively utilizing excess renewable energy. Figure 1 depicts the operation of a hydrogen-based energy system, where surplus the renewable generation is converted into hydrogen using an electrolyzer, stored in a hydrogen storage tank, and later utilized via fuel cells (FCs) to generate electricity when needed during peak load hours. Furthermore, the increasing complexity of power DNs requires a network reconfiguration for optimizing the energy flow through effective switching mechanisms, which can lead to improving the overall DN performance [1, 2].

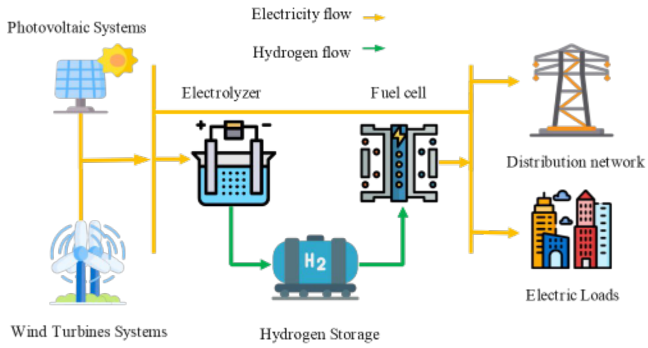

Fig 1. Diagram of the Green Hydrogen Storage Process

2. OPTIMIZATION PROBLEM FORMULATION

The multi-objective optimization problem is formulated to minimize total annual costs, real power losses, voltage deviation, and total emissions in the IEEE 33-bus distribution network. The multi objective function (MOF) is expressed as [3-5]:

$$\min(MOF) = \min\left(\varepsilon_1 C_{tot} + \varepsilon_2 TRPL + \varepsilon_3 TVD + \varepsilon_4 TE\right) \tag{1}$$

Where

$$C_{tot} = min(C_{Wind} + C_{PV} + C_{Grid} + C_{Loss} + C_{HES}) \tag{2}$$

$$TRPL = \sum_{t=1}^{24} \sum_{i=1}^{NT} P_{Loss(i,t)} \tag{3}$$

$$TVD = \sum_{t=1}^{24} \sum_{i=1}^{NB} \left| \left(V_{(i,t)} - 1 \right) \right| \tag{4}$$

$$TE = 365 \times \sum_{t=1}^{24} P_{Grid(t)} \times \left(SO_2^{Grid} + NO_x^{Grid} + CO_2^{Grid} \right) \tag{5}$$

Where $V_{(i,t)}$ denotes the electrical voltage at the node of branch i at the time t, and NB indicates the total number of buses or nodes in the network. In addition, SO_2^{Grid}, NO_x^{Grid}, CO_2^{Grid} refer to sulfur dioxide, nitrogen oxides, and carbon dioxide, respectively. C_{Wind}, C_{PV}, C_{Grid}, C_{Loss}, C_{HES} represent the total cost of wind, photovoltaic, grid, losses, and hydrogen systems, respectively.

THE MODIFIED GOLF OPTIMIZATION ALGORITHM

The Golf Optimization Algorithm (GOA) [6] has been developed to enhance search and exploitation capabilities through three novel modifications: the Fitness-Distance Balance mechanism, the prairie dog-inspired strategy, and the combination of quasi with opposite-based learning [7-9]. These modifications improve the traditional GOA by addressing issues such as premature convergence and poor performance in large-scale, non-linear problems.

3. THE SIMULATION RESULTS

The enhanced MGOA method was applied to optimize the IEEE 33-bus distribution system, considering smart switching and optimal placement of RES, electrolyzers, hydrogen storage, and fuel cells while accounting for uncertainties. Two scenarios were analyzed: Scenario #1 (base case) and Scenario #2 (with RES and hydrogen integration under smart reconfiguration). Figures 2–4 show the power generation and consumption profiles, while Figure 5 illustrates optimal switching operations. The results indicate a significant reduction in total costs, power losses, voltage deviation, and emissions, demonstrating the effectiveness of the proposed approach.

Table 1. Numerical Results for Optimal Operation of the IEEE 33-Bus System

Items	Scenario #1	Scenario #2
Optimal Location	----	25
		6
		31
Optimal Area of PVs (m2)	----	1.014e+04
		8400
		9658
Optimal size of WT (kw)	----	750
		750
		250
Optimal power factor of WT	----	0.7
		0.7
		0.7
Optimal size of Electrolyzers (kw)	----	285.2
		198.4
		396.8
Optimal size of Fuel Cells (kw)	---	132
		144
		132
Optimal size of Hydrogen tank (kg)	---	120.0906
		13.5952
		122.3565
Power losses (kW)	3.8294e+03	1390
Voltage deviation (p.u)	37.3592	18.11
Total annual cost (USD/kWh)	7.4969e+06	3.614e+06
Total annual emission (kg)	2.7579e+07	1.013e+07

As regards the optimal operation of the RESs and Hydrogen storages, the power generation and consumption profiles for the hybris systems 1, 2, and 3 over a 24-hour period are illustrated in Figures 2, 3, and 4, respectively, which provide a comprehensive comparison of the contributions from PV units, WTs, electrolyzers, and fuel cells in meeting the energy demands of the systems. The generation patterns for these RESs directly influence the operation of electrolyzers and fuel cells, which play a crucial role in maintaining system balance. Electrolyzers utilize excessive energy during periods of high renewable generation, effectively storing energy in the form of hydrogen. Conversely, fuel cells activate during low renewable energy availability periods, supplying the necessary power to bridge the gap between generation and consumption.

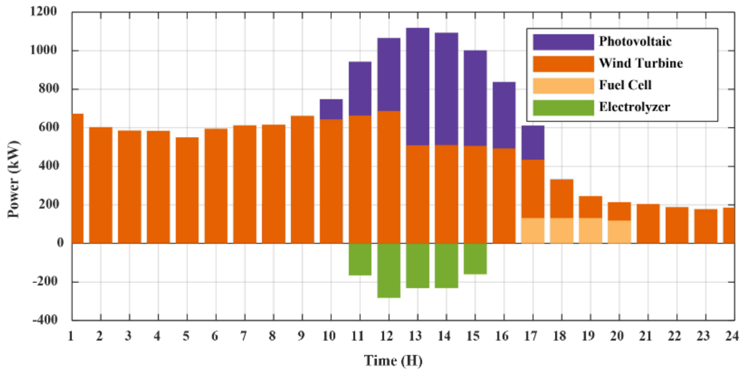

Fig. 2. Power Generation and Consumption Over 24 Hours for System 1

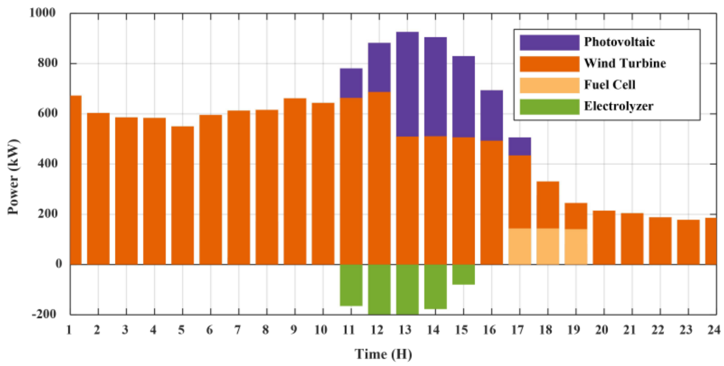

Fig. 3. Power Generation and Consumption Over 24 Hours for System 2

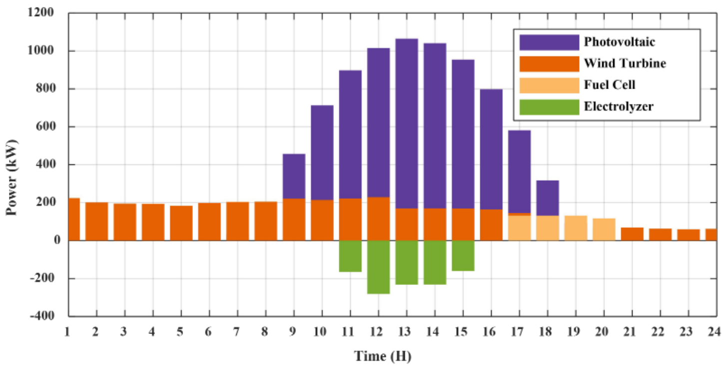

Fig. 4. Power Generation and Consumption Over 24 Hours for System 3

Figure 5 depicts the optimal switching operations of the studied DN over a 24-hour period, utilizing optimal network reconfiguration at each hour to maintain balance with maximum efficiency. It highlights periods of activity and inactivity for various switches, reflecting the network's operation and improving the DN performance.

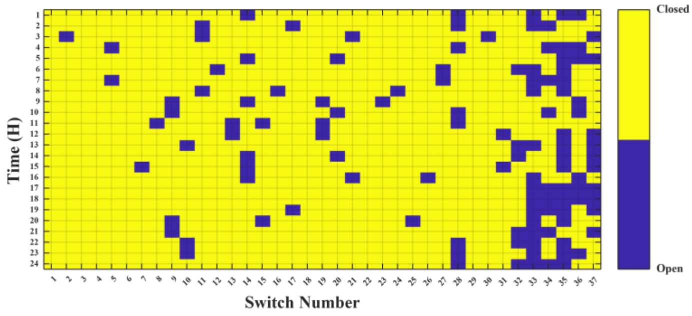

Fig. 5. Switch Status Over 24 Hours

The hourly optimal charging and discharging powers of each Hydrogen storage, as well as its state of charge (SOC), are presented in Figures 6,7 and 8 in each hybrid system. It is clear that the SOC rate increases noticeably during the hours of 11, 12, 13, 14, and 15, indicating active charging processes facilitated by the electrolyzers in all hybrid systems. This period corresponds to high renewable energy generation, particularly from PV units and wind turbines, providing surplus energy that is stored in the form of hydrogen. Conversely, a decline in the SOC rate is observed during the hours of 17, 18, 19, and 20, signifying discharging operations through fuel cells. This behavior is evident in both Hybrid system # 1 and Hybrid system # 3, where stored energy is utilized to meet the energy demand during reduced renewable energy availability. However, in Hybrid system # 2, there is no observable discharging activity at hour 20, suggesting that the system has sufficient renewable generation at that time.

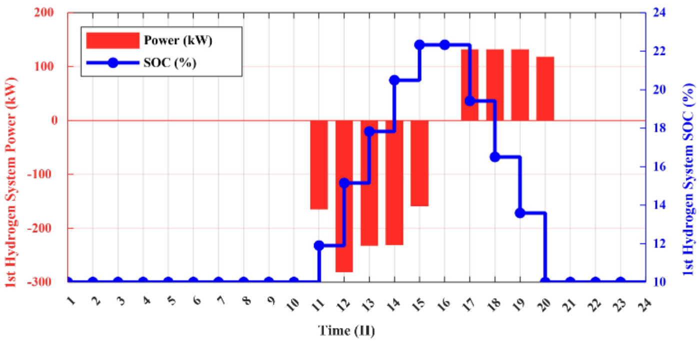

Fig. 6. The hourly exchanged power and SOC of the Hydrogen storage system in the (a) hybrid system # 1

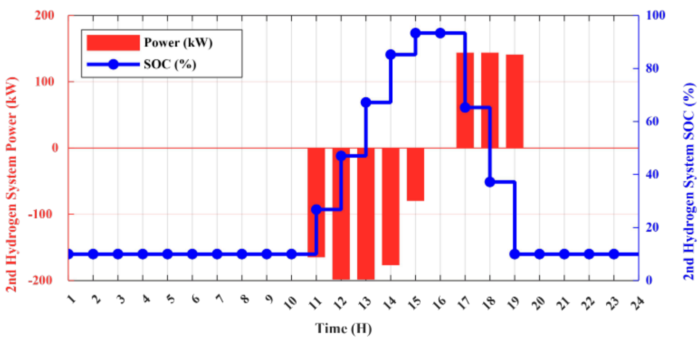

Fig. 7. The hourly exchanged power and SOC of the Hydrogen storage system in the (a) hybrid system # 2

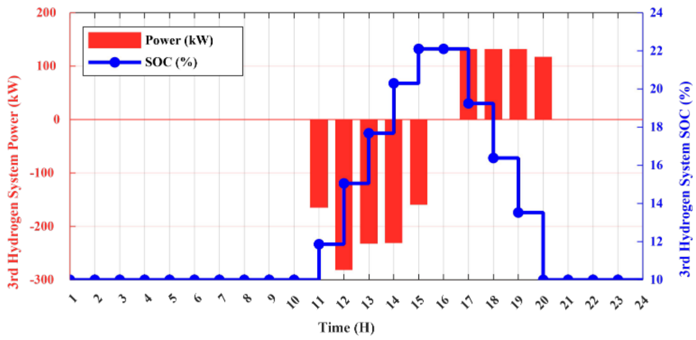

Fig. 8. The hourly exchanged power and SOC of the Hydrogen storage system in the (a) hybrid system # 3

Figures 9 and 10 illustrates the variations in the hourly voltage magnitude across bus number for two scenarios, highlighting the DN's technical performance. In Figure 9, representing the base case, a significant drop in voltage levels is observed across multiple buses. This indicates challenges in maintaining voltage stability under standard conditions, with noticeable deviations suggesting the DN's limitations in handling the existing load and network structure. In Figure 10, substantial improvements in voltage levels are evident due to the implementation of the energy management system.

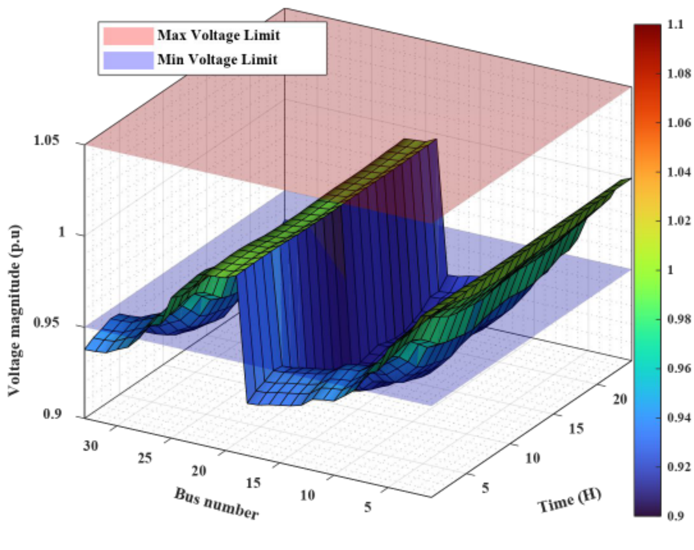

Fig. 9. The hourly voltage magnitude across bus number for Scenario #1

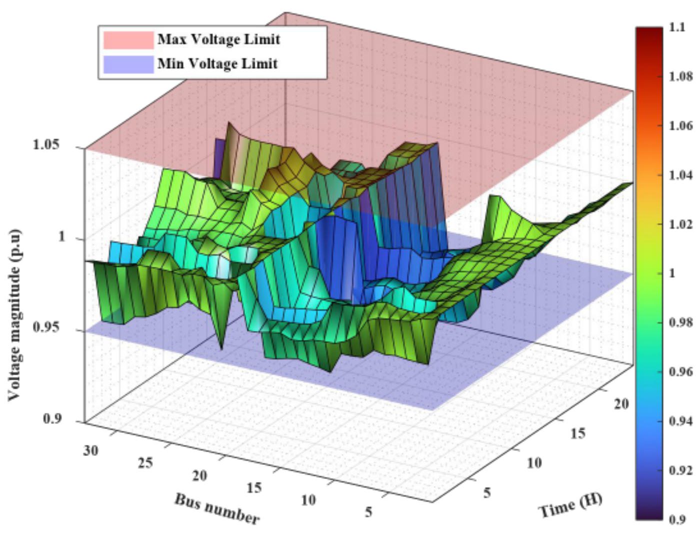

Fig. 10. The hourly voltage magnitude across bus number for Scenario #2

4. Conclusions

In this study, the enhanced MGOA method was implemented to optimize the IEEE 33-bus distribution system by integrating renewable energy sources and hydrogen storage under smart reconfiguration. The results showed a significant reduction in power losses from 3.8294e+03 kW in the base case to 1390 kW, while voltage deviation decreased from 37.36 p.u to 18.11 p.u. Additionally, the total annual cost was reduced from 7.4969e+06 USD/kWh to USD/kWh 3.614e+06 USD/kWh, and total annual emissions dropped from 2.7579e+07 kg to 1.013e+07 kg. These improvements confirm the effectiveness of the proposed approach in enhancing system efficiency, reducing operational costs, and minimizing environmental impact.

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5. References

[1] S. Ghaemi, X. Li, and M. Mulder, "Economic feasibility of green hydrogen in providing flexibility to medium-voltage distribution grids in the presence of local-heat systems," Applied Energy, vol. 331, p. 120408, 2023.

[2] M. Z. Oskouei and H. Mehrjerdi, "Optimal allocation of power-to-hydrogen units in regional power grids for green hydrogen trading: Opportunities and barriers," Journal of Cleaner Production, vol. 358, p. 131937, 2022.

[3] F. Sadaoui, B. Bouhadouza, and A. T. Hachemi, "Optimal reconfiguration of a distribution network integrated photovoltaic and wind systems using blood-sucking leech optimizer," Studies in Engineering and Exact Sciences, vol. 5, no. 2, pp. e11477-e11477, 2024.

[4] A. T. Hachemi et al., "Modified reptile search algorithm for optimal integration of renewable energy sources in distribution networks," Energy Science & Engineering, vol. 11, no. 12, pp. 4635-4665, 2023.

[5] A. T. Hachemi, F. Sadaoui, A. Saim, M. Ebeed, and S. Arif, "Dynamic operation of distribution grids with the integration of photovoltaic systems and distribution static compensators considering network reconfiguration," Energy Reports, vol. 12, pp. 1623-1637, 2024.

[6] Z. Montazeri, T. Niknam, J. Aghaei, O. P. Malik, M. Dehghani, and G. Dhiman, "Golf optimization algorithm: A new game-based metaheuristic algorithm and its application to energy commitment problem considering resilience," Biomimetics, vol. 8, no. 5, p. 386, 2023.

[7] S. Aras, E. Gedikli, and H. T. Kahraman, "A novel stochastic fractal search algorithm with fitness-distance balance for global numerical optimization," Swarm and Evolutionary Computation, vol. 61, p. 100821, 2021.

[8] A. E. Ezugwu, J. O. Agushaka, L. Abualigah, S. Mirjalili, and A. H. Gandomi, "Prairie dog optimization algorithm," Neural Computing and Applications, vol. 34, no. 22, pp. 20017-20065, 2022.

[9] G. He and X.-l. Lu, "Quasi opposite-based learning and double evolutionary QPSO with its application in optimization problems," Engineering Applications of Artificial Intelligence, vol. 126, p. 106861, 2023.