A Study on Improving Microgrid operation and Digital Twin using Hybrid Neural Network and Multi-Objective Genetic Algorithm in Energy Trading System

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에너지 거래 시스템에서 하이브리드 신경망과 다목적 유전 알고리즘을 활용한 마이크로그리드 운영 및 디지털 트윈 개선 연구

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Abstract

The study employs the use of a hybrid neural network and a multi-objective genetic algorithm to find the optimal trade-off in an energy management system. The neural network is used in training and validating the load, solar, and wind data, while the multi-objective genetic algorithm is used to find the optimal schedule and Pareto front that maximizes the profit and minimizes the investment cost in energy trading.

I. Introduction

The rising global energy demand across sectors like residential, industrial, transportation, and agriculture has driven the shift from fossil fuel-based power generation to renewable energy sources (RES), necessitating advanced technologies to enhance energy system efficiency and sustainability [1]. Microgrids (MGs), particularly at the village level, enable energy independence in rural areas by integrating solar and wind through prosumer-to-grid (P2G) mechanisms, though challenges like intermittent RES, dynamic pricing, and varying demand complicate energy scheduling and optimization [2]. The smart technology revolution, powered by Internet of Things (IoT), artificial intelligence (AI), machine learning, and digital twins (DT), facilitates real-time data analysis and system modeling, with DT providing virtual replicas for monitoring and control of MGs [3-5]. This study introduces a hybrid neural network and multi-objective genetic algorithm (HNN-MOGA) framework within a DT system to optimize village-level MG operations, focusing on predicting load and generation, optimizing trade-offs between profit, investment cost, and enabling real-time P2G energy trading. Validated through a MATLAB simulation of the Shinhyocheon village MG in South Korea, the framework demonstrates effective energy scheduling, demand response (DR), and resource allocation in energy storage system (ESS).

The review highlights extensive research on energy management systems (EMS), focusing on MG operations, energy trading, and the integration of RES using advanced techniques like multi-objective optimization, neural networks (NN), and DT technology. Studies such as [1-3] employ algorithms like non-sorting genetic algorithm II (NSGA-II) and particle swarm optimization (PSO) to optimize MG objectives, including profit, and reliability, incorporating dynamic pricing and P2G mechanisms. DT technology, as discussed in [4] and [5], provides dynamic virtual representations of physical systems, enhancing real-time energy management, predictive accuracy, and system efficiency in applications like smart grids and manufacturing. Research also addresses the challenges of dynamic electricity pricing and DR, with works in [4,5] developing models to optimize pricing strategies and energy scheduling using game theory and reinforcement learning. These studies underscore the role of advanced computational methods and smart technologies in improving the efficiency, reliability, and sustainability of modern EMS, particularly in decentralized frameworks like village-level MGs [6].

II. Method

The system model employs the use of NN to train the solar, wind, and load data. The multi-objective genetic algorithm (MOGA) is used to optimize the EMS operation.

Objective function:

Maximize profit (P_{profit})

$$P_{profit} = \sum_{t=1}^{T}\sum_{i=1}^{N}(E_{sell,i}(t)\, S_{sell}(t)\, \Delta t - E_{buy,i}(t) S_{buy}(t)\Delta t - C_{ESS}(E_{char,i}(t) + E_{disc,i}(t))\Delta t) \qquad (1)$$

where $E_{buy,i}$ is the amount of power purchased by prosumers in kilowatt-hours (kWh), $S_{buy}(t)$costs per kilowatt-hour for power purchased from the grid in US dollars per kWh ($/kWh), $E_{sell,i}(t)$ is the amount of power sold by each prosumer back to the grid in kilowatts (kWh), $S_{sell}(t)$ is revenue earned per kilowatt-hour for power sold to the grid in US dollars per kWh ($/kWh), C_{ESS} is the cost of ESS kWh of energy usage in US dollars per kWh ($/kWh). $E_{char,i}(t)$ and $E_{disc,i}(t)$ is the power stored and discharged from the battery for each prosumer in kilowatt-hours (kWh), Δt is time in hours. N is the number of prosumers, T is the time of the day.

Minimize investment cost (C_{invest})

$$C_{invest} = \sum_{i=1}^{N}(C_{pv} S_{cap} + C_{wd} W_{cap} + C_{ESS} ESS_{cap}) \qquad (2)$$

where C_{pv} be the cost per unit of solar capacity ($/kWh), C_{wd} be the cost per unit of wind capacity ($/kWh), C_{ESS} is the cost of the ESS capacity ($/kWh), S_{cap} be the solar capacity for prosumer in (kW), W_{cap} be the wind capacity for prosumer in (kW), ESS_{cap} be the battery capacity for prosumer in (kWh).

Figure 1 shows the hybrid optimization system with NN and MOGA. From Figure 1, we can see that the NN is used to train the load, solar, and wind data, while the MOGA optimizes the energy system to find the Pareto front and optimal schedule. The DT is used to monitor the operation and ensure an optimal trade-off.

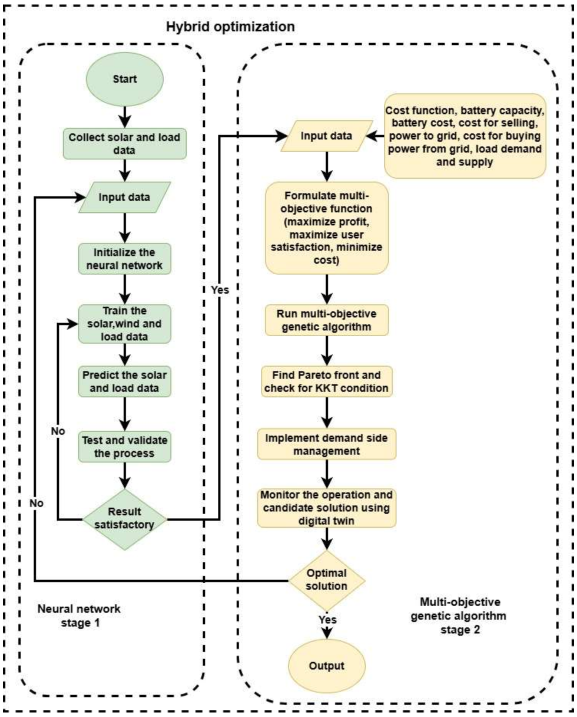

Figure 1: Flowchart of hybrid optimization

Simulation result and analysis

The Simulation parameters

Prosumers 4, selling price $ 0.5, buying price $ 0.4.

Figure 2 shows the Pareto front of the objective function, Figure 3 shows the energy sold versus bought during the trading period, and Figure 4 shows the optimal energy schedule for the load, battery, solar generation, and wind generation.

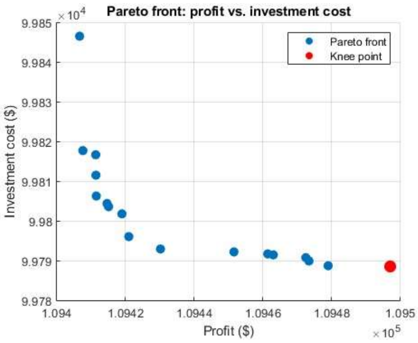

Figure 2: Pareto front for the objective functions

The HNN-MOGA is a vital tool in EMS. From the Pareto front, we have that the optimal values at the knee point are profit $109497.00, investment cost $99788.51, and simulation time 45.957 seconds.

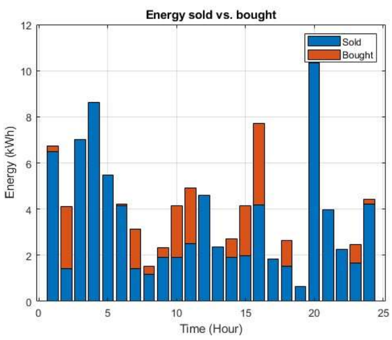

Figure 3 Energy sold versus bought in the microgrid

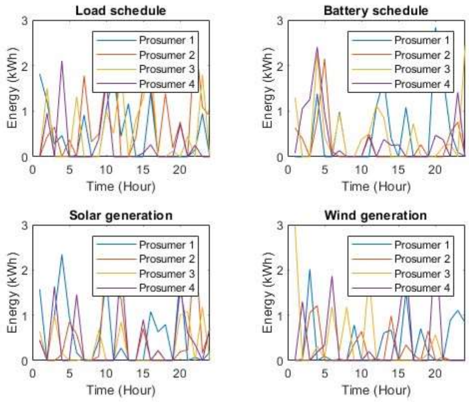

Figure 4: Optimal energy schedule

Figure 3 shows that more energy is sold than bought from the grid. Figure 4 shows the optimal schedule for prosumers.

III. Conclusion

The HNN-MOGA framework, implemented in MATLAB, uses NN to predict load, solar, and wind generation, while a MOGA optimizes energy scheduling, DR, and resource allocation, as demonstrated in the Shinhyocheon village MG case study in Gwangju, South Korea, with Grida Energy, highlighting its role in creating sustainable rural energy systems. The integration of DT technology enables real-time monitoring, proactive maintenance, and scenario analysis, enhancing forecasting accuracy and economic efficiency, with future research directions including scalability to more prosumers, and leveraging 5G and federated learning for improved communication and privacy in MG systems.

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