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# Optimizing demand-side energy management for stand-alone wind-solar microgrids in rural settlements: A case study for nomadic Yurt in Kazakhstan

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ABSTRACT

Nomadic communities often reside in remote regions requiring extensive transmission infrastructure, which is costly and contributes to higher greenhouse gas emissions. This study proposes a hybrid microgrid (MG) for the Shell Yurt Center, a representative nomadic dwelling in Kazakhstan. The system integrates renewable energy sources (RESs), including photovoltaic (PV), wind turbine (WT), and battery energy storage systems (BESS), to deliver a reliable and cost-effective energy supply. An analysis of a home energy management system (HEMS) is conducted using real-time data of the Yurt to support efficient demand-side management (DSM). The HEMS is designed to enhance energy efficiency and reduce overall energy costs through the smart scheduling of household appliances. Dynamic Programming (DP) and Genetic Algorithm (GA) are applied to manage energy usage under an unscheduled electricity pricing rate of $0.583/kWh as a baseline without using any optimization. Three scenarios are examined: Case 1 (minimal appliances with normal usage), Case 2 (maximum appliances with average usage), and Case 3 (maximum appliances with extreme usage). GA consistently outperforms DP in Case 1, resulting in reduced net present costs (NPC), levelized cost of electricity (LCOE), and lower maintenance costs. In Case 2, DP has a slight edge in NPC and LCOE, but GA maintains favorable maintenance costs. Case 3 shows that GA achieves the lowest NPC ($42,028), LCOE ($0.396/kWh), and maintenance costs ($466/year). Overall, the study establishes an optimal scheduling framework for renewable energy (RE) utilization for nomadic dwellers using a fully functioning MG complex.

## 1. Introduction

Currently, inadequate electricity supplies persist in rural areas and on some islands, despite the numerous potential renewable energy sources (RESs). The global advancements in renewable energy (RE) technologies have not only led to the consideration of solar photovoltaic (PV) and wind turbine (WT) systems as viable energy sources, but also as financially feasible [1,2]. Interestingly, by sizing the components of the hybrid microgrid (MG) system and enhancing their storage density, it becomes possible to calculate the system's cost and reliability. Among the RESs, WT and PV energy have several environmental benefits. Many countries recently introduced low-cost or even free policies to support and promote investment in WT and PV-related technologies. Nevertheless, the primary factor hindering public acceptance of WT and/or PV energy systems is the initial capital cost, despite their apparent advantages [3].

According to a recent report in [4], RE plays a significant role in global energy transmission, with some countries reporting annual RE growth rates exceeding 30%. Interestingly, most of the new RE installations are concentrated in rural communities. For instance, Ramihi et al. [5] conducted an in-depth analysis of RE potentials in rural communities of Australia. The study provides guidelines for selecting an appropriate site for optimal RE installation.

On the one hand, a techno-economic analysis was conducted for a standalone MG that powered a health clinic in KSA [6]. The DG/PV/BAT/Converter system modeled using HOMER achieved a cost of energy (COE) of $0.105/kWh with a 30% renewable fraction,

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**Nomenclature**

| | | | |
|---|---|---|---|
| BESS | Battery Energy Storage System | COE | Cost of Electricity |
| DG | Diesel Generator | DL | Daily Load |
| DP | Dynamic Programming | DR | Dynamic Response |
| DSM | Demand-side Management | EMS | Energy Management System |
| EV | Electric Vehicle | GA | Genetic Algorithm |
| GHG | Greenhouse Gas | HEMS | Home Energy Management System |
| HRES | Hybrid Renewable Energy System | ISSA | Improved Salp Swarm Algorithm |
| LCOE | Levelized Cost of Electricity | MODE | Multi-objective Differential Evolution |
| MSSA | Modified Sparrow Search Algorithm | NPC | Net Present Cost |
| PSO | Particle Swarm Optimization | PV | Photovoltaic |
| RE | Renewable Energy | RESs | Renewable Energy Sources |
| SOC | State of Charge | WT | Wind Turbines |

replacing added storage and converter capacities effectively. Another work [7] utilized HOMER for sizing and designing a hybrid system (FC/PV/DG/BAT) to fulfill the energy demands of a university building in the UAE. The results indicated that the proposed MG could achieve a high renewable fraction of 66% and a lower COE of $0.092 per kWh. The system comprises 3% DG, 24% FC, and 73% PV, all employed to meet the energy requirements. The authors designed an energy management system (EMS) for an MG with PV arrays and battery energy storage systems (BESS). By conducting case studies and simulations in MATLAB, the research enhanced the management of BESS charging and discharging based on demand while minimizing electricity usage under various weather conditions.

A techno-economic assessment of a hybrid renewable energy system (HRES) for Peruvian rural electrification was undertaken by [8]. Similarly, the study used HOMER software to analyze the optimal settings of PV, WT, and DG systems in three off-grid villages. The results showed a 97% reduction in cost and emissions, highlighting the need for more complex optimization methods. The study also introduced a predictive dispatch system modification to control surplus electricity supply in an independent HRES. The approach combined proactive battery controls and demand-side management (DSM) systems to optimize power efficiency and minimize power waste. The result shows a 7.5% decrease in excess electricity and 90% self-utilization, demonstrating its efficiency with current levels of deferrable load participation [9].

Furthermore, Akram et al. [10] optimized HRES for MGs in remote areas using HOMER with DSM for load shaping and enhancing the overall performance. The comparative analysis simplified decision-making by highlighting lower costs, emissions, and system complexities, thereby making a compelling case for HRES in rural electrification. The scope of the work was further advanced in [11] by emphasizing the standalone RES schemes of rural supply in Najran Province. The base optimization model integrated PV, WT, and BESS to minimize the cost and emissions. The competence of HOMER simulation was demonstrated by the increase in reliability and efficiency in the financial aspect, which calls for the uptake of localized renewable solutions, particularly among rural inhabitants. Rahmat et al. [12] conducted this type of study by modeling and simulating the integration investment of RESs in the Malaysian MG using HOMER Pro. Specifically, the PV, WT, and BESS were designed to be optimized economically for both equipment costs and emissions. These results highlighted the economic rationality and environmental impact of hybrid systems, encouraging the strategic development of renewable technologies for rural and remote communities.

### *1.1. Related work*

This section discusses various optimization methods for HRES optimization, focusing on minimizing energy costs and achieving optimal energy control of MGs as comprehensively highlighted in Table 1. It highlights the use of DSM programs, electric vehicle (EV) integration, and RESs to reduce operating expenses, emissions, and enhance system dependability. For instance, Li et al. [13] presented an optimization algorithm for scheduling flexible load in an integrated energy system. The study uses the time-of-use price from the generated energy to schedule the demand of the flexible load, which reduces the electricity purchase by 24.61%. In [14], a two-phase MG planning approach was proposed to coordinate EVs and controllable loads in response to fluctuating renewable generation. They used the modified sparrow search algorithm (MSSA) to minimize operational costs and emissions. A 24-hour simulation confirmed MSSA's potential to adapt to uncertainties in WT and PV electricity, highlighting the need for elaborate optimization in future power systems.

Dixit et al. [37] proposed a multi-objective differential evolution (MODE) algorithm for optimal daily power sharing in MGs with RESs, outperforming traditional methods like Particle swarm optimization (PSO) and genetic algorithm (GA) in cost and efficiency. Similarly, Yadav et al. [38] used HOMER to optimize HRES with multi-energy storage systems (MESS), integrating PV, WT, fuel cells, and BESS, achieving the lowest net present cost (NPC) and levelized cost of energy (LCOE). Adefarati et al. [39] designed a PV/WT/fuel cell hybrid network for Cape Town using the fmincon method, reducing grid energy use by 59.24% and greenhouse gas (GHG) emissions by 58%. The authors in [40,41] have highlighted the significant potential of wind energy for generating RE. Yadav et al. [42,43] applied the dragonfly and other algorithms to optimally design a PV/WT/BESS MG for remote regions of India, including Leh and Ladakh regions. The analysis ensures minimal LCOE and significantly reduces GHG emissions. The authors further discuss the importance of sensitivity analysis by varying parameters, including NPC, COE, and inflation rate, in [44]. The study highlighted that it is challenging to assess the microgrid performance at the design rate. Babatunde et al. [45] evaluated hydrogen storage in off-grid RESs using HOMER, demonstrating that PV-BESS was most economical, while PV-WT-BESS-fuel cell excelled technically and environmentally. Wu et al. [46] developed a techno-economic model for campus EV charging, combining PV sizing and charging control via PSO, cutting peak demand by 12% and energy costs by 9.2% at 25% EV penetration. Other studies focusing on smart homes and using optimization algorithms to cut GHG emissions and electricity costs for potential EV charging applications were proposed in [47–49]. Lastly, Bacha et al. [32] used PSO for standalone hybrid MGs in Algeria, achieving an LCOE of $0.09138/kWh for five homes, proving the algorithms' cost-effectiveness and adaptability.

This study advances HRES sizing by presenting a sequential hardware-software co-optimization process for a single, nomadic Shell Yurt in Astana, an area often overlooked in previous research. It uniquely employs measured, site-specific load data and clearly separates the base building loads from schedulable appliance loads. By combining a HOMER-based techno-economic sizing model with a custom dynamic programming (DP) and GA scheduler, the approach goes beyond HOMER's usual dispatching, enabling precise assessment of how DSM influences NPC, LCOE, and peak demand. This highlights the vital interplay between hardware capacity and operational scheduling policies.

**Table 1**
Summary of similar previous studies on HRES-based microgrids.

| Ref. | Year | Location | Method | Components | Objectives |
|---|---|---|---|---|---|
| [15] | 2022 | Bangladesh | HOMER/MATLAB | PV/WT/BESS/DG | • Designed optimized hybrid off-grid HRES<br>• Minimized $CO_2$ emissions, LCOE, and NPC |
| [16] | 2022 | Northern India | HOMER/MATLAB | PV/WT/BESS/DG | • Electrified rural areas using optimized HRES<br>• Minimized costs and assessed benefits |
| [17] | 2022 | Smart house | Hybrid GSA+PSO | PV/BESS/Grid | • Optimized energy consumption<br>• Integrated EVs and Demand response (DR) |
| [18] | 2022 | Malaysia | HOMER Pro | PV/WT/BESS/DG | • Designed system for telecom towers<br>• Minimized DG dependency<br>• Assessed RES configurations |
| [19] | 2022 | Saudi Arabia | HOMER Pro | PV/WT/BESS/DG | • Campus MG design<br>• Enhanced RES integration<br>• Reduced costs and emissions |
| [20] | 2023 | General | MILP | PV/WT/HESS/Grid | • Minimized annual costs<br>• Minimized carbon emissions<br>• Reduced grid dependence |
| [21] | 2023 | Kenya | Multi-objective | PV/WT/BESS/Flywheel | • Optimized LCOE<br>• Maximized Self-Reliance |
| [22] | 2023 | General | Hierarchical Model | PV/HESS/NGES/Grid | • Balance costs and efficiency<br>• Evaluated grid extension |
| [23] | 2024 | Malaysia | HOMER Pro | PV/WT/BESS/HESS | • Optimized HESS for EV charging<br>• Reduced GHG emissions |
| [24] | 2024 | Egypt | HOMER Pro | PV/WT/BESS/DG | • Minimized NPC, COE, LPSP<br>• Desert microgrid design |
| [25] | 2024 | Saudi Arabia | ISSA/GWO/FPA | PV/WT/BESS/Grid | • Reduced NPC and emissions<br>• Optimized EV infrastructure |
| [26] | 2024 | India | AVOA/PSO/WOA/MFO | PV/WT/BESS | • Fully renewable MG<br>• Minimized LCOE and $CO_2$ |
| [27] | 2024 | Colombia | MALO/MGOA/MPSO | PV/DG/BESS/Grid | • Minimized grid costs<br>• Reduced losses and emissions |
| [28] | 2024 | Iran | HOMER Pro | PV/WT/BESS/DG | • Reduced fossil fuel use<br>• Optimized cost and impact |
| [29] | 2024 | Afghanistan | HOMER Pro | PV/WT/BESS/DG | • Sustainable energy solution<br>• Analyzed RES potential |
| [30] | 2024 | Nigeria | HOMER/GOA | PV/WT/BESS/DG/Biogas | • Optimized COE and NPC<br>• Rural electrification |
| [31] | 2024 | Bangladesh | PVsyst 7.2 | PV | • Solar EV charging<br>• Environmental benefits |
| [32] | 2024 | Algeria | SFS/SOS/PSO | PV/WT/BESS/DG | • Minimized LCOE and LPSP<br>• Reduced dummy load |
| [33] | 2025 | India | GWO/AVOA/DA | PV/WT/BESS | • Minimized LCOE<br>• Optimized excess energy generation<br>• Analyzed GHG emissions |
| [34] | 2025 | Egypt | Lagrange Multiplier | PV/WT/DG | • Minimized NPC and LCOE<br>• Improved reliability |
| [35] | 2025 | General | CGWO | PV/WT/BESS/DG | • Minimized total cost<br>• Reduced shortages |
| [36] | 2025 | Remote areas | HPWOA | PV/WT/BESS/DG | • Minimized LCOE, TNPC, LPSP |
| | Proposed | Kazakhstan | Homer Pro+DP/GA | PV/WT/BESS | • Used real-time measured load data<br>• Optimized scheduling of appliances<br>• Assessed DSM on NPC, LCOE and peak demand |

### 1.2. Motivation and contribution

Kazakhstan has limited research on hybrid (PV-WT) MGs, particularly for rural settlements. This highlights a significant gap in the green energy transition, despite the country's abundant wind and solar irradiance resources, as reported in [50]. Although some large-scale RE projects exist in Kazakhstan, such as the Badamsha Wind Farm [51] and Nura Solar Park [52], these primarily focus on utility-scale generation. This study aims to contribute to Kazakhstan's "National Concept for Transition to Green Economy 2050" [53] by conducting DSM assessments of hybrid WT-PV MGs, particularly targeting rural applications. This paper extends beyond conventional optimization approaches to maximize renewable energy utilization in standalone MGs. The EMS strategy adopted in this work is based on an expert system using DP and GA, which not only manages the power flow but also schedules household appliances to optimize electricity cost. A real-world case study from Kazakhstan is analyzed to validate the proposed approach. The summary of the contribution of this work is as follows:

- Development of a DP and GA-based technique for standalone MGs that schedules home appliance loads to minimize investment, maintenance, and electricity costs.
- Conducting a techno-economic analysis of HRES using a fully functioning Shell Yurt in Astana, Kazakhstan, assessing NPC, LCOE, operational costs, and environmental impact to support strategic investment decisions.
- Assessment of various scheduling scenarios for loads with different durations and numbers of appliances using real case study data to evaluate the impact of multiple parameters on MG operations and provide insights for standalone MG investment planning in Kazakhstan.

The remaining parts of this manuscript are organized as follows: Section 2 describes the system configuration and load profiles of the MG Yurt center in Astana, Kazakhstan. Moreover, Section 3 introduces the study location and available resources. Section 4 represents the mathematical modeling of hybrid energy system components. Furthermore, Section 5 presents the results and discussion on the standalone MG. Finally, the conclusion is provided in Section 6.

## 2. The Yurt microgrid project

The Shell Yurt, a traditional "Yurt" building, is a key component of Nazarbayev University's RE complex, shown in Fig. 1. It is an autonomous, energy-efficient residential development with a unique circular shape inspired by a nomadic home. It integrates sustainable technologies like geothermal, WT, and PV. The Yurt's BESS technology allows it to operate independently for extended periods, making it suitable for remote locations. The test facility serves as a research platform for sustainable energy solutions and is part of a broader green economy program.

### 2.1. System configuration

As shown in Fig. 2, Shell Yurt's MG system is a hybrid alternating current/direct current (AC/DC) setup that uses a heat pump and RESs to increase energy efficiency. On the AC side, the heat pump uses RE to heat or cool the Yurt load, while WT and PV supply the needed power. The DC side, where PV generates power and charges a BESS, is connected to an AC/DC converter. This design enables flexible EMS, allowing the system to increase the usage of RE sources and provide a steady supply.

### 2.2. Operating strategy

The Yurt operating plan utilizes a sustainable and efficient HRES system, consisting of a WT with a 5.10 kW capacity and PV cells with a 4.5 kW capacity. These RESs work in tandem, capturing solar energy during the day and wind energy during windy conditions. The WT generates AC power, which is converted into DC via an AC/DC converter, while the PV provides DC electricity. The BESS stores excess energy produced by PV and WT, ensuring power availability during low energy output and serving as a backup source during high demand or insufficient RESs. The energy load of the Yurt is controlled by a heat pump, and a hybrid charge control technology prevents deep drain or overcharging. The system remains stable during periods of heavy consumption or fluctuations in energy supply, utilizing an automated voltage regulator and a ballast resistor module. The Yurt's energy needs are mostly met by PV energy during the day, with any excess energy used to charge the battery bank. This operating method increases energy self-sufficiency while reducing reliance on the utility grid.

**Table 2**
Hourly Yurt and appliance load profile.

| Hours | Yurt Load (kW) | Appliance Load (kW) |
|---|---|---|
| 0 | 0.703 | 0 |
| 1 | 0.714 | 0.9 |
| 2 | 1.835 | 3.1 |
| 3 | 2.156 | 0 |
| 4 | 2.191 | 0 |
| 5 | 2.176 | 0 |
| 6 | 2.323 | 0 |
| 7 | 2.256 | 0 |
| 8 | 2.284 | 0 |
| 9 | 2.305 | 0 |
| 10 | 2.216 | 0.8 |
| 11 | 1.884 | 3 |
| 12 | 0.743 | 3 |
| 13 | 0.558 | 3 |
| 14 | 0.738 | 4.9 |
| 15 | 0.654 | 4.9 |
| 16 | 1.269 | 0 |
| 17 | 1.774 | 0 |
| 18 | 1.337 | 1.1 |
| 19 | 1.852 | 3 |
| 20 | 2.271 | 0 |
| 21 | 1.776 | 0 |
| 22 | 0.607 | 0 |
| 23 | 1.767 | 0 |

## 3. Study location and resources

The study area is Astana, Kazakhstan, located in the north-central region at 51.16° latitude and 71.42° longitude, as shown in Fig. 3. A comprehensive standalone MG System framework will be developed using regional RES data, considering both financial and environmental risks. Key inputs for the system design include production capacity, meteorological data, seasonal load profiles, and precise site coordinates. HOMER software selects the optimal system architecture by evaluating multiple configurations [55]. The design process considers LCOE, NPC, and Operation and Maintenance (O&M) costs. HOMER then performs a techno-economic analysis to support system planning, policy-making, and long-term site development. Accurate load and weather data are essential for EMS operation. Load profiles help EMS evaluate distributed generation systems (DGS) and BESS performance, while weather data supports RES output forecasting, since forecast accuracy is vital for reliable MG performance.

### 3.1. Electrical load profile of the area considered

To collect information on the patterns of energy usage of different loads, field research was conducted on-site. The tools and processes used have an impact on the electrical load's characteristics. Using power analyzer equipment, electrical loads are directly measured once a day for one hour. The HOMER application was used to enter the load data that had been gathered. As shown in Table 2, a daily load profile has been produced by inventorying the current loads and load capacity using the power meters' hourly readings. In order to assess power consumption, the load demand and loading duration (h) will be included. The daily load and the 24-hour scheduling plots are shown only as illustrative examples to help readers understand the load composition and the impact of various scheduling strategies. All techno-economic results, including NPC and LCOE, are based on the year-round simulation dataset. Utilizing Eq. (1) [56], the total power demand (kWh) is obtained.

The chosen site's daily demand pattern is reflected in the average load profile. The seasonal demand pattern of domestic load for a household section within a one-year period is depicted in Fig. 4, and shows normal load demand and load utilization at the designated location. The term daily load (DL) refers to the total amount of energy used for


**Fig. 1.** The energy-efficient Shell Yurt situated at the Nazarbayev University Campus [54]. The oval Yurt, which is the main load, is powered by one WT of 5.1 kW. The 4.5 kW PV serves as additional RESs for the Yurt. The complete system uses dual-RESs to power the Yurt during winter (heating) and summer (cooling) seasons.

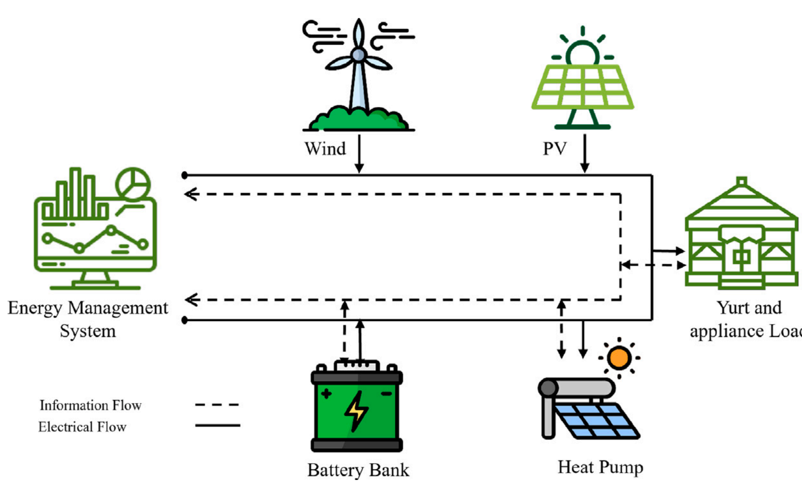


**Fig. 2.** Configuration diagram of the Yurt microgrid system.

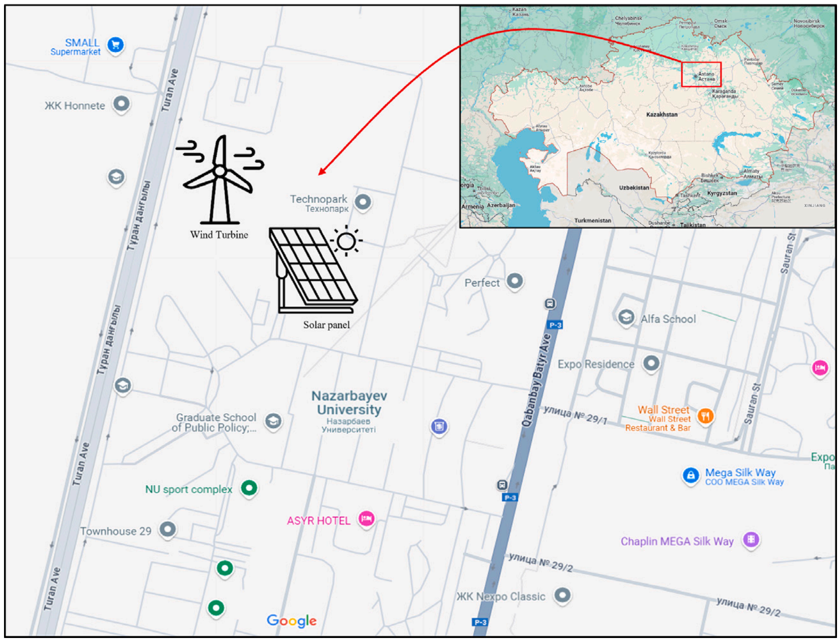


**Fig. 3.** Location of Yurt Center in Nazarbayev University, Astana, Kazakhstan.

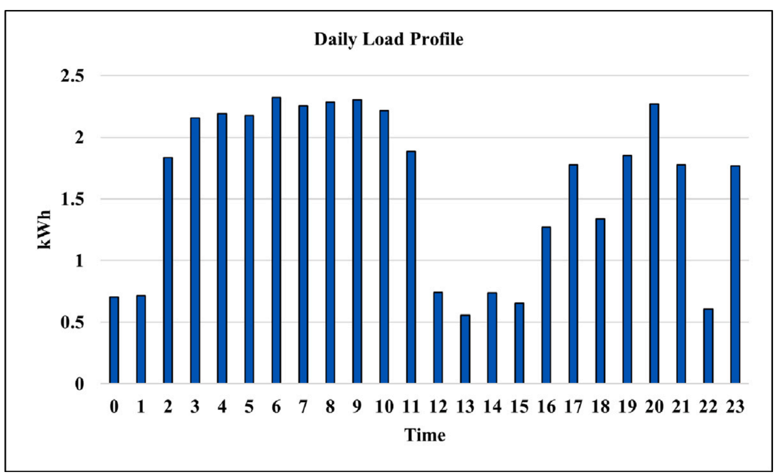


**Fig. 4.** Daily load profile.

residential purposes in the area. For DL, the HOMER software showed a daily load of 11.25 kWh/d and a peak load of 1.17 kW.

$$\text{Total Demand (kWh)} = \sum_{i=1}^{n} (\text{Load (kW)} \times \text{Duration (h)}) \tag{1}$$

**Remark 1.** It is worth noting that the Yurt load refers to the non-shiftable, essential energy demand, primarily driven by the heat pump and core lighting. The appliance load encompasses the deferrable and flexible loads (e.g., washing machine, electric cooker) that the HEMS schedules for optimal utilization of renewable energy. The system peak is defined as the maximum instantaneous power demand (kW) observed on the microgrid at any moment, which is the sum of the Yurt load and the time-shifted appliance load.

### 3.2. Resources

The National Aeronautics and Space Administration's (NASA) surface meteorology and solar energy World data collection is used by the HOMER Energy Website to provide information on wind speed and solar radiation [57]. To get information on wind speeds and solar radiation, HOMER is used to enter the study site's latitude, longitude, and time zone. Climate variables like wind and sun have an impact on the amount and effectiveness of RES in a given area. Fig. 5 shows how to generate daily, seasonal, and annual load profiles using HOMER software. The wind and sun radiation characteristics of the potential site should be examined in the first phase to optimize the usage of WT and PV energy resources for system performance modeling. As a result, Figs. 6, 7, and 8 display meteorological data including temperature, wind speed, and hourly solar irradiance.

## 4. Mathematical modeling of the HRES components

The MG comprises PV, WT, BESS, controllers, and load demand. Integrating multiple RESs enhances system reliability, performance, and capacity. The system design is influenced by current load demand, technical specifications, costs, and local solar and wind resources. HOMER software manages energy balance over time, evaluates system performance, and calculates emissions for each component. It also controls the arrangement of RES within HRES operations and manages

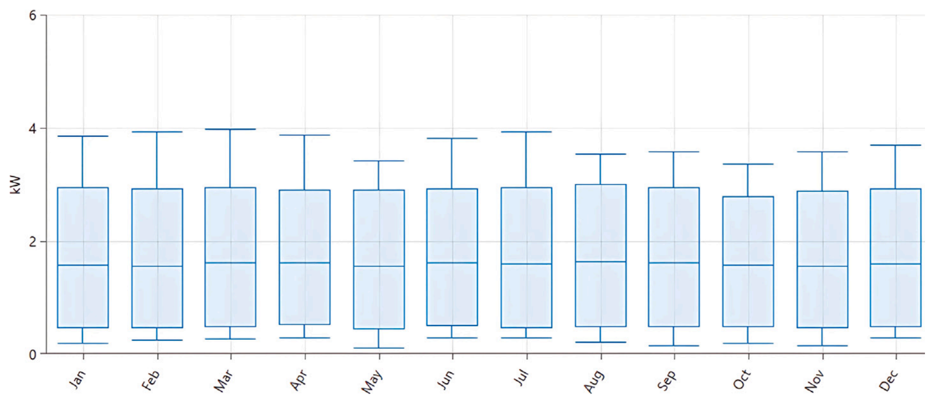


**Fig. 5.** Seasonal load profile.

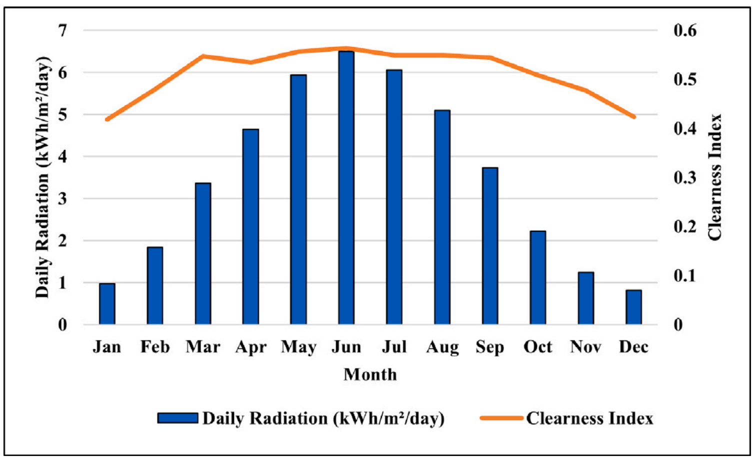


**Fig. 6.** Solar irradiance and cleanness index.

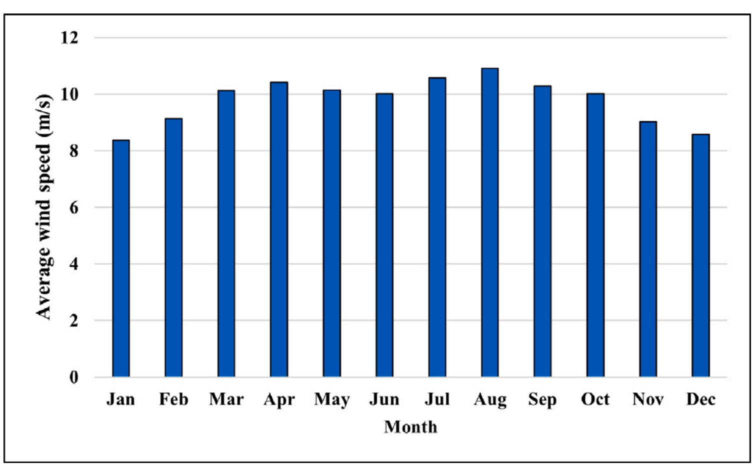


**Fig. 7.** Monthly average wind speed.

BESS charging and discharging processes [58]. By testing various RES combinations, HOMER identifies the optimal configuration that meets site-specific load requirements and technical criteria. A comprehensive techno-economic analysis is conducted, including capital, O&M, and replacement costs, NPC, LCOE, and associated risks. The study's economic evaluation assumes a project lifespan of 25 years.

### 4.1. Photovoltaic array (PV)

A PV array converts sunlight into electrical energy using a semiconductor. Solar energy conversion is a key renewable resource with broad applications. PV systems are reliable, eco-friendly, quiet, and easy to install, with low O&M costs and no moving parts. However,

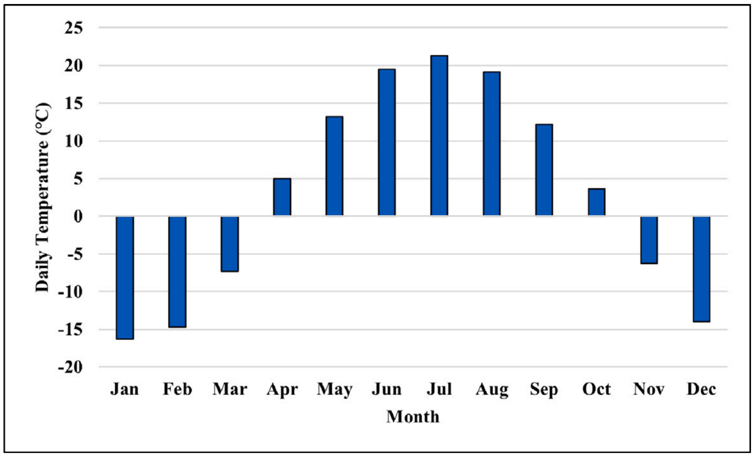


**Fig. 8.** Monthly average ambient temperature.

they face challenges such as high capital costs and intermittent output. Selecting a PV system requires evaluating site-specific factors, such as solar irradiance, weather conditions, cell temperature, shading, snow, and rated efficiency. HOMER software calculates PV RE generation based on these variables using Eq. (2) [59].

$$P_{\mathrm{pv}} = M_{\mathrm{pv}}\,\mathrm{NF}_{\mathrm{pv}}\left(\frac{A_T}{A_{\mathrm{STC}}}\right)\left[1+\alpha_T(L_c - L_{c,\mathrm{STC}})\right] \tag{2}$$

In this context, $M_{\mathrm{pv}}$ refers to the rated capacity of the PV array (kW), $NF_{\mathrm{pv}}$ denotes the PV derating factor (%), $A_T$ is the solar radiation incident on the PV array during the current time step (kW/m$^2$), $A_{\mathrm{STC}}$ represents the solar radiation under the standard test conditions (1 kW/m$^2$), $\alpha_T$ signifies the temperature coefficient of power (° C), $L_c$ is the PV cell temperature at the current time step (° C), and $L_{c,\mathrm{STC}}$ represents the PV cell temperature under the standard test conditions (25 °C).

### 4.2. Wind turbine (WT)

The power generated by the WT can be represented using the relation of Eq. (3) [60]:

$$P_W(t) = N_{WT} \times \begin{cases} 0 & 0 \le V(t) \le V_{Cin} \;\&\; V(t) \ge V_{CO} \\ P_{WT}\dfrac{V^3(t) - V_{Cin}^3}{V_R^3 - V_{Cin}^3} & V_{Cin} < V(t) < V_R \\ P_{WT} & V_R \le V(t) < V_{CO} \end{cases} \tag{3}$$

where $N_{WT}$ depicts the number of WTs and $P_{WT}$ depicts the rated WT output power. The bounds of the WT for ensuring safety, including $\upsilon_{Cin}$, $\upsilon_R$, and $V_{CO}$ represent cut-in, rated, and cut-off wind speeds, respectively. Finally, the $V(t)$ represents the variable wind speed.

### 4.3. Battery bank

The microgrid is equipped with a power source storage unit as a backup to provide dependable and continuous functioning in the event of a power loss. The lifetime throughput and the storage float life are two different characteristics that might limit the storage bank's lifespan in HOMER. HOMER uses Eq. (4) to calculate the storage bank's lifetime [59].

$$B_{\mathrm{batt}} = \begin{cases} \dfrac{M_{\mathrm{batt}} \cdot N_{\mathrm{lifetime}}}{N_{\mathrm{thrpt}}} & \text{if limited by throughput} \\ R_{\mathrm{batt,f}} & \text{if limited by time} \\ \min\left(\dfrac{M_{\mathrm{batt}} \cdot N_{\mathrm{lifetime}}}{N_{\mathrm{thrpt}}}, B_{\mathrm{batt,f}}\right) & \text{if limited by both} \end{cases} \tag{4}$$

Where $B_{\mathrm{batt},f}$ is the float life of the BESS (yrs); $B_{\mathrm{batt}}$ life of the BESS (yrs); $M_{\mathrm{batt}}$ is the number of batteries; $N_{\mathrm{lifetime}}$ is the lifetime throughput of the BESS (kWh); and $N_{\mathrm{thrpt}}$ is the annual BESS throughput (kWh/yr).

Most importantly, the State of Charge (SOC) of the BESS is a key metric that defines the current amount of available energy in the battery as a % of its total capacity. Essentially, it is an indicator of the battery's current status. The HOMER Pro models the dynamic charging and discharging behavior of the BESS by calculating the SOC at each time step using an iterative formula. This calculation is crucial for optimizing the energy storage, ensuring the battery is utilized efficiently, and maintaining a necessary energy reserve. The model ensures a realistic representation of the battery's performance by incorporating both its total capacity and its efficiency. The model used in HOMER Pro to calculate the SOC at a given time $t$ is an update based on the SOC at the previous time step $T-1$ as shown below [61]:

$$\mathrm{SOC}(t) = \mathrm{SOC}(T-1) + \frac{P_{\mathrm{chagt}}(t) \times \eta_{\mathrm{bat}} - P_{\mathrm{dischg}}(t)}{C_{\mathrm{bat}}} \tag{5}$$

where SOC($t$) depicts SOC at time $t$, SOC($T-1$) depicts the SOC at the previous time step, $P_{\mathrm{chagt}}(t)$ is the power used to charge the battery in kW, $P_{\mathrm{dischg}}(t)$ is the Power discharged from the battery in kW, $\eta_{\mathrm{battery}}$ is the efficiency and $C_{\mathrm{bat}}$ is the battery capacity in kWh. It is worth noting that HOMER Pro allows the limit of charging or discharging to be set. These limits are set in the battery component under minimum SOC ($SOC_{\mathrm{min}}$) and maximum SOC ($SOC_{\mathrm{max}}$), satisfying the bound $SOC_{\mathrm{min}} \le SOC(t) \le SOC_{\mathrm{max}}$. A limit of 20%–80% (i.e., 0.2–0.8) was chosen in this study as it is a recommended/default range ensuring battery efficiency and longevity.

## 5. Simulation results and discussion

This study aims to use HOMER software to develop an optimal MG design. It analyzes results from various scenarios, each depicting different levels of RES availability. The section focuses on the simulation findings. Three scenarios and an MG control system combining PV, WT, BESS, Yurt load, and appliance load are evaluated using the current Yurt construction as a case study:

- **Case 1:** Minimum appliance with normal usage. This scenario considers only four basic appliances, namely the electric cooker, AC, washing machine, and fridge, under normal operating conditions.
- **Case 2:** Maximum appliance with average usage. This case includes an additional six appliances, compared to Case 1 (10 in total), with an average usage.

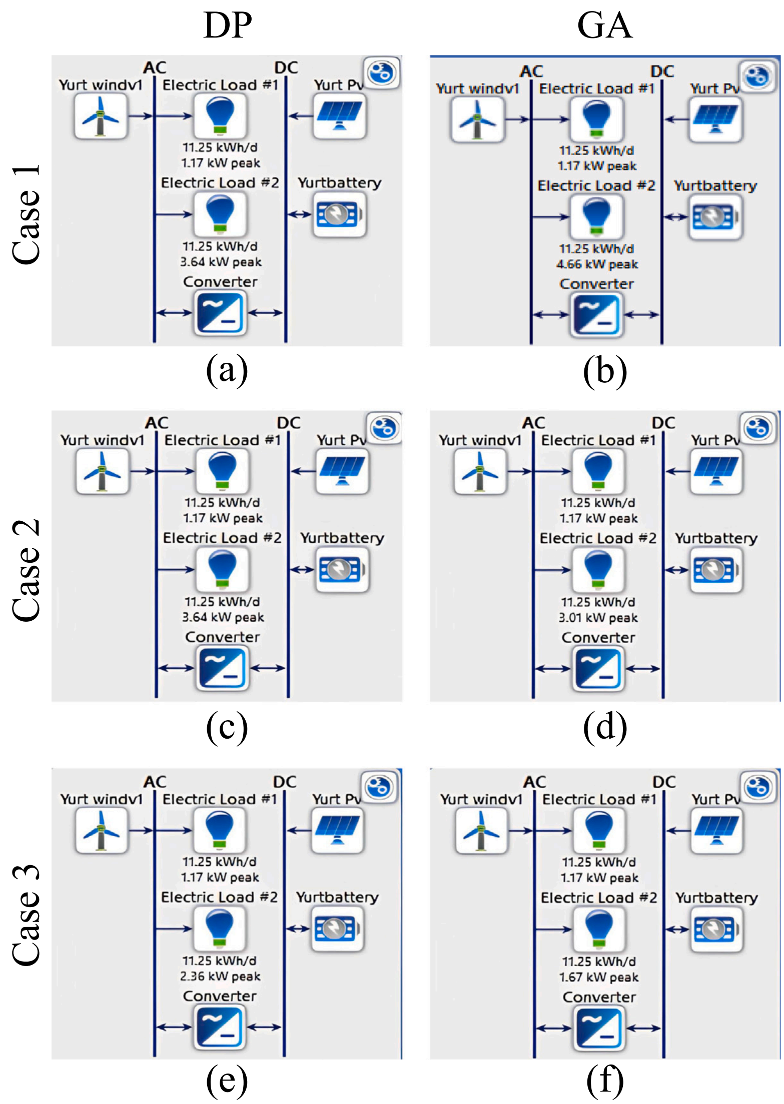


**Fig. 9.** Configurations of standalone Yurt for all the considered cases. Note that electrical load #1 is the Yurt load while electric load #2 is the appliance load that was scheduled using DP and GA.

- **Case 3:** Maximum appliance with extreme usage. This scenario is similar to case 2, but with extreme usage (additional operating hours) of the appliances.

The wattage of appliances, weight, and task duration are taken as variables to resolve the objective function in the model, which includes 10 appliances with wattages of 2, 2, 1.5, 0.8, 1.2, 1.5, 1.5, 1.1, 2, and 1.5 kW. The average operational hours of the appliances mentioned are taken as: 2, 6, 1, 24, 4, 1, 1, 1, 2, 2, and extreme operational hours are 4, 8, 2, 24, 5, 2, 1, 2, 3, 3 h, respectively. Fig. 9 shows the system configuration used in all cases: a standalone Yurt powered by a HRES comprising PV, WT, and BESS. A converter ensures efficient AC/DC energy conversion. Two load scheduling methods, DP and GA, were applied. In Case 1, with a daily load of 11.25 kWh and peak demand of 1.17 kW, DP leads to a peak system load of 3.64 kW, as shown in Fig. 9(a), while GA allows for a higher 4.66 kW peak, as illustrated in Fig. 9(b). In Case 2, the peak remains 3.64 kW with DP as shown in Fig. 9(c), but GA lowers it to 3.01 kW, as illustrated in Fig. 9(d). In Case 3, DP results in a 2.36 kW peak, as shown in Fig. 9(e), and GA further reduces it to 1.67 kW, as illustrated in Fig. 9(f). These results highlight GA's superior flexibility in adapting to load variations while maintaining the same daily energy consumption.

Fig. 10 illustrates the simulation and optimization results for Cases 1, 2, and 3 of the MG system based on DP and GA approaches. Both models incorporate PV, WT, BESS, and a bidirectional converter. The PV and WT systems achieve annual energy production, as shown in Fig. 10(a) for both the DP and GA models. The detailed PV generation profiles are displayed in Fig. 10(b). Similarly, the WT unit's generation profiles are depicted in Fig. 10(c). A BESS was integrated into the MG design to supply power cost-effectively during periods of low generation or emergencies. In both models, the battery was configured with charging and discharging thresholds set at 80% and 20%, respectively, to enhance performance and lifespan, operating as a DC supply linked to the MG's DC bus bar. The annual battery state of charge (SOC) is shown in Fig. 10(d). To manage bidirectional power flow between AC and DC buses, a converter was used, functioning as both an inverter and a rectifier. Fig. 10(e) shows the converter output profiles.

**Remark 2.** It is worth noting that the tariff of $0.583/kWh is derived by the HOMER when no optimization algorithm is applied for the scheduling. Therefore, it serves as a benchmark for comparing the optimized LCOE to the unscheduled tariff. The goal was to emphasize that the optimized standalone PV/WT/BESS system achieves an LCOE significantly lower than that of using the RESs without scheduling, thereby demonstrating its economic viability.

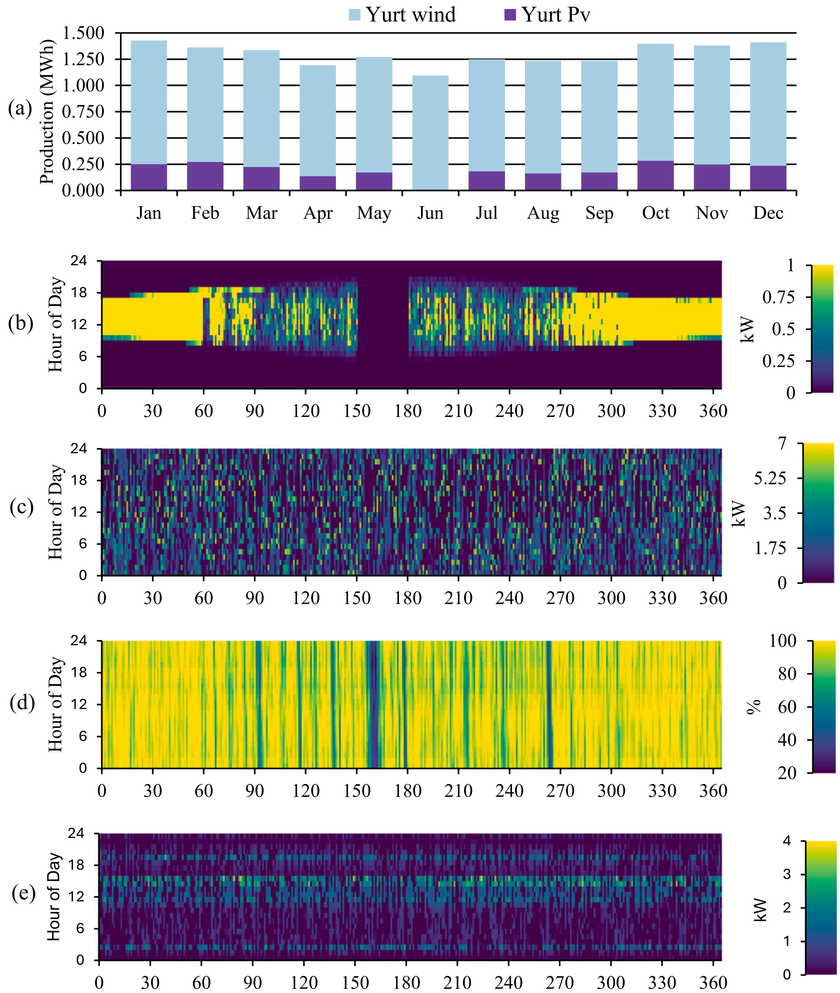


**Fig. 10.** (a) Monthly RE production of PV and Wind (b) Daily RE Production of PV (c) Daily RE production of Wind (d) Daily SOC of battery (e) Output Power of Inverter (kW).

**Case 1: Minimum appliance with RES**

Table 3 compares DP and GA scheduling for appliance optimization in a standalone Yurt powered by RESs. Both align appliances use PV and WT availability but employ different strategies. The electric cooker operates during the solar peak (14:00–15:00) in both cases. DP schedules the air conditioner for nighttime (2:00) and midday (11:00–15:00), while GA restricts it to 11:00–16:00 for solar use. For the washing machine, DP sets it at 19:00 (wind use), and GA at 15:00 (solar use). As shown in Fig. 11, smart scheduling aligns loads with renewable peaks, staggers high-demand use, and ensures the continuous operation of essentials like refrigeration. This enhances RES utilization and, according to economic analysis, offers a rapid payback through smart controller integration.

In addition, Table 4 illustrates that the DP method results in a total installation cost of $44,319, with an LCOE of $0.418/kWh and an annual operating cost of $506. GA slightly reduces costs to $43,832, with an LCOE of $0.413/kWh and annual operating expenses of $495. For non-scheduled loads, electricity costs $0.583/kWh, compared to $0.418/kWh in scheduled cases. While the cost difference appears small, it has a significant long-term impact, especially in high-demand settings. DP exhaustively evaluates all scheduling options, while GA heuristically searches for near-optimal solutions using evolutionary strategies. The study analyzes intelligent appliance scheduling using RE generation patterns, focusing on common household appliances like refrigerators, washing machines, air conditioners, and electric cookers. It reveals significant economic and operational advantages. The optimal scheduling framework, based on PV and WT power availability, results in energy cost savings of $0.418/kWh in the demand-driven scenario and $0.413/kWh in the GA scenario.

**Case 2: Maximum appliance with average usage**

Table 5 shows that both DP and GA effectively balance energy demand with renewable supply. DP schedules high-power appliances (cooker, geyser, AC) between 11:00 and 19:00 for optimal PV use, while GA distributes loads more evenly, leveraging both solar and off-peak wind energy. Essential loads like refrigerators run continuously in both methods. Shiftable appliances (washing machine, vacuum cleaner) are flexibly scheduled, where DP favors midday (13:00–14:00), while GA uses early morning (02:00) and late evening (21:00–23:00). Overall, DP and GA enable predictable scheduling, as shown in Fig. 12.

The DP technique has a total installation cost of $42,900, with an LCOE of $0.404/kWh and an annual operating cost of $469. GA, on the other hand, slightly increases the total installation cost to $43,901, with an LCOE of $0.414/kWh and an annual operating cost of $506, as shown in Table 6, affecting long-term energy consumption, especially in high-energy-demand environments.

**Case 3: Maximum appliance with extreme usage**

Table 7 shows that DP schedules high-power appliances (cooker, geyser, AC) between 11:00 and 19:00 to align with peak PV output, ensuring efficient use of solar energy. GA, on the other hand, distributes loads more evenly across the day, including early morning and evening,

**Table 3**
Power consumption and operation times under DP and GA scheduling (Case 1).

| Appliances | Power (kW) | Duration (h) | DP optimal time scheduling | GA optimal time scheduling |
|---|---|---|---|---|
| Electric cooker | 2.0 | 2 | 14, 15 | 14, 15 |
| AC | 2.0 | 6 | 2, 11, 12, 13, 14, 15 | 11, 12, 13, 14, 15, 16 |
| Washing Machine | 1.5 | 1 | 19 | 15 |
| Fridge | 0.8 | 24 | 1, 2, 10, 11, 12, 13, 14, 15, 18, 19 | 2, 3, 4, 6, 7, 9, 14, 15, 16, 18, 19, 20, 22, 23 |

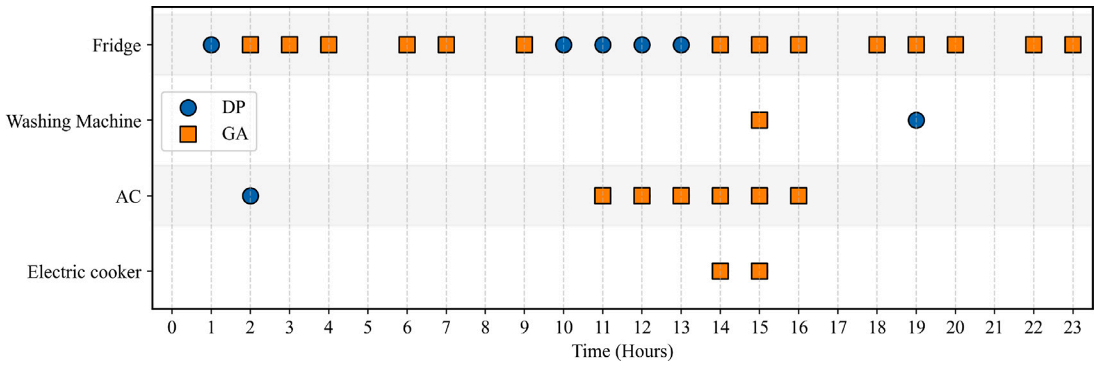


**Fig. 11.** Optimal scheduling analysis for household appliances using DP and GA (Case 1).

**Table 4**
MG cost analysis for minimum appliances using DP and GA (Case 1).

| | DP | | GA | |
|---|---|---|---|---|
| NPC ($) | 44,319 | | 43,832 | |
| LCOE ($/kWh) | 0.418 | | 0.413 | |
| Maintenance Cost ($/yr) | 506 | | 495 | |
| | PV | Wind | PV | Wind |
| Rated Capacity (kW) | 4.50 | 5.10 | 4.50 | 5.10 |
| Capital Cost ($) | 3780 | 15,000 | 3780 | 15,000 |
| Specific Yield (kWh/kW) | 519 | – | 519 | – |
| Hours of Operation (hrs/yr) | – | 5570 | – | 5570 |
| Lifetime (Years) | 25 | 25 | 25 | 25 |
| Total Production (kWh/yr) | 2334 | 13,211 | 2334 | 13,211 |
| Maintenance Cost ($/yr) | 76.0 | 150 | 76.0 | 150 |
| LCOE ($/kWh) | 0.164 | 0.099 | 0.164 | 0.099 |

**Table 5**
Power consumption and operation times for DP and GA scheduling (Case 2).

| Appliances | Power (kW) | Duration (h) | DP optimal time scheduling | GA optimal time scheduling |
|---|---|---|---|---|
| Electric cooker | 2.0 | 2 | 14, 15 | 11, 12 |
| AC | 2.0 | 6 | 2, 11, 12, 13, 15, 16 | 11, 12, 14, 15, 16 |
| Washing Machine | 1.5 | 1 | 14 | 2 |
| Fridge | 0.8 | 24 | 1, 2, 3, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19 | 1, 2, 6, 7, 9, 10, 11, 13, 14, 15, 17, 18, 19, 21, 22 |
| Water Pump | 1.2 | 4 | 2, 14, 16, 17 | 2, 4, 22 |
| Dryer | 1.5 | 1 | 1 | 15 |
| Vacuum Cleaner | 1.5 | 1 | 13 | 9 |
| Iron | 1.1 | 1 | 15 | 18 |
| Water Heater (Geyser) | 2.0 | 2 | 11, 19 | 17, 18 |
| Dishwasher | 1.5 | 2 | 12, 18 | 11, 23 |

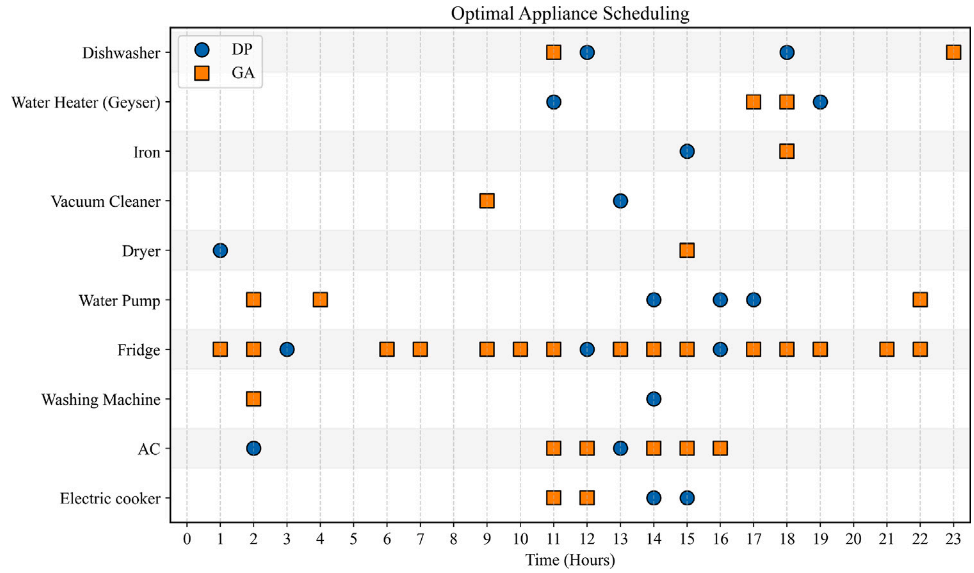


**Fig. 12.** Optimal scheduling analysis for household appliances using DP and GA (Case 2).

**Table 6**
MG cost analysis for maximum appliance with average usage using DP and GA (Case 2).

| | DP | | GA | |
|---|---|---|---|---|
| NPC ($) | 42,900 | | 43,901 | |
| LCOE ($/kWh) | 0.404 | | 0.414 | |
| Maintenance Cost ($/yr) | 469 | | 506 | |
| | PV | Wind | PV | Wind |
| Rated Capacity (kW) | 4.50 | 5.10 | 4.50 | 5.10 |
| Capital Cost ($) | 3780 | 15,000 | 3780 | 15,000 |
| Specific Yield (kWh/kW) | 519 | – | 519 | – |
| Hours of Operation (hrs/yr) | – | 5570 | – | 5570 |
| Lifetime (Years) | 25 | 25 | 25 | 25 |
| Total Production (kWh/yr) | 2334 | 13,211 | 2334 | 13,211 |
| Maintenance Cost ($/yr) | 76.0 | 150 | 76.0 | 150 |
| LCOE ($/kWh) | 0.164 | 0.099 | 0.164 | 0.099 |

**Table 7**
Power consumption and operation times under DP and GA scheduling (Case 3).

| Appliances | Power (kW) | Duration (h) | DP optimal time scheduling | GA optimal time scheduling |
|---|---|---|---|---|
| Electric cooker | 2.0 | 4 | 11, 12, 14, 15 | 12, 13, 14, 15 |
| AC | 2.0 | 8 | 2, 11, 12, 13, 14, 15, 16, 19 | 12, 13, 14, 15, 16, 17, 18, 19 |
| Washing Machine | 1.5 | 2 | 13, 17 | 7, 8 |
| Fridge | 0.8 | 24 | 1, 2, 3, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19 | 1, 4, 5, 6, 7, 8, 9, 10, 11, 16, 17, 18, 19, 20, 21, 22 |
| Water Pump | 1.2 | 5 | 4, 6, 11, 17, 19 | 10, 11, 12, 13, 14 |
| Dryer | 1.5 | 2 | 2, 12 | 18 |
| Vacuum Cleaner | 1.5 | 1 | 16 | 2 |
| Iron | 1.1 | 2 | 1, 16 | 1, 2 |
| Water Heater (Geyser) | 2.0 | 3 | 7, 9, 15 | 9, 10, 11 |
| Dishwasher | 1.5 | 3 | 5, 8, 20 | 4, 5, 6 |

effectively utilizing off-peak WT energy. Shiftable loads (washing machine, vacuum cleaner) show distinct patterns. The DP prefers midday (13:00–14:00), while GA shifts usage to early morning (02:00) or late evening (21:00–23:00) to leverage wind energy and off-peak hours. DP emphasizes predictable, PV-centric scheduling, and GA offers more adaptive and balanced load distribution, as shown in Fig. 13. The unscheduled load cost baseline is $0.58/kWh. DP results in a $43,674 installation cost, $0.411/kWh LCOE, and $515 annual O&M. GA shows a slightly lower installation cost of $41,884, an LCOE of $0.395/kWh, and $478 annual O&M, as shown in Table 8.

In summary, Table 9 compares the DP and GA algorithms for designing an efficient EMS across the three cases, using the following metrics: NPC, LCOE, and maintenance cost. In Case 1, GA slightly outperforms DP with lower NPC ($43,832 vs. $44,319), LCOE ($0.413 vs. $0.418/kWh), and reduced maintenance cost ($495 vs. $506/yr). In Case 2, DP proves more cost-effective, offering lower NPC ($42,900 vs. $43,901), LCOE ($0.404 vs. $0.414/kWh), and maintenance cost ($469 vs. $506/yr). In Case 3, GA again retains a slight advantage in NPC ($43,674 vs. $42,028), LCOE ($0.411 vs. $0.396/kWh), and maintenance cost ($515 vs. $466/yr). Overall, GA generally performs better. However, DP can outperform GA in specific scenarios, such as Case 2. The optimal algorithm depends on particular system goals and constraints.

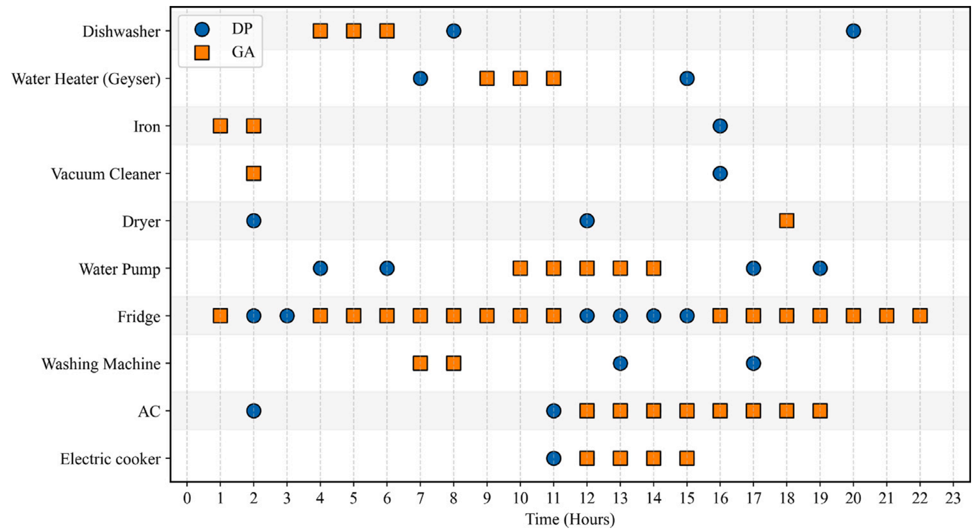


**Fig. 13.** Optimal scheduling analysis for household appliances using DP and GA (Case 3).

**Table 8**
MG cost analysis for maximum appliances with extreme usage using DP and GA (Case 3).

| | DP | | GA | |
|---|---|---|---|---|
| NPC ($) | 43,674 | | 41,884 | |
| LCOE ($/kWh) | 0.411 | | 0.395 | |
| Maintenance Cost ($/yr) | 515 | | 478 | |
| | PV | Wind | PV | Wind |
| Rated Capacity (kW) | 4.50 | 5.10 | 3.23 | 5.10 |
| Capital Cost ($) | 3780 | 15,000 | 2914 | 15,000 |
| Specific Yield (kWh/kW) | 519 | – | 640 | – |
| Hours of Operation (hrs/yr) | – | 5570 | – | 5570 |
| Lifetime (Years) | 25 | 25 | 25 | 25 |
| Total Production (kWh/yr) | 2334 | 13,211 | 2071 | 13,211 |
| Maintenance Cost ($/yr) | 76.0 | 150 | 58.6 | 150 |
| LCOE ($/kWh) | 0.164 | 0.099 | 0.144 | 0.099 |

**Table 9**
Summary of optimizations between DP and GA across all three cases.

| Case | Condition | Metric | DP | GA |
|---|---|---|---|---|
| Case 1 | Minimum appliances | NPC ($)<br>LCOE ($/kWh)<br>Maintenance Cost ($/yr) | 44,319<br>0.418<br>506 | 43,832<br>0.413<br>495 |
| Case 2 | Maximum appliances with average usage | NPC ($)<br>LCOE ($/kWh)<br>Maintenance Cost ($/yr) | 42,900<br>0.404<br>469 | 43,901<br>0.414<br>506 |
| Case 3 | Maximum appliances with extreme usage | NPC ($)<br>LCOE ($/kWh)<br>Maintenance Cost ($/yr) | 43,674<br>0.411<br>515 | 42,028<br>0.396<br>466 |

## 6. Conclusion

This study investigates the optimization of HEMS using DP and GA under unscheduled electricity rate of $0.583/kWh. Across the three analyzed operational scenarios, GA mostly outperforms DP in terms of NPC, LCOE, and O&M costs. In the baseline scenario (Case 1), GA reduced NPC by 1.1% and improved LCOE by 1.2% compared to DP, offering notable savings for residential users. Under high-demand conditions (Case 3), GA achieved the lowest NPC ($42,028) and LCOE ($0.396/kWh), demonstrating its strength in handling complex, multi-variable optimization through evolutionary strategies like selection, crossover, and mutation. Unlike DP, GA effectively avoids local optima and explores a diverse range of scheduling options.

This work highlights GA's advantages in real-world HEMS by integrating software-hardware co-optimization, offering practical value to homeowners, utility providers, and policymakers. It supports global sustainability goals by showcasing how computational intelligence can improve residential energy efficiency. The success of GA suggests its broader potential for optimizing energy systems, including MGs and renewable integration. The conducted analysis provided an optimal framework for RE utilization, benefiting nomadic dwellers by enabling efficient use of the generated power, particularly in remote communities that employ a standalone hybrid PV-WT MG system.

In future work, the effectiveness of the proposed method will be further tested and evaluated in multi-area power grids, including many microgrids, renewable energy sources, and energy storage systems.

## CRediT authorship contribution statement

**Abdul Moeed Khan:** Writing – original draft, Visualization, Validation, Software, Investigation. **Ahmad Bala Alhassan:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Funding acquisition. **Anvar Kolumbetov:** Writing – review & editing, Data curation. **Auwal Haruna:** Writing – review & editing, Formal analysis. **Vijayakumar Gali:** Writing – review & editing, Validation, Formal analysis. **Nguyen Gia Minh Thao:** Writing – review & editing, Visualization, Supervision. **Ton Duc Do:** Writing – review & editing, Supervision, Resources.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Data availability

The data associated with this study can be accessed via An Optimized Dataset for Off-grid Nomadic Yurt in Astana, Kazakhstan. Any additional information can be provided by the corresponding author upon reasonable request.

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