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Embracing Artificial Intelligence for Forecast-Based Energy Optimization: Advancing Sustainable Power Systems Towards SDG Achievement

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Abstract

The increasing complexity of balancing grid power with renewable energy sources, amid rising global energy demands, underscores the need for intelligent and cost-effective energy management solutions. This research proposes an Artificial Intelligence (AI)-driven approach that leverages advanced forecasting and optimization techniques to enhance energy utilization, operational efficiency, and cost reduction. A key component of the system is an Autoregressive Integrated Moving Average (ARIMA) model, trained on historical consumption data to accurately predict energy demand and support real-time decision-making. The framework dynamically toggles between renewable and grid energy sources based on forecasted demand and real-time availability. When conditions are favourable, the system prioritizes renewable energy to reduce reliance on the grid and lower operational costs. In less favourable conditions, it strategically draws on grid power to preserve renewable reserves and maintain uninterrupted supply, or intelligently combines both sources when needed. To address the limitations of static, grid-dependent energy systems, particularly in emerging economies, the proposed model integrates ARIMA with a Genetic Algorithm (GA). This hybrid approach enhances the system's ability to navigate complex, non-linear energy demand patterns by conducting global searches across vast solution spaces, resulting in improved adaptability and optimization accuracy. Aligned within Uganda's Vision 2040 and the United Nations Sustainable Development Goals (SDGs), both of which place real weight on making energy and infrastructure more affordable and accessible, this work positions itself as a practical, scalable approach to energy management. It speaks most directly to SDG 7 Affordable and Clean Energy and SDG 13 Climate Action, though the alignment is not merely symbolic. The evaluation results, while still open to further validation in real-world settings, suggest noticeable gains in cost-efficiency, energy optimization, and overall system scalability. Taken together, these outcomes point to a framework that could realistically support more resilient and adaptive power systems, particularly in rapidly developing economies where such improvements are not just desirable but, in many cases, overdue.

Key Words: *Artificial Intelligence (AI), Autoregressive Integrated Moving Average (ARIMA) model, Genetic Algorithm (GA), Sustainable Development Goals (SDGs)*

Introduction

The global shift towards sustainable energy systems has gained significant momentum with the advancement and widespread adoption of renewable energy sources such as solar and wind. These energy sources are not only abundant and inexhaustible but also clean, producing zero greenhouse gas emissions during operation and offering low operating costs post- installation (Nekrasov, 2021; Amponsah, Kington, Aalders, Hough & Green, 2024). Their integration into national energy strategies has reshaped the global energy landscape, enabling a gradual but impactful transition from fossil fuel dependence to more environmentally friendly and sustainable energy solutions. Beyond mitigating the effects of climate change, renewable energy contributes significantly to global sustainability agendas, particularly the United Nations (UN) SDGs 7 (Affordable and Clean Energy) and 13 (Climate Action) (South & Alpay, 2025).

In response to the pressing need to achieve these goals, many nations have prioritized sustainability within their energy policies. As a result, renewables have transitioned from supplementary alternatives to key components of national energy portfolios (Dechamps, 2023). However, despite their benefits, sources such as solar and wind present notable operational challenges due to their intermittent and weather-dependent nature. Their variability leads to reliability issues, especially in standalone systems (Zhang & Kong, 2022). Without adequate energy storage infrastructure, these systems struggle to consistently meet base load demand, particularly during peak consumption or low-generation periods (Kroposki, Johnson, Zhang, Gevorgian, Denholm, Hodge & Hannegan, 2017). Additionally, the inherently fluctuating and often non-linear nature of energy demand, shaped by consumer behaviour, time-of-day usage patterns, and environmental factors, compounds the difficulty of maintaining a stable, efficient, and cost-effective energy supply. This challenge is further exacerbated by the need for seamless energy source allocation, or source shifting, between grid power and renewables. If not intelligently managed, this process can lead to system inefficiencies, energy instability, and increased operational costs (Kabir, Kumar, Kumar, Adelodun & Kim, 2018).

Traditional energy switching methods often rely on grid-dominant configurations governed by static rules or time-based schedules. These approaches are inadequate for handling the dynamic variations in energy demand and renewable availability (Paterakis, Erdinç & Catalão, 2017). Their limitations are especially evident during peak demand periods, where reliance on the grid leads to increased energy costs and the underutilization of more affordable, cleaner renewable sources (Hirth, 2013). Overcoming these inefficiencies requires intelligent energy management systems capable of real-time monitoring, predictive analytics, and adaptive decision-making to optimize energy flow and resource utilization. Recent advancements in time-series forecasting, particularly the use of the ARIMA model, have shown promising results in modelling energy consumption trends and seasonal variations (Box, Jenkins, Reinsel & Ljung, 2015). ARIMA is especially effective in generating accurate linear forecasts from historical consumption data. However, its linear structure limits its ability to capture the non-linear and abrupt demand variations typical of renewable-integrated systems. As a result, emerging research increasingly supports hybrid forecasting approaches that combine ARIMA with machine learning (ML) models such as Long Short-Term Memory (LSTM) networks to improve adaptability and accuracy in com- plex real-world conditions (Shariff, 2022).

While intelligent energy management systems, especially those based on hybrid forecasting, offer significant improvements in operational efficiency by dynamically prioritizing renewables and strategically managing grid use and storage, there remains a need for more robust and flexible optimization techniques. These systems must be capable of conducting global searches across complex, high-dimensional solution spaces to optimize energy source utilization while minimizing cost. This research proposes the integration of ARIMA with a GA, a derivative-free optimization method that relies solely on fitness evaluations, making it particularly effective when gradients are difficult to compute. GAs can handle binary, integer, real-valued, and mixed variable types, which provides advantages over many traditional methods limited to continuous variables (Bakirtzis & Kazarlis, 2016). While ARIMA does not fully capture the more complex, non-linear patterns in energy demand compared to models like Prophet or LSTM, its selection here is quite deliberate. It offers a level of simplicity and interpretability that fits the short-term forecasting scope of this study, and, perhaps just as importantly, keeps the overall system tractable.

In Uganda's context, the 2023 Renewable Energy Policy, aligned with Vision 2040, emphasizes diversifying the energy mix through increased renewable integration (Kimuli & Kirabira, 2025). This national agenda supports the development of intelligent, efficient energy management systems to drive socio-economic growth, which is in line with SDG 1. It is also aligned with broader regional and global initiatives, including the East African Community (EAC) energy strategy, the African Union's Agenda 2063, and SDG 7 and 13. However, achieving a sustainable and diversified energy system introduces new complexities in balancing variable supply with dynamic demand.

This paper introduces a novel intelligent energy management framework that combines ARIMA-based demand forecasting with GA-driven optimization to dynamically allocate energy between grid and solar sources. The proposed system is designed to minimize operational costs, enhance energy efficiency, and support Uganda's broader sustainability goals through intelligent, real-time renewable integration.

Our key contributions are as follows:

1. We formulate the problem and identify, collect, and curate a context-specific dataset to support the development and validation of a robust forecasting model.

2. We propose an intelligent energy management system that utilizes demand forecasting to optimize renewable energy usage within a hybrid grid environment.

3. We enhance energy source allocation by integrating ARIMA forecasting with a GA, enabling optimized utilization of both renewable and grid power while minimizing costs.

4. We evaluate the performance of the proposed system through simulations, demonstrating alignment with SDG objectives and real-world feasibility.

The remainder of this paper is structured as follows: Section 2 reviews related work. Section 3 details the proposed frame- work. Section 4 presents the results and discussion, and Section 5 concludes the paper.

Related work

The shift toward renewable energy has been strongly influenced by international recommendations, particularly the UN SDGs, mainly 7 and 13. These goals have accelerated the transition to renewable energy by highlighting its numerous advantages, including reduced long-term costs and environmental sustainability (Nekrasov, 2021; Verbruggen, Fischedick, Moomaw, Weir, Nadaï, Nilsson, Nyboer & Sathaye, 2010). As a result, renewable energy has become a global priority, driven by the urgent need to mitigate climate change, decrease dependence on fossil fuels, and enhance energy sustainability (Borowski, 2022; Owusu & Asumadu-Sarkodie, 2016).

In line with this global momentum, Uganda is increasingly investing in renewable energy sources such as solar and wind to meet its Vision 2040 objectives and align with SDGs 7 and 13 (Mundu, 2021; Gustavsson, 2015). However, a major challenge remains: the intermittent and unpredictable nature of renewable energy resources, combined with the lack of advanced energy management systems, continues to hinder the efficient and reliable supply of electricity. Multiple studies have highlighted these limitations. For example, (Zhang & Kong, 2022) emphasizes that the performance of solar and wind systems is highly dependent on weather conditions and time of day, which limits their reliability in standalone configurations. Similarly, (Kroposki, et. al., 2017) notes that without adequate storage infrastructure, renewable energy systems struggle to maintain consistent baseload supply, especially during periods of high demand or low generation.

Conversely, traditional grid systems powered by fossil fuels offer stable and dispatchable energy but come with significant environmental and economic costs. Research by (Kabeyi & Olanrewaju, 2022) outlines how fossil-fuel-dominant grids contribute heavily to greenhouse gas emissions and pollution, undermining progress toward SDGs 7 and 13. Moreover, the International Energy Agency (IEA) highlights the rising costs of fossil fuel extraction and the long-term risks of depending on finite resources (IEA, 2020). These challenges contrast with the objectives of this research, which aims to achieve cost-effective energy utilization aligned with global sustainability goals.

Due to the limitations of both standalone renewable systems and conventional grids, recent literature has increasingly focused on hybrid energy systems. Comprehensive reviews, such as (Islam, Yu, Giannoccaro, Mi, La Scala, Rajabi & Wang, 2024), demonstrate that integrating renewable energy sources with grid backup and storage solutions enhances system reliability, reduces emissions, and improves flexibility. These hybrid systems allow for dynamic energy management, drawing from the grid when renewables are insufficient and vice versa.

However, many of these models lack intelligent, demand-driven switching mechanisms, resulting in suboptimal energy allocation and increased operational costs. Moreover, incorporating high shares of renewables into isolated systems requires significant investment in infrastructure and sophisticated control systems. As noted by (Mathiesen, Lund, Connolly, Wenzel, Østergaard, Möller, Nielsen, Ridjan, Karnøe & Sperling, et al., 2015), while technologies like batteries and pumped hydro storage have im- proved reliability, they also contribute to system complexity and cost. To overcome these challenges, accurate energy demand forecasting has emerged as a vital component for optimizing hybrid systems, particularly when dealing with variable renewable inputs. Time-series forecasting techniques, especially ARIMA, have been widely applied for short-term load prediction due to their effectiveness in modelling linear trends and sea- sonal patterns (Box, et al, 2015). ARIMA has shown strong performance in forecasting energy demand based on temporal and behavioural consumption trends. However, existing energy switching systems often rely on rigid, centralized control frameworks that do not effectively adapt to fluctuating energy supply and demand. These limitations contribute to increased grid dependence during peak periods, leading to higher energy costs and carbon emissions (Paterakis, et al.,2017). Furthermore, the lack of accurate forecasting mechanisms can result in energy surplus or shortage during critical periods, diminishing system efficiency (Hirth, 2013, Ssemakula et al, 2023).

Although recent studies, such as (Shariff, 2022), have proposed integrating ARIMA with ML models like LSTM networks for enhanced forecasting accuracy and adaptability, these models of- ten overlook cost-effectiveness and intelligent energy allocation in real-time operations. To address these gaps, this research proposes a novel hybrid technique that combines ARIMA with a GA approach. GAs are well-suited for multi-objective optimization, capable of identifying Pareto-optimal solutions while balancing exploration and exploitation through evolutionary operations like crossover and mutation (Bakirtzis & Kazarlis, 2016). Their versatility allows them to be easily integrated with other methods, including ARIMA for time series forecasting, neural networks for pattern recognition, and fuzzy logic for uncertainty handling. This adaptability enables the development of more intelligent, efficient, and responsive energy management systems.

The proposed approach enhances operational efficiency by intelligently prioritizing renewable energy when available, reducing reliance on the grid, and lowering overall costs. By integrating insights from both global studies and Uganda's specific energy context, this work aims to establish a robust and scalable energy management framework aligned with Uganda's Vision 2040 and the UN SDGs.

A Proposed Unified Framework

As illustrated in **Figure**.1, the proposed approach addresses the shortcomings of existing systems by integrating advanced demand forecasting with an intelligent energy source allocation mechanism.

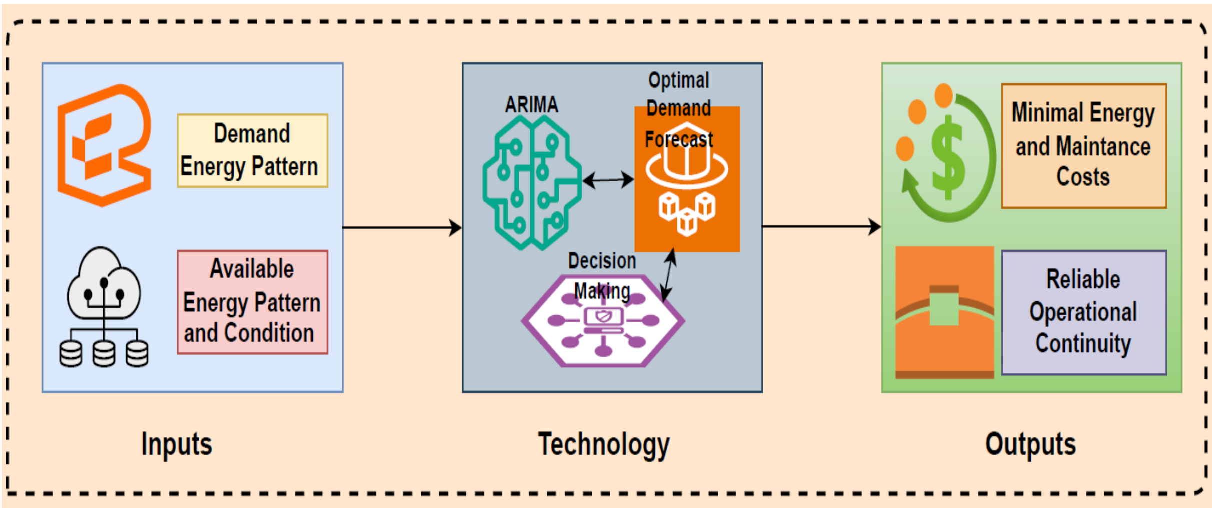

Figure 1: Proposed Energy Optimization Framework

The system clarifies to better reflect the underlying control logic, particularly how decisions are made when switching between energy sources. At its core, the framework combines ARIMA-based demand forecasting with a GA for optimization. The forecasting model captures time-of-day usage patterns, seasonal variations, and appliance-level consumption, and when paired with machine learning elements, it accommodates both linear and non-linear demand behaviours. This provides a more reliable basis for downstream decision-making, rather than relying on static or purely reactive rules.

Basing on that, the control logic for energy allocation is now more explicitly defined. At each time step (hourly), the system evaluates the forecasted demand alongside solar availability, which is inferred from battery charge levels and generation conditions. If solar energy is sufficient to meet the predicted demand, the system prioritizes solar usage. However, when battery levels fall below a defined threshold or solar supply is inadequate, the grid is engaged to ensure continuity of supply. This decision process is not entirely binary; rather, it allows for shared usage where necessary, depending on system constraints.

To further formalize this, the GA operates on candidate solutions representing possible allocation decisions, with an objective function that minimizes total operational cost while satisfying key constraints. These include meeting demand (reliability), respecting battery capacity and availability limits, and implicitly reducing emissions by favouring renewable energy where feasible. The fitness function therefore balances cost, energy sufficiency, and efficient switching behaviour. The block diagram in Figure. 2 illustrates the different decision steps of the system.

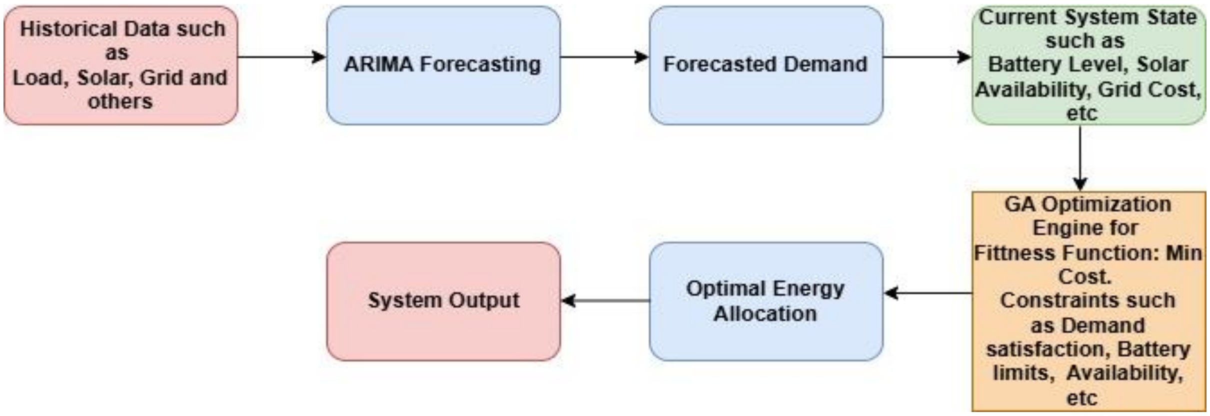

Figure 2: System Block Diagram

Key Components of the Framework

Auto-regressive Integrated Moving Average (ARIMA)

The ARIMA model, also known as the Box–Jenkins model, was developed by George Box and Gwilym Jenkins for time series analysis and forecasting. It combines Autoregressive (AR) and Moving Average (MA) components, applied to data differenced *d* times to achieve stationarity. In this framework, the AR component models the relationship between current values and their past observations (lags), while the MA component accounts for past forecast errors, allowing the model to capture both underlying trends and random variations in the data. The general form is denoted as ARIMA *(p, d, q)*, where *p* represents the AR order, *d* the degree of differencing, and *q* the MA order.

To ensure the model assumptions are reasonably satisfied in this study, stationarity was first assessed using the Augmented Dickey Fuller (ADF) test, with differencing applied where necessary. Seasonal patterns in energy demand, which are difficult to ignore in practice, are handled using a Seasonal Autoregressive Integrated Moving Average (SARIMA) extension, enabling the model to capture periodic fluctuations more effectively. In addition, residual diagnostics were conducted to verify that the model adequately represents the data, providing some confidence in its suitability for short-term energy demand forecasting.

The AR part of the model is represented as:

$$yt = \alpha i\, yt - 1 + \cdots + \alpha p\, yt - p + et \qquad (1)$$

where y_t is the value at time t, α_i are the AR coefficients, e_t is the error term, and p is the AR order. Moreover, Eqn. 1 shows that the AR model relies on past observations to predict the current value.

On the other hand, the MA component of the model is ex- pressed as:

$$yt = et - \theta i\, et - 1 + \cdots + \theta q\, et - q \qquad (2)$$

where y_t is the value at time t, θ_i are the MA coefficients, e_t is the error term, and q is the MA order. As shown in Eqn. 2, the MA model depends on the current error and weighted past error terms.

The complete ARIMA model combines the AR model from Eqn.1 and the MA model from Eqn.2, and is expressed as:

$$yt = et - \alpha 1\, yt - 1 - \cdots - \alpha p\, yt - p - \theta 1\, et - 1 - \cdots - \theta q\, et - q \qquad (3)$$

The parameter definitions in Eqn.3 follow those given in Eqns.1 and 2. In this form, the current value y_t is influenced by both past observations and past error terms. The ARIMA modelling process typically involves three main stages: testing for stationarity, determining appropriate values for p and q, and selecting the best-fitting model.

Determination of AR and MA Value

Once the time series data is transformed into a stationary state, the initial estimates for the AR and MA components can be determined. This is done using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). ACF and PACF plots are generated to visually identify appropriate values for AR and MA. In these plots, the vertical bars represent the correlation coefficients (lags), while the horizontal line indicates the threshold for statistical significance, helping to assess whether a particular lag is meaningful.

Proposed Genetic Algorithm (GA)

Although the formulated energy optimization problem can be solved using exact methods, the complex nature of fluctuating demand patterns and the diverse characteristics of energy sources makes such approaches less practical. Traditional methods like gradient descent often struggle with non-convex landscapes and are prone to getting trapped in local optima. In contrast, GAs offers a more robust and flexible solution by performing global searches across complex solution spaces. Moreover, GA is inherently parallel, evaluating multiple solutions simultaneously, making them ideal for distributed computing environments where sequential techniques like simplex or hill-climbing are inefficient. Their robustness in noisy, stochastic, or time-varying environments allows for reliable performance where deterministic algorithms often fail. Additionally, GA is excellent in multi-objective optimization by identifying Pareto-optimal solutions and maintaining a strong balance between exploration and exploitation through crossover and mutation. Their adaptability is further enhanced by the ease with which they can be hybridized with other techniques, such as ARIMA for time series forecasting, neural networks for pat- tern recognition, or fuzzy logic for handling uncertainty, enabling the development of more intelligent and adaptive energy management systems.

In the proposed algorithm, the GA operators are implemented as follows:

Chromosome Representation:

Each individual in the GA population represents an allocation decision for a single hour, encoded as a binary pair:

- [0, 0] Grid only
- [0, 1] or [1, 0] Shared use of grid and solar
- [1, 1] Solar only

The initial population is randomly generated to encourage exploration of diverse energy allocation strategies.

Fitness Evaluation:

Each individual's fitness was evaluated based on the total cost associated with its switching decision. The fitness function considered several key factors, including:

- the forecasted energy demand for the specific hour (as predicted by the ARIMA model),
- solar energy availability, derived from the current battery charge level,
- the cost differential between grid and solar energy, and
- penalties applied for unmet demand or inefficient switching behaviour.

Solutions that successfully met the energy demand at the lowest cost were deemed more optimal and were assigned higher fitness scores, corresponding to lower total operational costs.

Selection Process:

A tournament selection method is employed. In each round, a subset of individuals is randomly sampled, and the one with the highest fitness is chosen as a parent. This promotes the propagation of high-performing solutions.

Crossover and Mutation:

Selected parents undergo one-point crossover, where their binary-encoded strategies are combined at a randomly selected point to generate offspring. This facilitates the ex- change of effective traits and broadens the search space. Mutation introduces random bit flips in the binary pair, encouraging exploration of new solutions and reducing the risk of premature convergence.

Feasibility Check and Penalization:

After crossover and mutation, newly generated offspring replace the previous population. The process of evaluation, selection, crossover, mutation, and replacement is repeated for a fixed number of generations. Infeasible solutions are penalized to guide the population toward valid and cost-effective strategies.

Optimal Solution Identification:

At the end of all generations, the individual with the best fitness is selected as the optimal allocation decision for the hour. The pseudocode in Algorithm 1 enumerates the steps of the proposed GA.

Algorithm 1: Proposed Algorithm for the Allocation Decision of Different Energy Sources

```
Input:  battery_level, solar_availability, grid_cost
Output: Lowest_Cost_Value

Initialize system parameters:
    battery_level, solar_availability, grid_cost

For each time step t (hourly):
   demand_t = ARIMA_Forecast(historical_data, t) // Demand Forecast
   solar_t = get_solar_availability(battery_level) // Read System state
   grid_t  = get_grid_status()
   population = initialize_population()   // Initialize GA Population

   For generation = 1 to MaxGen:

        For each individual in population:
            allocation = decode(individual)  // Decode chromosome

            if allocation meets demand constraints:  // Evaluate constraints
                cost = compute_cost(allocation, demand_t, solar_t, grid_t)
                fitness = 1 / (cost + penalty)
            else:
                fitness = very_low_value

        population = selection_crossover_mutation(population)

    best_allocation = select_best(population)  // Select best solution

    if best_allocation == solar_only and battery sufficient: // Execute decision
        use_solar()
    elif best_allocation == grid_only:
        use_grid()
    else:
        use_hybrid_solar_grid()

    update_battery_level()  // Update system state
    cost_and_performance()
```

Performance Evaluation

This section presents the performance metrics and benchmark techniques used to evaluate the proposed method, followed by a brief description of the experimental and simulation setup, and concludes with a summary of the results and their interpretation.

Performance Metrics and Benchmark Techniques

Working from the understanding that several SDGs, particularly those tied to access and infrastructure, place real emphasis on reducing the cost of essential services (South & Alpay, 2025), our analysis narrows in on cost as a central indicator. More specifically, we examine the average cost of energy consumption across different techniques, tracking how it varies over hourly intervals during the experiment. This time-based view, while somewhat simple, makes it easier to see where certain approaches perform better and, just as importantly, where they fall short in practical terms.

To make the comparison meaningful, four configurations were examined: Solar Only (SO), Grid Only (GO), a combination of Solar and Grid setup (SGB), and the Genetic Algorithm Allocation (GAA) approach guided by ARIMA-based forecasting. Each was tested under the same operating conditions, across comparable time periods, so that any differences in performance could be attributed to the methods themselves rather than uneven scenarios. It is a fairly controlled setup, admittedly, but it gives a clearer sense of how each approach behaves when cost is treated as the main concern.

Experimental and Simulation Environment Setup

This section briefly discusses the experimental design and simulation environment setting, with an effort to keep the evaluation reasonably grounded and transparent. We based on time-series energy data collected over a defined period, which is partitioned into training and testing sets. The training portion supports the development of the ARIMA forecasting model, while the testing set is used to evaluate performance under unseen conditions. A short-term forecasting horizon is adopted, with simulations conducted over 5, 10, 15, and 20-hour intervals to capture variations in performance across different operational timeframes. All approaches are evaluated under consistent conditions to ensure fairness in comparison.

In addition, fitness evaluation is based on the total operational cost of each solution, taking into account forecasted demand, available solar energy (inferred from battery charge levels), cost differences between grid and solar sources, and penalties for unmet demand or inefficient switching. Solutions that satisfy demand at lower cost are assigned higher fitness scores, as explained under fitness evaluation section.

Performance is evaluated using both forecasting and system-level metrics. Forecast accuracy is assessed using MAPE and RMSE, while system performance is measured in terms of cost savings, renewable energy utilization, and unmet demand. Although the setup remains somewhat simplified, it provides a structured basis for comparing methods and highlights the practical impact of integrating forecasting with optimization.

Results and Discussion

This section evaluates how well the proposed intelligent energy allocation method performs when set against more conventional approaches. The focus is mainly on energy cost across different hourly durations, as a way of gauging how efficiently energy is used under varying conditions. Four distinct configurations are considered, offering a comparative view of performance across different scenarios.

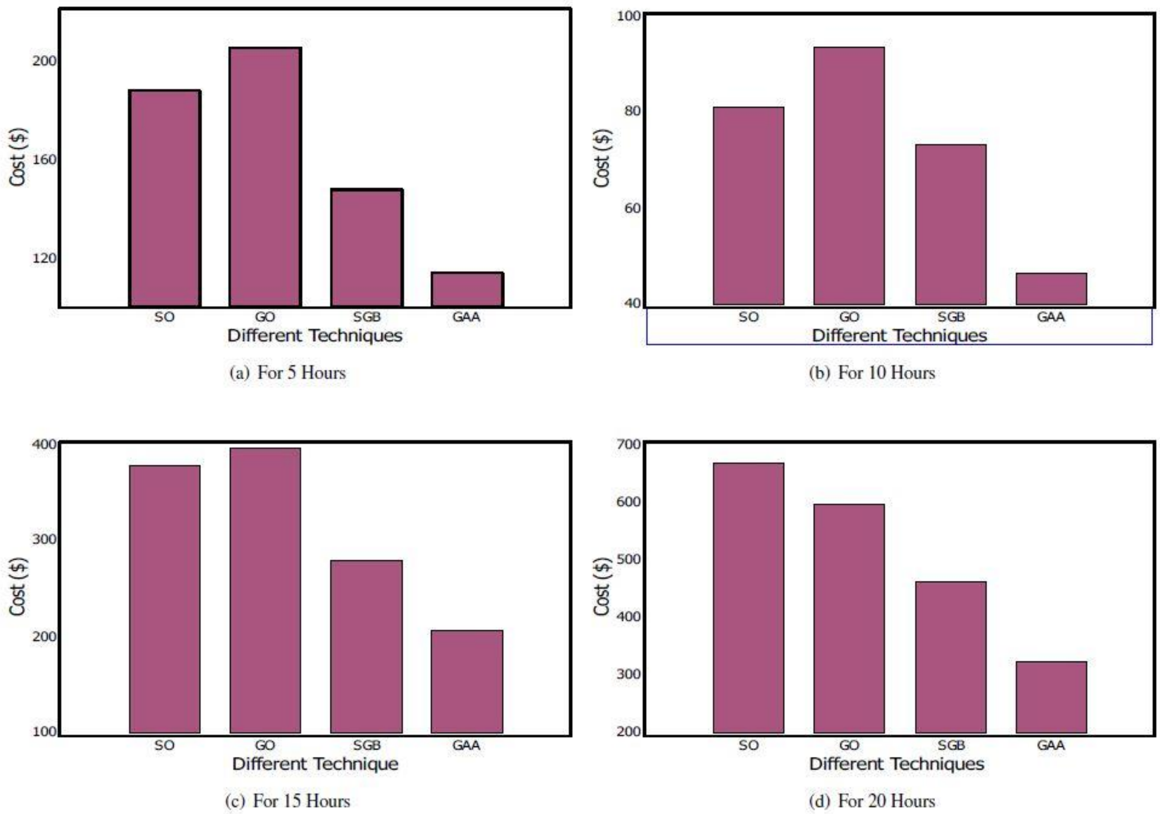

Figure 2: Cost analysis experiments conducted over various time durations (in hours)

Figure 2 shows a clear and fairly consistent trend: the proposed method outperforms the other configurations, particularly in reducing operational costs. The improvement is most pronounced over shorter time horizons, such as 5 and 10 hours, where the cost reductions are noticeably greater than those of the conventional approaches. As the duration increases, however, the margin of improvement becomes slightly less distinct, which is perhaps not surprising. This overall performance gain can largely be attributed to more accurate forecasting, which enables better, timely decisions on whether to use solar energy, grid power, or a combination of both sources.

Conclusion

This study has demonstrated that integrating AI-driven forecasting techniques with multi-objective optimization approaches can significantly improve energy source allocation and management, achieving efficient energy utilization at a rea- sonable cost. The hybrid model developed aligns well with the implementation of global sustainability goals, particularly the UN SDGs 7 and 13, and supports Uganda's Vision 2040 as well as broader regional frameworks such as the EAC energy strategy and the African Union's Agenda 2063.

Specifically, we employed a hybrid approach combining the ARIMA model for accurate energy demand forecasting with a GA for optimal energy source selection. The experimental results confirmed that this combination consistently produced optimal and cost-effective energy allocation solutions across all test scenarios. While the GA-ARIMA hybrid performed effectively, further research is recommended to enhance the model's predictive accuracy and adaptability. One promising direction is integrating ARIMA with neural networks to create a second predictive layer. This would allow the system to refine future energy allocations based not only on demand patterns and energy availability but also on previous allocation outcomes. Additionally, future work will focus on reducing the time complexity of the system by leveraging advanced deep learning techniques and optimizing the underlying algorithmic structure.

Declarations

Competing interests: The authors declare that they have no competing interests.

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Figure 2: Cost analysis experiments conducted over various time durations (in hours)

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