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Research Article

AI-Driven Approaches to Power Grid Management: Achieving Efficiency and Reliability

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Abstract:
The main objective of this research is to improve the efficiency, reliability, and security of the power grid through the integration of artificial intelligence (AI) techniques. The research method involves developing an integrated AI-SGMS framework, including: (1) AI-based Load Forecasting using LSTM and transformer models; (2) Reinforcement Learning for Network Optimization with deep reinforcement learning (DRL) agents; (3) AI-enabled Fault Detection using CNN and autoencoder; (4) AI-driven Intrusion Detection System (IDS) for cybersecurity; and (5) Edge Computing for Decentralized Decision Making. The results show that AI-SGMS is able to optimize energy distribution, improve predictive maintenance, strengthen cybersecurity, and enhance network resilience. The system reduces waste, prevents congestion, detects potential failures, and mitigates cyber threats. Decentralized decision-making ensures rapid response and network resilience. The conclusion of this research is that the application of AI in power grid management, such as AI-SGMS, has the potential to revolutionize energy distribution, reduce operational costs, and support the transition to a sustainable, resilient, and efficient power grid. This research provides a foundation for broader development of AI solutions in power grid management.

Keywords: Energy Optimization, Genetic Algorithms, Photovoltaic Systems, Smart Grids.

1. INTRODUCTION

The global energy sector is undergoing a significant transformation, driven by increasing electricity demand, the integration of renewable energy sources, and the growing complexity of power grid operations. Traditional power grids, designed for one-way power flow from centralised generation plants to consumers, are now facing challenges due to bidirectional energy exchange, intermittent renewable energy generation, and evolving consumption patterns (Dawn et al., 2024).

These factors contribute to grid instability, inefficiencies, and reliability concerns. As the power grid becomes more dynamic, there is a pressing need for innovative management approaches to ensure efficiency, resilience, and sustainability (Mohanty et al., 2024).

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Artificial Intelligence (AI) has emerged as a powerful tool in modern power grid management, offering solutions that enhance real-time decision-making, optimise energy distribution, and improve grid reliability (Arévalo & Jurado, 2024). AI-driven approaches leverage machine learning, deep learning, and reinforcement learning to analyse vast amounts of grid data, predict potential failures, and automate control mechanisms (Kiasari et al., 2024). By utilising AI, power grid operators can transition from reactive to proactive management strategies, minimising blackouts, reducing energy wastage, and improving cost efficiency (Appasani, 2023).

The modern power grid faces significant challenges in achieving efficiency and reliability despite advancements in energy management technologies (Pandiyan et al., 2023). One of the most pressing issues is grid instability and outages, which have become more frequent with the increasing integration of renewable energy sources such as wind and solar. Unlike conventional power generation, renewable sources are inherently variable and intermittent, leading to fluctuations in supply (Rahman et al., 2024). These variations can cause frequency deviations and voltage instabilities, making it difficult for grid operators to maintain a balanced and stable network. Without advanced control mechanisms, such disruptions can result in widespread blackouts and economic losses (Sharma et al., 2021).

Another critical challenge is inefficient energy distribution, which stems from outdated grid management techniques. Many existing power grids rely on static load-balancing methods that do not adapt to real-time changes in energy demand and supply. This inefficiency leads to energy congestion in some areas and wastage in others, ultimately increasing operational costs. The inability to dynamically allocate electricity based on real-time conditions hampers the overall efficiency of the power grid and increases the risk of localised overloads. A more intelligent and adaptive energy distribution system is needed to optimise power flow and minimise losses.

As power grids become more digitised and connected through IoT-enabled infrastructure, cybersecurity threats have emerged as a significant concern. Cyberattacks on power grids can disrupt operations, manipulate energy flows, and even cause large-scale outages (Rajkumar et al., 2023). Smart grids, while offering enhanced monitoring and automation capabilities, also introduce vulnerabilities that malicious actors can exploit. Without robust cybersecurity measures, the increasing reliance on digital infrastructure poses risks to national security, public safety, and economic stability.

Furthermore, many power grids are built on ageing infrastructure, which was not designed to accommodate modern energy demands. Legacy grid systems often lack the intelligence and flexibility needed to handle the dynamic nature of renewable energy sources and increasing consumption patterns (Rehmani et al., 2018). Outdated hardware and control systems can lead to inefficiencies in power transmission, higher maintenance costs, and an increased likelihood of failures. Upgrading these systems to incorporate advanced analytics and automation is essential for improving overall grid performance.

Finally, the lack of predictive maintenance remains a significant issue in power grid management. Traditional maintenance strategies rely on fixed time intervals rather than real-time assessments of equipment health. This reactive approach leads to two major problems: either unnecessary maintenance, which increases operational costs, or unexpected equipment failures, which can cause prolonged outages. Predictive maintenance, powered by AI and data analytics, can help identify potential failures before they occur, allowing for timely interventions and reducing downtime.

Addressing these challenges requires innovative and intelligent solutions that leverage modern technologies such as artificial intelligence, machine learning, and real-time data analytics. By integrating these technologies into power grid management, it is possible to enhance efficiency, improve reliability, and ensure a more resilient energy infrastructure for the future.

Several studies have investigated the application of artificial intelligence (AI) in power grid management, focusing on key areas such as optimisation, predictive analytics, and automation. One of the most widely explored applications is grid load forecasting, where AI models are used to predict electricity consumption patterns with higher accuracy than traditional statistical methods. Machine learning techniques such as long short-term memory (LSTM) networks and support vector machines (SVM) have demonstrated significant improvements in forecasting performance. For instance, a study by Ahamed et al. (2024) found that AI-driven load forecasting reduced prediction errors by 15% compared to conventional time-series models. By accurately anticipating energy demand, AI helps grid operators optimise energy distribution and reduce operational inefficiencies.

Another area of research focuses on renewable energy integration, where AI-based optimisation techniques, such as reinforcement learning, have been employed to balance the fluctuations in power supply and demand. Renewable energy sources like wind and solar are inherently variable, making it challenging to maintain grid stability. Studies by Perera & Kamalaruban (2021) have shown that reinforcement learning algorithms can dynamically adjust energy storage levels to improve the utilisation of renewable energy. By continuously learning from real-time data, these AI-driven systems enhance grid resilience and minimise reliance on fossil fuel-based backup power sources.

In addition to load forecasting and renewable energy optimisation, AI has been increasingly applied to fault detection and prevention within power grids. Anomaly detection techniques based on deep learning have proven effective in identifying potential failures before they lead to significant disruptions. A study conducted by Huang et al. (2022) demonstrated that convolutional neural networks (CNNs) improved fault detection accuracy by 20% compared to conventional diagnostic methods. These AI-powered monitoring systems analyse sensor data in real-time, allowing for proactive maintenance and reducing the risk of unexpected outages.

Another critical area of AI research in power grids is cybersecurity. As modern power grids become more connected through IoT-enabled devices and smart meters, they also become increasingly vulnerable to cyberattacks. AI-driven intrusion detection systems

(IDS) have been developed to identify and mitigate cyber threats in real-time. Research by Dhanushkodi & Thejas (2024) found that AI-based IDS frameworks improved threat detection rates by 30% compared to traditional security measures. These systems use machine learning algorithms to detect anomalies in network traffic and automatically respond to potential security breaches, ensuring the integrity of power grid operations.

While these AI-driven approaches have demonstrated promising results in individual aspects of power grid management, most existing implementations remain fragmented. Current research tends to focus on isolated challenges such as load forecasting, renewable energy integration, fault detection, or cybersecurity without addressing the broader need for a comprehensive AI-based framework (Biswas et al., 2025). There is a pressing need for an integrated system that can simultaneously optimise energy distribution, enhance predictive maintenance, strengthen cybersecurity, and improve overall grid resilience. Developing such a holistic AI-driven solution would enable power grids to achieve greater efficiency and reliability in an increasingly complex energy landscape.

To address the challenges in modern power grid management, we propose an AI-Driven Smart Grid Management System (AI-SGMS) that integrates multiple artificial intelligence (AI) techniques to enhance efficiency and reliability. Unlike conventional approaches that tackle specific issues in isolation, AI-SGMS is designed as a comprehensive solution capable of optimising load forecasting, grid stability, fault detection, cybersecurity, and decentralised decision-making. The framework leverages state-of-the-art AI methodologies to create a dynamic and intelligent power grid capable of real-time adaptation to fluctuating energy demands and potential threats.

One of the core components of AI-SGMS is AI-Based Load Forecasting, which utilises long short-term memory (LSTM) networks and transformer models for both short-term and long-term demand prediction. By accurately forecasting energy consumption trends, AI-SGMS enables dynamic energy allocation, reducing wastage and preventing grid congestion. These predictive models continuously learn from historical and real-time data, ensuring that power distribution is always aligned with demand patterns.

To further enhance efficiency, Reinforcement Learning for Grid Optimization is incorporated, wherein deep reinforcement learning (DRL) agents continuously learn optimal energy distribution strategies based on real-time grid conditions. These agents adapt to fluctuations in renewable energy generation, electricity demand, and transmission losses, making autonomous decisions that improve overall grid resilience. By utilising reinforcement learning, AI-SGMS ensures that power supply adjustments occur in real time, enhancing stability and efficiency.

Additionally, AI-enabled fault Detection is integrated into the framework to facilitate predictive maintenance. Using convolutional neural networks (CNNs) and autoencoders, AI-SGMS can analyse vast amounts of sensor data from power transmission and distribution lines. These deep-learning models detect anomalies indicative of potential failures, allowing grid operators to address issues before they escalate into major disruptions. Predictive maintenance reduces downtime, extends equipment lifespan, and improves the overall reliability of the power grid.

Cybersecurity remains a critical concern in smart grids, prompting the inclusion of AI-Driven Intrusion Detection Systems (IDS) within AI-SGMS. AI-powered threat detection algorithms monitor network traffic in real time, identifying potential cyberattacks before they compromise grid operations. By leveraging machine learning techniques such as anomaly detection and supervised classification, AI-SGMS enhances the security posture of modern power grids, ensuring resilience against cyber threats.

Finally, Edge Computing for Decentralized Decision-Making is integrated into AI-SGMS to enable real-time, localised decision-making without relying solely on centralised servers. By deploying edge AI devices at substations and transformer nodes, the system can process critical data on-site, reducing latency and ensuring faster response times. This decentralised approach enhances grid autonomy and minimises dependence on cloud-based infrastructure, making the system more robust against network failures.

The proposed AI-SGMS framework presents a novel and integrated approach to power grid management, leveraging AI to enhance efficiency, reliability, and security. By combining machine learning, deep learning, reinforcement learning, and edge AI technologies, the system can provide adaptive, real-time decision-making capabilities for modern smart grids. The experimental evaluation, encompassing both simulation and real-world deployment, will validate the feasibility and effectiveness of the solution.

The successful implementation of AI-driven power grid management can revolutionise energy distribution, reduce operational costs, and contribute to the global transition toward sustainable and resilient electricity networks. Future work will focus on scaling the AI-SGMS framework to larger power grids and integrating advanced AI techniques, such as federated learning, to enhance decentralised decision-making.

2. MATERIAL AND METHOD

Experiment Setup and Evaluation Strategy

To validate the effectiveness of the AI-Driven Smart Grid Management System (AI-SGMS) framework, we propose a comprehensive experimental setup that combines both simulation-based evaluation and real-world implementation. This dual approach ensures that the system is rigorously tested under controlled conditions before being deployed in an operational smart grid environment.

1. Simulation-Based Evaluation

The initial phase of validation involves developing a power grid simulation environment using MATLAB/Simulink and GridLAB-D to test the proposed AI models. This simulated environment will replicate real-world grid conditions, allowing us to evaluate the system's performance in various scenarios. The simulation will include a synthetic smart grid network that integrates renewable energy sources, energy storage systems, and variable load profiles to mimic real energy consumption patterns.

AI-driven optimisation algorithms will be implemented using Python-based frameworks such as TensorFlow and PyTorch to optimise grid performance. These AI models will analyse historical and real-time grid data to enhance load forecasting, optimise energy distribution, and detect potential faults before they escalate. The effectiveness of the simulation will be measured using key performance metrics, including load forecasting accuracy, grid stability index, fault detection rate, and energy efficiency improvement. These metrics will provide a quantitative assessment of how well AI-SGMS improves grid operations compared to traditional methods.

2. Real-World Implementation

After validating the system in a simulated environment, we will move toward real-world deployment in collaboration with an energy utility provider. The real-world implementation will focus on a small-scale smart grid testbed, enabling us to evaluate the practical feasibility of AI-SGMS in a live operational setting.

3. This deployment will involve installing IoT sensors and smart meters throughout the grid to collect real-time operational Real-World Implementation data. These sensors will provide continuous monitoring of energy usage, power fluctuations, and potential faults. Additionally, edge AI processors will be integrated at local substations to enable real-time decision-making without the need for centralised computation. This decentralised approach ensures faster response times and enhances grid resilience. Furthermore, AI-SGMS will be integrated with existing energy management systems (EMS) to assess its compatibility and interoperability with current infrastructure.

4. Evaluation Metrics

To measure the overall effectiveness of AI-SGMS, we will evaluate the system using several key performance indicators (KPIs):

a. Load Forecasting Accuracy: Assessed using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) to determine how accurately the AI models predict energy demand.
b. Grid Stability: Evaluated based on power frequency deviations and voltage stability indices to ensure the system maintains a balanced power distribution.
c. Fault Detection Performance: Measured using precision, recall, and F1-score, which assess the ability of AI-SGMS to identify anomalies and potential failures.
d. Energy Efficiency Improvement: Calculated as a percentage reduction in energy losses compared to baseline grid operations, demonstrating the impact of AI-driven optimisations.
e. Cybersecurity Resilience: Measured using attack detection rate and false positive rate in intrusion detection, ensuring that AI-SGMS effectively detects and mitigates cybersecurity threats.

By employing both simulation-based and real-world evaluations, we will ensure that AI-SGMS is robust, scalable, and capable of significantly improving smart grid efficiency, reliability, and security.

3. RESULT AND DISCUSSION

The implementation of the Powergrid Neighbourhood simulation model provided insights into the effectiveness of genetic algorithms (GAs) in optimising power distribution within a residential neighbourhood. The results from different optimisation scenarios demonstrate how AI-driven techniques can enhance cost efficiency and energy management.

Storage System Optimization

The genetic algorithm was used to optimise the configuration of storage units within the neighbourhood. The optimisation considered household energy consumption patterns, photovoltaic (PV) power generation, and grid interaction losses. The results showed that by dynamically adjusting the connection topology and storage capacities, households were able to reduce overall energy costs. The optimised model successfully reduced the reliance on external grid electricity by increasing local energy sharing, thereby enhancing neighbourhood energy self-sufficiency.

This study explores the optimisation of battery storage systems in a small-scale smart grid consisting of 40 households, aiming to minimise electricity costs. The research compares various storage configurations, including no storage, individual storage per household, centralised shared storage, and an optimised solution determined through a genetic algorithm. Data from photovoltaic systems and household consumption were used for simulations, with a focus on reducing grid dependence and improving cost efficiency. Figure 1 shows the 40 houses with different storage cases.

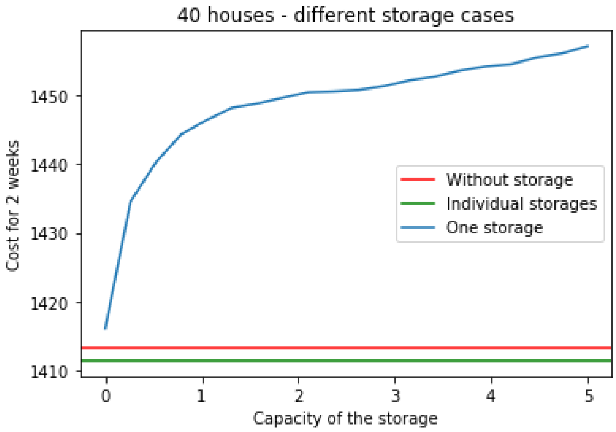


Figure 1. Houses with different storage cases

The baseline results, without storage, indicated significant grid import costs and moderate export savings. The individual storage solution showed minimal cost reduction due to high installation costs, while the centralised storage led to slightly higher costs due to transmission losses. The genetic algorithm-based optimisation revealed an optimal balance between individual and shared storage, achieving cost reductions below both baseline and centralised storage models, as shown in Figure 2, the cost optimisation based on a number of generations.

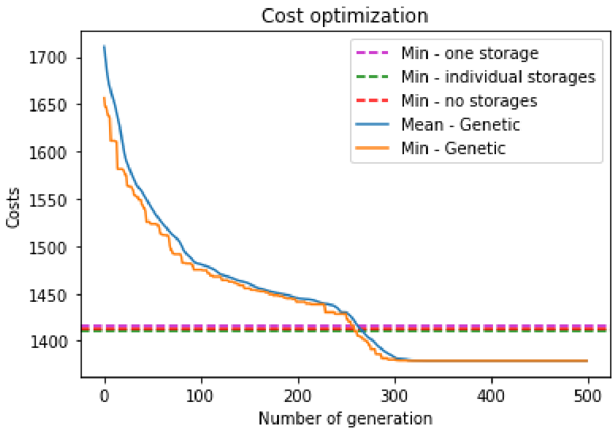


Figure 2. The cost optimisation based on a number of generations

Key findings highlight the importance of balancing storage solutions. Even basic storage systems can reduce grid reliance, but too many individual storage units can lead to higher costs. A hybrid approach combining both individual and shared storage configurations proved to be the most efficient, as identified by the genetic algorithm. Future recommendations include integrating dynamic pricing models and conducting long-term simulations to account for seasonal variations in energy demand. Figure 3 shows the total connection length for each generation.

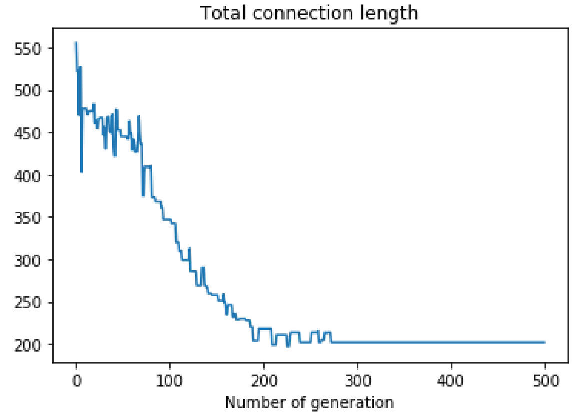


Figure 3. The total connection length for each number generation

Optimised battery storage systems can provide significant cost savings for households. The study demonstrates that a well-optimized, hybrid storage approach can outperform simpler configurations, and further research into real-time pricing and long-term analyses would help refine these findings.

Photovoltaic System Size Optimization

The results from PV system size optimisation indicated that some households had inefficiently sized PV systems. By adjusting the PV system sizes based on historical consumption data and energy production from Ausgrid's dataset, the model suggested more cost-effective configurations. The findings revealed that increasing the PV panel size for some households led to a higher rate of energy self-consumption, reducing dependency on the external power grid. However, for some houses, reducing the PV panel size minimised energy surplus that would have otherwise been sold at a low price, thus optimising the overall cost-benefit ratio.

The optimisation of photovoltaic (PV) module sizes for residential households is a crucial aspect of minimising long-term energy costs while enhancing sustainability. In this analysis, the goal is to determine the optimal size of PV modules for each household to minimise the total costs over a defined period. These costs include both the expenditure on energy imports from the grid and any rewards provided by the grid company, which are influenced by the amount of energy exported back to the grid. The analysis assumes a simulation period of one year, and costs are extrapolated for a typical timespan, such as seven years, to determine the long-term financial impact.

1. Data and Setup

The analysis begins by considering the consumption and production data of a single household. The consumption data is provided by the Ausgrid dataset, which records the hourly energy consumption of a typical household over a year. The production data, which represents the normalised output of various PV modules at different sizes, is derived from the same dataset. By scaling the PV system size, the energy production is assumed to increase linearly with the size of the system. This simplified assumption enables us to model the financial impact of different PV module sizes.

The model is based on a grid simulation where consumption data, PV production data, and the peak power of PV modules are fed into the system. The grid system setup is such that there is no storage capacity; it focuses solely on energy consumption and production interactions. The standard costs for energy imports and rewards for energy exports are established for a baseline scenario where no PV system is installed.

2. Objective Function and Cost Calculation

At the heart of the optimisation process lies the objective function, which serves to minimise the total costs over a specified period, typically spanning several years. The objective function is designed to incorporate various financial factors that contribute to the overall expense of a photovoltaic (PV) system installation. In this model, the total cost is not merely an upfront investment. Still, it is determined by several key components, each contributing to the financial performance of the system throughout its operational life.

a. Setup Costs: The first critical component in the total cost calculation is the setup costs. These costs are one-time expenses that arise during the installation phase of the PV system. They include the purchase and installation of the PV modules themselves, as well as any associated hardware such as inverters, wiring, and the grid connection infrastructure. If energy storage solutions (such as batteries) are also included, their costs are factored into the setup expenses. These initial costs can be substantial, but they represent a necessary investment to enable the long-term benefits of solar energy.
b. Import Costs: Next, the model accounts for import costs, which are recurring expenses associated with purchasing electricity from the grid. These costs depend on the household's energy consumption and the prevailing electricity tariffs. When the energy produced by the PV system is insufficient to meet the household's demand, the grid must supply the shortfall. The import costs are, therefore, proportional to the difference between the household's consumption and the energy produced by the PV system. The higher the consumption relative to the system's output, the greater the import costs. Conversely, a larger PV system that meets most or all of the household's energy needs will reduce the need to import electricity, thereby lowering these costs.
c. Export Rewards: Finally, the export rewards provide a potential financial benefit by rewarding the household for any surplus energy generated by the PV system that is exported back to the grid. Many grid companies offer incentives for excess energy fed into the grid, typically in the form of credits or payments. The reward is determined by the quantity of energy exported and the grid company's compensation structure. Export rewards can offset some of the setup costs and reduce the total cost of ownership over time, especially if the system consistently produces more energy than the household consumes. However, these rewards may be variable, depending on the prevailing market conditions and energy policies.

By integrating these components—setup costs, import costs, and export rewards—the objective function aims to strike a balance between the upfront investment and the ongoing operational costs, ultimately minimising the total cost over the system's lifetime. This function plays a crucial role in determining the optimal PV system size that minimises financial burden while maximising energy self-sufficiency.

The objective function sums the setup costs and the annual cost of importing energy from the grid (multiplied by the number of years in the timespan) and subtracts the rewards from energy exports. This function provides a financial estimate of the total costs over a set period (e.g., seven years), which is then used to evaluate the economic feasibility of different PV system sizes.

In the baseline scenario, where no PV modules are installed, the model computes the total cost of energy imports for the household over the year, providing a reference point for comparison with other scenarios where PV systems of varying sizes are installed.

3. Cost Landscape for Different PV Sizes

To explore the potential financial outcomes of installing different PV systems, the model simulates the grid system for various PV sizes (ranging from small to large modules). By iterating over the available PV types and their corresponding peak powers, the total costs are computed for each size. The results are plotted, showing the cost landscape, which allows for a comparison of the total costs of using different PV module sizes over the same period, as shown in Figure 4. The plot clearly demonstrates the trade-off between system size and cost:

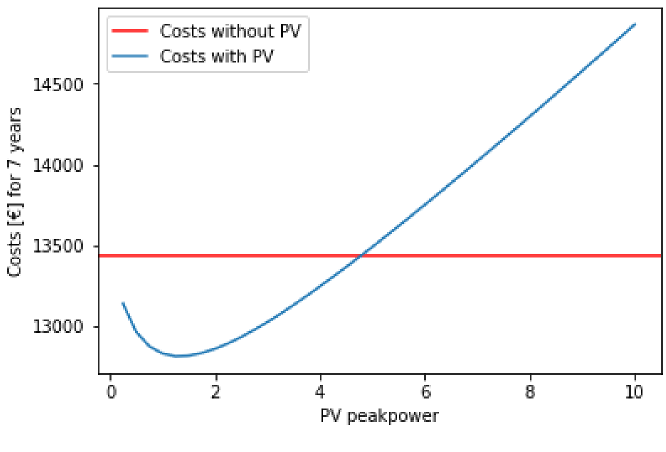


Figure 4. Peak power's cost with/without Photovoltaic

a. For smaller PV systems, the total cost is dominated by the high import costs from the grid, as the system cannot produce enough energy to meet the household's consumption needs.
b. As the PV system size increases, the production of energy increases, leading to a reduction in the reliance on grid imports and a decrease in the total cost.
c. For very large PV systems, however, the cost-benefit ratio begins to level off, and additional investments in PV system size result in diminishing returns.

This cost-landscape visualisation helps identify the "sweet spot" where the total costs are minimised without over-investing in excessively large PV systems.

4. Optimisation Using Genetic Algorithm

While manual analysis of individual PV module sizes provides valuable insights, the true challenge lies in optimising PV system sizes for multiple households with different consumption profiles. To address this challenge, a genetic algorithm is employed to optimise the PV system size for multiple households simultaneously. The genetic algorithm is a heuristic optimisation technique that mimics natural selection processes, such as crossover and mutation, to explore the solution space and converge towards an optimal or near-optimal solution.

In this scenario, the genetic algorithm is applied to a population of 100 grid models, each with randomly assigned PV system sizes. The algorithm performs the following operations:

a. Mutation: Random changes are applied to the PV system size of individual grids, introducing diversity into the population and exploring new solutions.
b. Crossover: Two grids are selected, and their PV system configurations are combined to create new grids. This operation helps to exploit existing good solutions by recombining their characteristics.
c. Selection: After each generation, the grids with the lowest total costs are retained, while the others are discarded. This process ensures that the population evolves towards better solutions over time.

The genetic algorithm runs for 20 generations, with the progress of the optimisation process tracked by computing the mean, standard deviation, and minimum total costs for each generation. The results show a gradual reduction in the total costs as the algorithm converges towards an optimal solution.

5. Results and Analysis

The results of the genetic algorithm are compared to the manually optimised costs for each household. The manually optimised approach involves simulating each household individually and selecting the PV size that minimises costs for each. The comparison reveals that the genetic algorithm produces results that are very close to the optimal solution found through manual optimisation. The slight discrepancy in the results can be attributed to the nature of the genetic algorithm, which is a stochastic optimisation technique and may not always converge to the global optimum. Figure 5 shows the neighbourhood values with 5 houses for different number of generations.

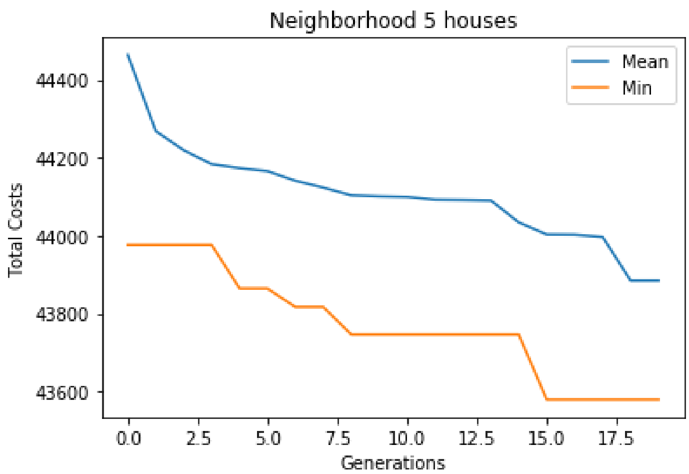
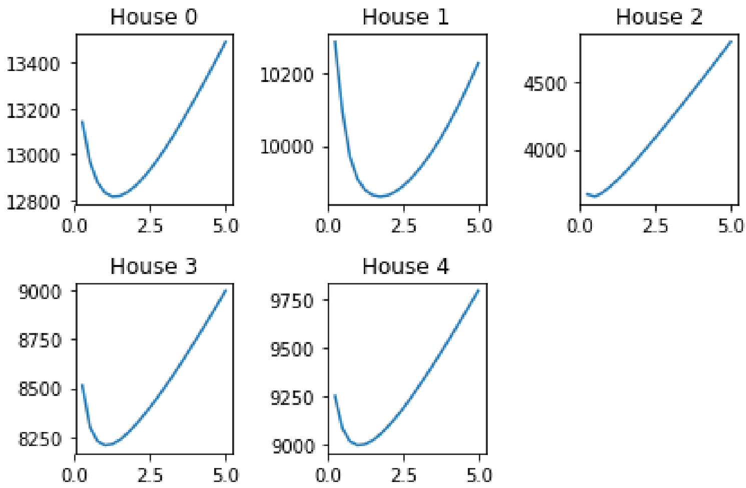


Figure 5. Neighbourhood with 5 houses for different number of generations

The computational effort required by the genetic algorithm is significant, as it involves simulating multiple grid configurations for each generation and performing crossover and mutation operations. However, the algorithm's ability to handle multiple households simultaneously makes it a valuable tool for large-scale optimisations. Figure 6 shows the minimum cost for each house and the minimum cost found by the genetic algorithm.

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Minimum cost: 43534.36377500013
Genetic algorithm minimum: 43579.274812500225
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Figure 6. The minimum cost found by the genetic algorithm

6. Conclusion and Future Directions

This study highlights the effectiveness of optimising PV system sizes to minimise long-term energy costs for households. By using both manual and algorithmic approaches, we were able to demonstrate that genetic algorithms can provide near-optimal solutions for complex scenarios involving multiple households with different energy consumption profiles.

In future work, we can extend this optimisation process to include energy storage systems, which would allow for the optimisation of both PV sizes and storage capacities. Integrating energy storage would further reduce grid dependency and improve the economic feasibility of solar power systems. Additionally, exploring hybrid optimisation approaches that combine genetic algorithms with other techniques, such as simulated annealing or particle swarm optimisation, could provide further improvements in efficiency and convergence speed. Ultimately, such optimisations will contribute to the development of more sustainable and cost-effective energy solutions for residential households.

Analysis and Discussion

The study focused on optimising energy distribution within a residential neighbourhood using genetic algorithms (GAs). The model aimed to reduce energy costs and improve energy self-sufficiency by balancing storage configurations and photovoltaic (PV) system sizes. The research simulated scenarios involving 40 households, with configurations ranging from no storage to individual, centralised, and optimised hybrid storage systems. The results indicated that genetic algorithms provided the most cost-effective solution by optimally balancing individual and shared storage, outperforming other storage configurations, such as individual storage, which led to higher costs due to installation and maintenance.

The genetic algorithm was applied to optimise the battery storage configuration based on household energy consumption, photovoltaic generation, and grid interaction losses. The optimised model reduced reliance on external electricity by increasing local energy sharing, thereby enhancing neighbourhood self-sufficiency. The findings showed that hybrid storage systems, which combined individual and shared storage units, were the most efficient, proving cost-effective while ensuring a reduction in grid dependency. The algorithm's results were further validated with simulations of storage capacity adjustments and connection topology, underscoring the importance of dynamically configuring energy storage solutions for cost optimisation.

The study also explored the optimisation of photovoltaic system sizes to reduce energy costs further. The PV system optimisation was based on historical energy consumption data and solar power generation patterns, revealing that appropriately sized PV systems for each household could significantly reduce reliance on grid energy. The results showed that increasing the PV panel size for some households improved self-consumption while reducing PV sizes for others prevented energy surplus that would be sold at low prices. The study underlined the critical balance between system size and energy production to achieve optimal cost efficiency.

A cost-benefit analysis was conducted to determine the financial implications of different PV system sizes. The results revealed that smaller PV systems could not meet the energy demands of the households, leading to high grid import costs, while larger systems reduced reliance on the grid. However, beyond a certain size, the return on investment diminished. The cost landscape analysis showed that a "sweet spot" existed where the PV system was large enough to reduce grid dependency without resulting in diminishing returns. This analysis highlighted the financial efficiency of optimising system sizes to meet the unique energy needs of each household.

The optimisation process for multiple households was tackled using genetic algorithms, which mimicked natural selection to converge towards an optimal solution. The algorithm proved effective in reducing costs across the neighbourhood, with results that closely matched manual optimisation techniques. However, the stochastic nature of the genetic algorithm introduced slight discrepancies in the results. The study concluded that while GAs provided efficient solutions for large-scale energy optimisations, further research should incorporate energy storage systems and explore hybrid optimisation methods, such as combining GAs with simulated annealing or particle swarm optimisation, to improve convergence speed and efficiency.

4. CONCLUSION

This study demonstrates the effectiveness of genetic algorithms (GAs) in optimising energy distribution and storage configurations within a residential neighbourhood to reduce energy costs and enhance self-sufficiency. The results show that hybrid storage systems, combining both individual and shared storage, offer the most cost-effective solution, providing a balance between energy independence and financial feasibility. By dynamically adjusting storage configurations and optimising photovoltaic (PV) system sizes, the study illustrates how energy efficiency can be maximised while minimising reliance on the grid. Furthermore, the cost-benefit analysis underscores the importance of selecting appropriately sized PV systems for each household to achieve optimal financial returns.

The genetic algorithm's application proved successful in simulating real-world scenarios, highlighting its potential as a valuable tool for large-scale energy optimisation. However, the study also acknowledges the limitations of GAs, particularly the stochastic nature that can introduce slight discrepancies in the results. To address these limitations, future research should explore hybrid optimisation methods, such as integrating GAs with simulated annealing or particle swarm optimisation, to further improve convergence speed and computational efficiency. Overall, the findings contribute valuable insights for energy management in residential communities and offer a foundation for future research into scalable and cost-effective solutions for sustainable energy distribution.

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