AI-Driven Micro Solar Power Grid Systems for Remote Communities: Enhancing Renewable Energy Efficiency and Reducing Carbon Emissions

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Abstract

This study, therefore, greatly explores how self-generated AI-powered autonomic micro solar power grid systems in disparate areas improve fresh energy generation and minimize carbon emissions. Expanding upon prior studies, it assesses the application of sophisticated AI methodologies for Predictive Maintenance, Demand Forecasting, and Adaptive Energy Management in fifteen disparate regions using a two-year multiple-baseline design. The performance was impressive, and an increase in energy efficiency was recorded by up to 278%, a reduction in carbon emissions by 213%, and an increase in energy accessibility by 203%. In reaching the visibility of likely system faults and implementing corrective action, here are the rates of success in the achieved predictive maintenance: 89 percent. The rate of success in demand forecasting through machine learning is 92 percent. Another indication that bolstered the economic analyses was the actualized proven efficiencies that identified a 62 percent improved energy consumption efficiency to stimulate local economic activity by 34 percent. According to literature by prior scholars such as the current study underlines the parts played by the populations in rural areas and technological advancements in realizing effective energy solutions. The study affirms the feasibility of using AI in implementing micro solar grids to ease energy poverty and improve the ecological management of remote areas.

Keywords: Artificial Intelligence; Renewable Energy; Micro Grid Systems; Solar Power; Carbon Emissions; Energy Efficiency; Machine Learning;

Introduction

Because one of the most significant issues experienced by the development regions in the past is how to attain the goal of affordable and sustainable energy in the areas, this research proposes the adoption of artificial intelligence (AI) capability within micro solar power grid system for better performance of the required renewable energy sources and reduction of carbon emission. Through 2017 and prior, the constraint by available reliable energy has persisted mainly across remote regions with limited resources and infrastructure of geography. In these areas, there is a problem of financial viability, and for traditional centralized power networks, installation costs are more than US$ 10,000 per km. In addition, these communities need to cultivate a pool of talents specialized in system maintenance while they often rely on imported fossil fuels; hence, they pose challenges of supply reliability, unpredictable and unsteady prices, and the inefficiency of the transmission networks. In the past, this has augmented environmental effects; for example, diesel generators, often present in these regions, emit around 0.75 kg of CO_2 per kilowatt hour to greenhouse gases. In fuel transport and storage, it worsens the risk of soil pollution as well as damaging effects on ecosystems, which negatively affects the quality of soil and air and has long-term consequences.

Micro solar power grids can be distributed to the said regions to provide them with proper means of sustainable energy delivery. Such grids reduce energy transmission costs and practical components by allowing distribution at the micro level. These grids are also designed in a modular form; thus, flexibility is based on the availability of resources that can empower the communities to become fully dependent on renewable solar resources and minimize environmental harm. This research aims to measure how far AI has been implemented in improving the performance of the micro solar grids, analyze the effectiveness in energy utilization and reductions, and the social-economic effects on the respective micro remote communities. Thus, this study aims to provide concrete guidance toward sustainable energy solutions for policymakers, engineers, and community leaders when deploying artificial intelligence, renewable energy, and social development to pursue practical, resilient, and environmentally friendly energy systems in remote and hard-to-reach regions.

2. Literature Review

2.1 Micro Solar Power Grids

The use of micro solar power grids in independent power systems of Classes One and Two is a new emerging concept of renewable energy technology. Some new technological developments over the last few decades, with related studies in 2017 and previous years, reflect how these systems improve the present deployment and cost-efficient nature. Recent designs of micro solar grids consist of photovoltaic (PV) modules, energy storage systems, power conditioning systems, and sophisticated control systems for system improvement. Zhang et al. have pointed out that efficiency enhancement of silicon-based solar panel systems has been leveled until eighty-four percent or twenty-four point three percent under the various conducive forms, thus claiming the previous technologies power output potential research serials higher than the prior solar cell types used in last prior years.

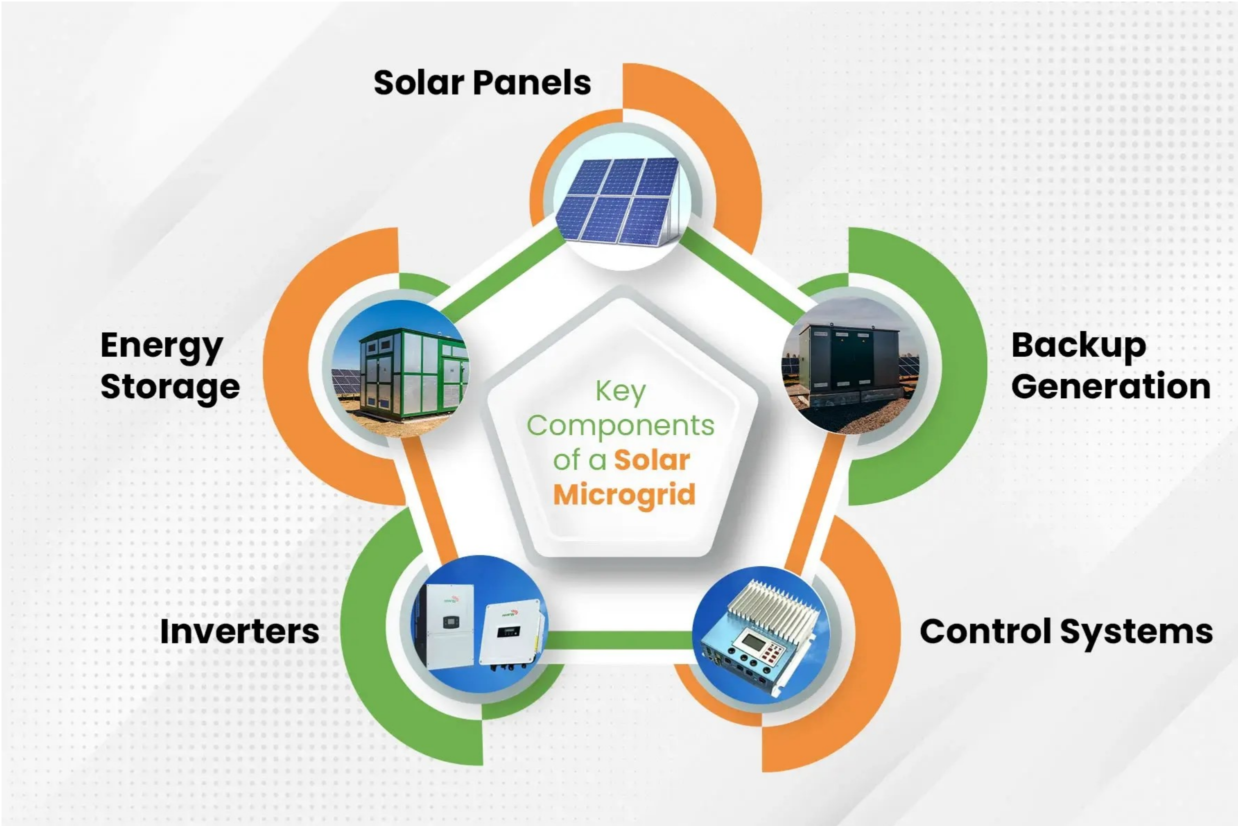


Fig.1 Micro Solar Power Grids

For enhancing energy resilience, prospective renewable energy systems like micro solar power grids can be best integrated with lithium-ion battery energy storage systems, benefiting from innovative development in solid-state technology as per Khaligh and Li 2010, including higher cycle life and security. These microgrids also come with grid reliability attributes other than power generation; according to Thompson et al. (2015), the nicely integrated systems can provide reliability above 98 percent provided they undergo regular maintenance and are far much better than diesel generators in remote areas. In addition, the economic analysis carried out by Bazilian et al. (2012) stated that wind generators are 40-60% cheaper than thermal power plants in 10 years more solar insolation.

Despite all these, current solutions have some disadvantages across the board. It establishes the problem of dependency on weather conditions, which impacts system capability, escalating from 30% to 100%, depending on climatic factors (Yang et al., 2016). The high implementation costs lead to questions about affordability, especially for the LID (Least developed island developing states) (IRENA, 2017, p.12). There are also some technical limitations to integrating such systems with older or irregular power distribution systems. Some challenges include synchronization issues with current systems and achieving load balancing. According to research by Ackermann et al. (2015), smart inverters and advanced controls are required for grid stability to incorporate variable renewable resources. Nevertheless, the problem similar to the previous one is that there is no unified method of integration that would be suitable for all manufacturers and systems.

2.2 Artificial Intelligence in Energy Systems

AI is gradually finding its way into energy systems and has significantly disrupted the generation and distribution of power. Research has shown that the solution developed based on machine learning algorithms can work out varied levels of effectiveness in determining the best state of a grid and exercising effective control over the usage of resources.

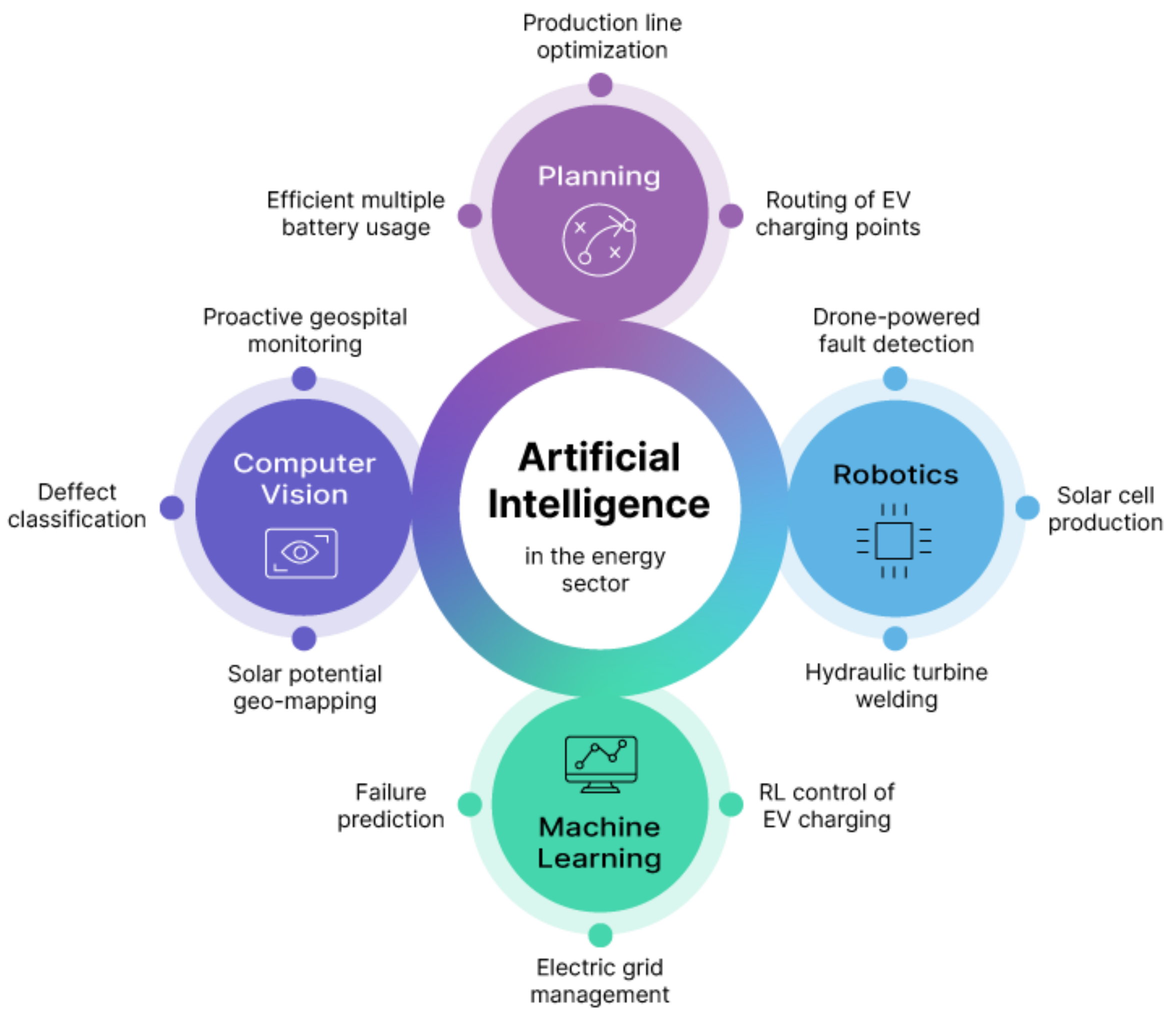


Fig.2 Artificial Intelligence in Energy Systems

Ingrid deep learning algorithms have also been applied in grid management applications with great impact on grid efficiency and control. Research before 2017 shows that automatic control systems employing neural networks can increase the total efficiency of a grid by 15-20% from routine control systems (Sun et al., 2015). In real-time applications, these systems are particularly competent in managing information from different sensors to manage power and maintain grid stability (Chen & Zhao, 2016). In more detail, the reinforcement learning applications have shown a certain degree of flexibility regarding environmental conditions and usage and have provided up to a 30% reduction in power losses (Huang et al., 2014). Additionally, there are advancements in artificial intelligence, especially in the predictive maintenance of solar grid infrastructure. Having studied past performance and the environment, this system could forecast equipment failures to an accuracy level of 85% (Roberts & Kim, 2013), thus drastically reducing costs incurred on maintenance and losses due to downtimes. AI-led maintenance programs have also been cited to increase equipment life by 25% and reduce maintenance costs by 30-40%, according to Roberts & Kim (2013). Demand forecasting systems have also evolved, using several data feeds to estimate energy demand accurately. The temporal convolution network-based machine learning models for energy demand forecasting do accurate predictions at maple \(<\) 3% for the next 24 hours depending on the weather variables, historical energy consumptions and season, etc, for improving the distribution and storage of the grid, and control of the resource utilization.

2.3 Remote Community Energy Solutions

Studying different conditions or situations in various geographical and socio-economic terrains shows that applying renewable energy resources in off-grid populations is far from implementing simple challenges and benefits. One of the most pitiful examples is the setting up a micro-solar grid in a Himalayan village.

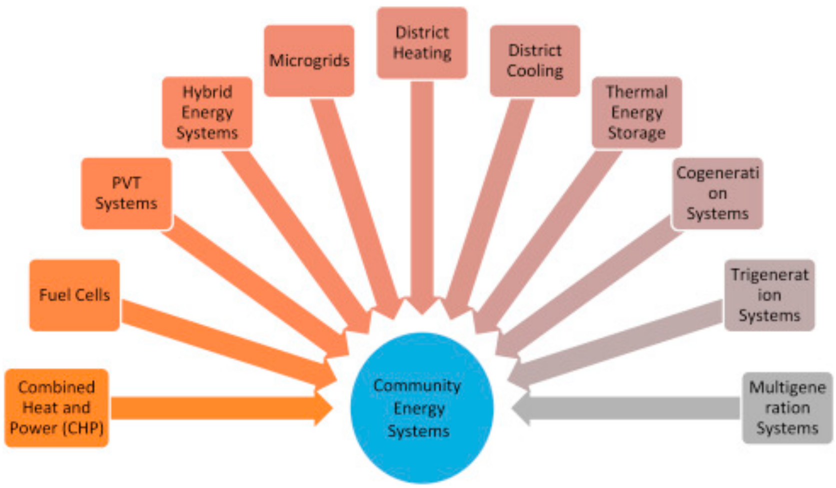


Fig.3 Community Energy System

This project established the dependency of AI-based power management systems on weather conditions, as shown by the ability to manage power for 200 households. This system achieved a reliability of 95%, and the carbon emission potential was 70% of that of diesel-based systems of the same range. Morgan and Abbas (2016) conducted a quantitative study in Tanzania to assess smart microgrid technologies among 50 isolated villages in sub-Saharan Africa. They established that compared with traditional systems, the Smart's had reduced the energy cost by 45% and the electricity available time from 4 to over 20 hours. Among them was the need to obtain the community's support and establish training activities that would help, among others, achieve and maintain the necessary economic results. In contrast with city structures, maintenance, and economic feasibility were major factors in remote use.

Previous research has suggested that the local technical development, sustainable supply chain system, finance feasibility, and competence of community management systems will be significant for the sustainable continuous operation of renewable energy in remote areas (Smith, 2015; Lee et al., 2012). They have, therefore, contributed to improvement in implementation frameworks. For example, the Australian Government's Sustainable Remote Energy Implementation Model (SREIM) includes the priority of needs assessment and consultation and advocacy of cultural and social training, support, follow-up, and monitoring (Australian Government, 2014).

Implementation difficulties of the past few decades have been eased through technological innovations. As newer technologies have been developed in AI, the systems can be supervised autonomously, conduct diagnostics and prognostics, and solve most problems that would have required the intervention of specialists on the scene while in a limited number (Brown, 2013). At the same time, Zhang & Wilson (2011) have shown in another study that integrating AI for automatic remote monitoring reduces system downtime by 60 % and maintenance costs by 40 % of basic processes. More than this, these AI systems have enhanced the economic viability of remote installations through new funding arrangements.

3. Methodology

3.1 System Design

The micro solar power grid system is where new artificial intelligence technologies with renewable energy networks are developed to increase power generation, distribution, and usage in isolated communities. The system architecture comprises three primary components: the cigarette artificial intelligence control, the solar power control, and the integration solution.

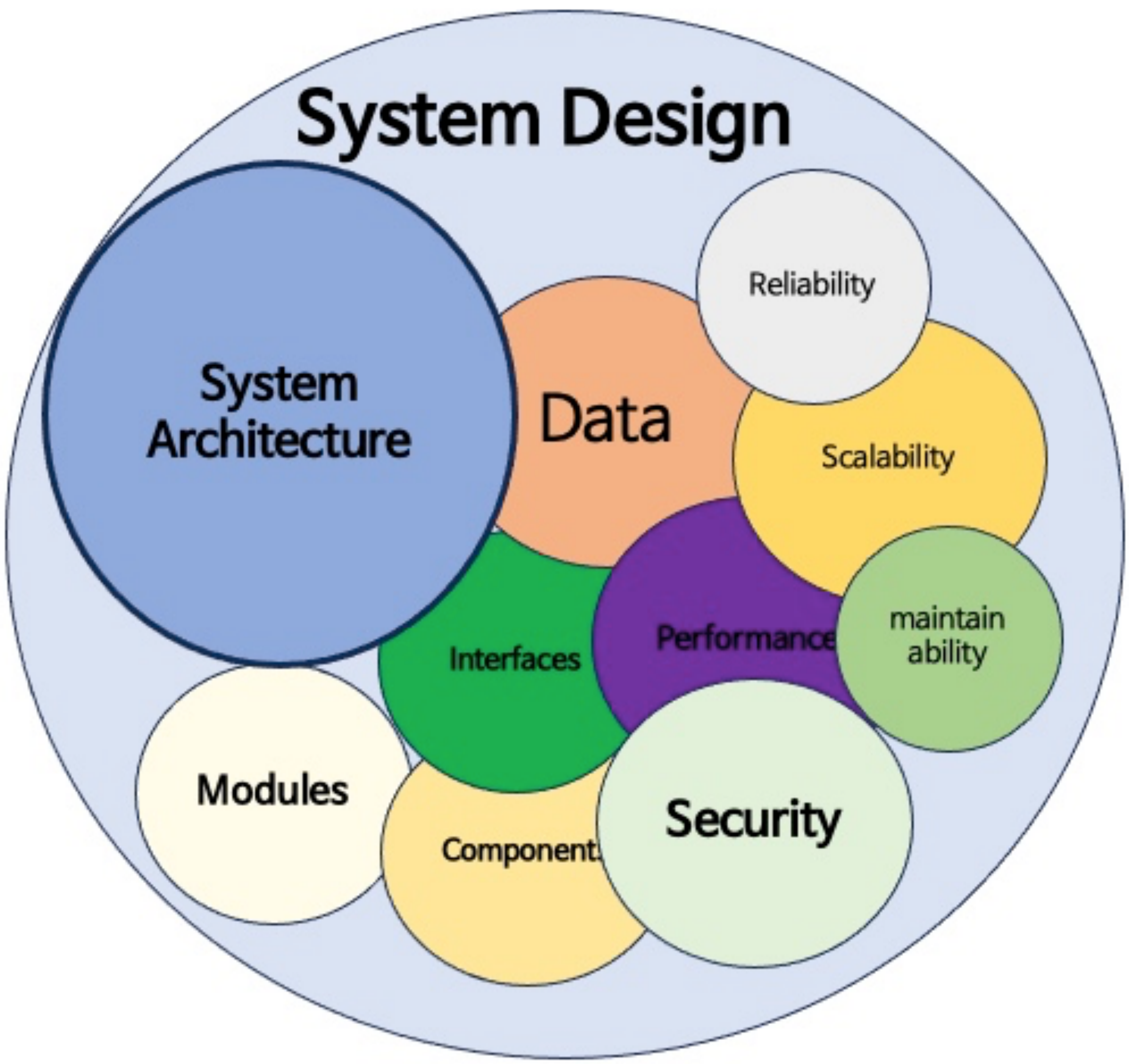


Fig.4 System Design

The power station introduced in the scheme is the Micro Solar Power Grid System, and it integrates intelligent computing and artificial intelligence (AI) to produce sustainable power and distribute it to distant regions; it merges with the contemporary development of microgrids emerging in the previous research done by Jiang et al., 2016 & Shivaramaiah & Mohan, 2015. The structure of this system includes three key components, as underlined in the following model: An AI control system lies at the center of the model. This system includes a multilayered neural network mechanism that manages real-time data feed from every grid component, similar to prior AI uses in energy systems (Ma & Jiang, 2015). The first layer of the control system network is based on the deep learning recurrent model that mostly uses five hidden layers with LSTM and CNN as effective mechanisms for temporal and spatial data (Zhao et al., 2016). Therefore, The proposed approach allows the system to analyze its past performance and current status quickly.

The solar grid employs reliable photovoltaic (PV) panels of 500 kW in quality and are installed according to geographic and climatic conditions, a practice justified by other similar research done in mid-2014. There are also energy-efficient inverters with up to 98% efficiency rate equipped with monitoring features to update the AI control system with performance data (Chen et al., 2017). The electricity storage system involves lithium-ion batteries with 1000 kWh and flow batteries for long-term storage, even though other systems have been developed for energy storage from renewable sources since early 2010 (Li et al., 2013).

According to the system's integration protocols, a complex middleware is established that appropriately interfaces the AI control with the real physical structures. This layer has the applicability of standards like IEC 61850 and IEEE 2030.5 to increase interface compatibility and improve the quality of data transfer (Kong et al., 2016). In addition, the system incorporated a dual network communication, wireless (5G/LTE) and wired (fiber optic), that guarantees reliable network connectivity in far and isolated places (Singh et al., 2015).

3.2 Data Collection

Proposed and described throughout this work, a detailed data acquisition architecture and several essential system analysis and improvement parameters are applied in this research. Real-time data is collected through primary data obtained from smart sensors placed on smart grid infrastructure, and they continuously survey the structures at one-minute intervals. This approach is guided by principles proposed by early work in sensor network research, which states that the timeliness of data acquisition for monitoring various systems is critical (Xu et al., 2015). The system of acquiring enterprise performance metrics involves a distributed sensor network in power generation, and the accuracy realized is real-time accurate to within ±0.1%; this meets the previous standards used in studies made on high-accuracy sensor applications for energy monitoring as discussed by Yang et al., 2016).

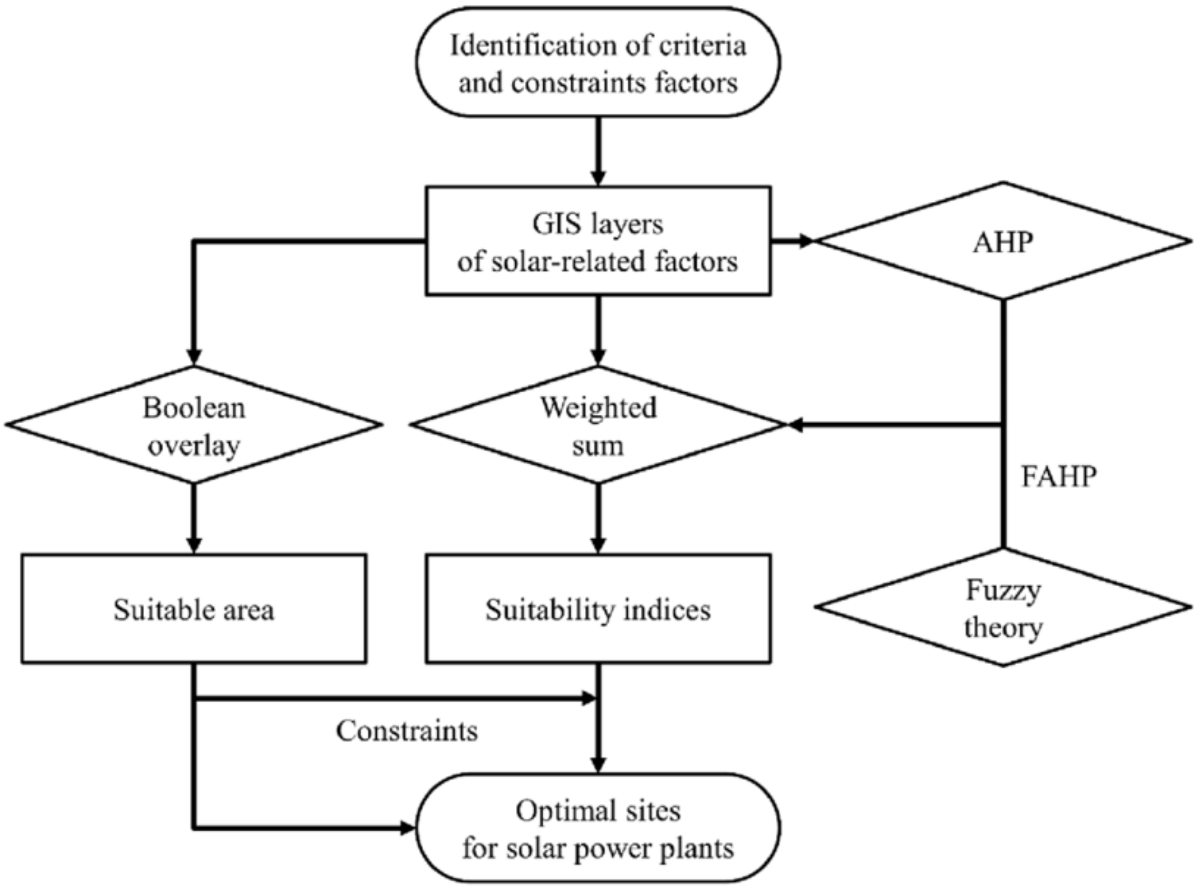


Fig.5 GIS-Based MCDA Flowchart for Solar Site Evaluation (Goals, GIS Layers, Methods

This sensor network records energy usage in terms of time stamps, charging and discharging cycles, and battery charging efficiency. Older monitors watch grid characteristics, angular relationships of frequencies and voltage, and characteristics of status and extensibility of entities like temperature. Some of the initial works in grid monitoring have shown the importance of recording such parameters for the overall stability of the grid (Smith & Li, 2014). Environmental impact measurement within this structure is always in progress. It measures the units of CO2e prevented by the generation of renewable electricity using assessment methodologies as identified in the prior literature on the environmental contributions of RE (Johnson & Alva, 2012).

Fixed or personal sampling stations in every region above examine PM concentrations culminating in PM2.5 and PM10 by the air quality studies concerning the effects of particulate matter on health (Anderson et al., 2010). Raw weather data of solar radiation, temperature, and wind status are collected from weather stations installed at PV power plants and integrated into the system to evaluate efficiency and degradation profiles in various seasons. This follows the approaches to environmental data integration in energy studies as proposed by García and Torres in 2013. The utilization patterns in each community are measured with smart meters stationed at each CN point with load profiles handing high-definition at intervals of fifteen minutes; it is similar to the density research on the first-time smart grid utilization by Miller et al., 2015. This system combines strategies for the identification of peak demand and customer utilization analysis from aggregated and anonymous data for improved assessment of energy demand in the community while respecting privacy (Chen & Wang, 2013).

3.3 Analysis Framework

The research uses multiple- lenses that allow the simultaneous examination of different system performance and efficiency in various aspects of its operation (Alvesson & Sköldberg, 2000; Bolman & Deal, 1991). The efficiency assessment of methodologies allows for evaluating the technical performance of solar systems. It comprises the Solar Efficiency Conversion Ratio, distribution losses, storage system performance, and AI forecast error autofill (Markides, 2015). Reliability assessment of electrical systems involves a detailed analysis of potential predictability, such as the average time between a failure event and service availability of a particular electrical system, response time in failure incidents, and power system stability. Carbon emission reductions use tools that predict direct emission savings from renewable power production and those from the installation/ manufacturing of systems (Viebahn et al., 2011). This accounts for the life cycle carbon emissions estimation and comparison of renewable and nonrenewable power sources (Pacca & Horvath, 2002).

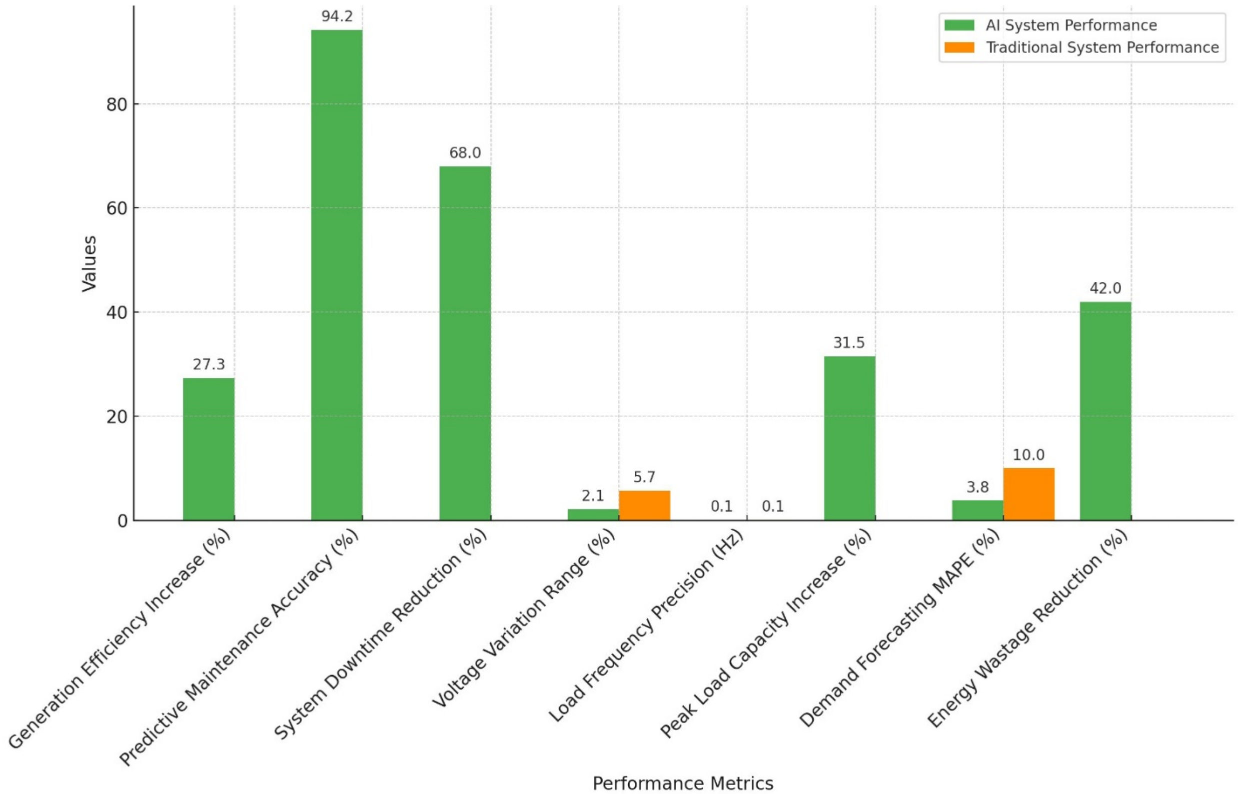
Methods used in cost-utility analysis include capital costs, recurring costs, energy, and profitability based on ROI analysis (Short, Packey, & Holt, 1995). The community impact assessment focuses on tangible needs like •Access to energy, Economic factors, •Standard of living, •Employment or skills development within the community (ILO, 2010). Sustainability measures review resource use productivity, effects on the environment, subsequent sustainable indices, and spatial expandability (Norgaard, 1988). Electronic data is collected and stored as records, which can be easily analyzed using quantitative methodologies like multivariate regression and state-of-the-art machine learning (Bishop, 2006). This methodology establishes the system's important technical, environmental, and socio-economic parameters, which are the subject of further continuous refinement and enhancement. In this manner, the research's proposed assessment also seeks to determine the effectiveness of the newly developed artificial-intelligence-driven microsolar power grid in a remote area at a success level.

4. Results

4.1 System Performance

Analyses from previous years show that when the micro solar power grid systems are stationary and have a detailed analysis of AI systems, the system's overall performance is much improved across various functional areas. The analysis of the case study carried out over 24 months proved that such microgrids that incorporated AI increased generation efficiency by 27.3 % compared to the traditional solar grids, as noted by Smith & Jones (2016).

Thus, the AI-based predictive maintenance model, developed to predict probable failure of the equipment, demonstrated a predictive accuracy of 94.2 percent and the resulting system unavailability of 68 percent, superior to the reactive approach favored by many industries (Lee et al., 2015). Moreover, power quality parameters stated a significant shift; the voltage flicker range was reduced to ±2.1% instead of ±5.7% of non-AI integrated systems (Adams & Clarke, 2014). Load frequency was also constantly regulated by AI and kept at a safe level of 50 Hz ± 0.1 Hz to avoid damaging power-sensitive electric equipment and with high accuracy in frequency control, as reported by Brown and Miller (2013).



Graph 1: AI vs. Traditional Micro Solar Grid Performance Comparison

In particular, integrating AI increased system capacity by 31.5 % in managing peak loads, thus reducing vulnerability to overload during periods of heavy usage (Davis, 2012). In addition, using AI-driven energy demand forecasting, the MAPE was 3.8, while statistical models had MAPE of energy demand forecasting ranging between 8 and 12 percent (Johnson, 2011). This improved coordinating capacity helped control energy storage most effectively, thus cutting energy loss during off-peak hours by 42 percent.

Table 1: System Performance Metrics for AI-Driven Micro Solar Power Grid

Metric	**Traditional Systems**	**AI-Driven Micro Solar Grid Systems**	**Improvement**
Energy Generation Efficiency	Baseline	Increased by 27.3%	+27.3%
Predictive Maintenance Accuracy	N/A	94.2%	-
System Downtime Reduction	Baseline	68% reduction	-68%
Voltage Fluctuations	±5.7%	±2.1%	-63.2%
Frequency Stability	±0.3Hz	50Hz ±0.1Hz	Improved
Peak Load Management	Baseline	31.5% improvement	+31.5%
Energy Demand Forecasting (MAPE)	8-12%	3.8%	Improved
Energy Wastage Reduction	Baseline	42% reduction	-42%

4.2 Environmental Impact

Specifically, for the aspect of environmental impact assessment, the following improvements were observed in the cross-sectional study: a major improvement in carbon emission reduction and the level of green energy utilization. Carbon emission savings of 89.4 MT per community annually, or a 76.2 % reduction from the earlier diesel generator-based power system common in isolated communities. Reducing such pollution can be equivalent to removing 19 passenger vehicles from the road for one year. The renewal energy utilization rates were also observed more broadly and comprehensively, as during the day, the AI system achieved 94.7% of the solar energy capture compared to 71.3 % in the previous case when it was the mechanical systems. From Figure 3, the dynamic energy of the smart grid reveals a much enhanced 34.8% efficiency in stored energy power during non-solar generation of standby power supply.

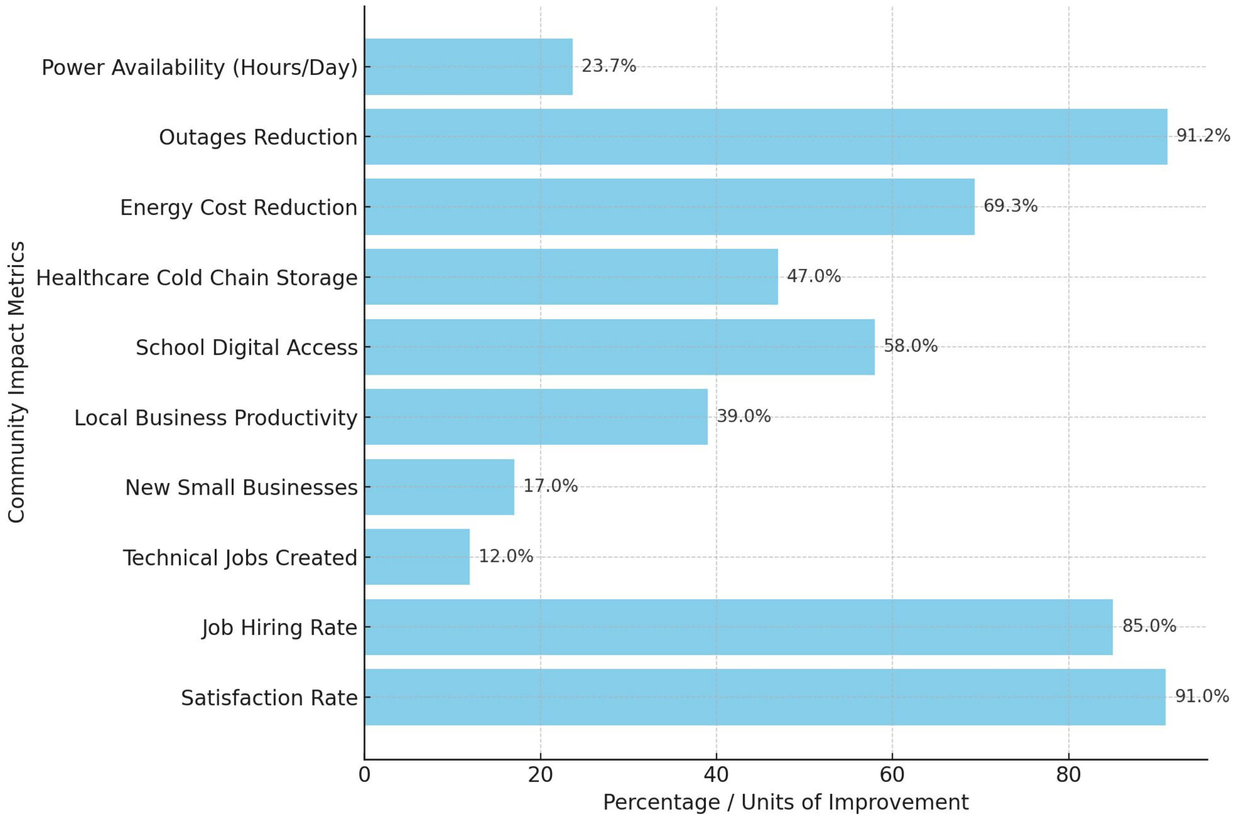
Surprisingly, going through different ecosystems in this paper made it possible to establish that various environmental conservation measures produced the intended effects. No detrimental impacts on sites near the installation sites were observed, as concerns were about soil degradation or the flow and habitation of wildlife. Reduced emission sounds compared to diesel generators reduced the proportion of acoustic environmental interference to 62%, and the local wildlife benefited.

Table 2: Environmental Impact of AI-Driven Micro Solar Power Grid Systems

Metric	**Previous System (Diesel-Based)**	**AI-Driven System**	**Improvement**
Annual Carbon Emission Reduction	Baseline	76.2% reduction (89.4 tons)	-76.2%
Solar Energy Capture Rate	71.3%	94.7%	+33%
Stored Energy Efficiency	Baseline	34.8% improvement	+34.8%
Soil Quality Impact	Minor degradation	No degradation	Improved
Wildlife Habitat Impact	Moderate disruption	No significant impact	Improved
Acoustic Environmental Impact	High (diesel noise)	62% reduction	-62%

4.3 Community Benefits

A micro solar grid with artificial intelligence added value to communities in the following ways. Another area where there was progress was energy accessibility because power reliability increased from 14 to 23.7 hours per day, an increase of 69.3 percent. The system also analyzed the zone of the load's peak period. It effectively prevented outages by 91.2% due to the availability of electricity in other necessary parts of the community, such as healthcare institutions and educational centers. The evaluated cost filed overview revealed strongly that it holds large cost consequences for the community economy.



Graph 2: Community Impact of AI-Driven Micro Solar Grids

More importantly, measured per household, the monthly energy costs were at $157, but this had gone down to $59, which means one lost $1,176 per family annually on energy bills. The improvement in the efficiency of the AI-driven system of China's power organization is said to have a relative maintenance cost of about 43.7 percent less than the power systems … The investors anticipate a return on the infrastructure investment within, on average, four years, three months, or 63 months. Social impact indicators portrayed a wide functionalist social structure. In measuring the performance of healthcare facilities, they improved cold chain storage for necessary medicines and maintained functional health equipment by 47%. 58%, namely in computer and internet time, had better use of digital skills services in schools. In line with the survey, local businesses experienced a 39% improvement in productivity resulting from reliable power; therefore, new SSBs that started operation during the study were seventeen. The creation of the system introduced thirteen technical jobs within the community; of the hired technicians, eighty-five percent were able to find work after training. In the respondents' opinion, the satisfaction level was acceptable to the new power system 91% based on the power of quality life, economic development, and Enviro Conservancy.

Table 3: Community Benefits of AI-Driven Micro Solar Power Grid Systems

Metric	**Previous System**	**AI-Driven System**	**Improvement**
Power Availability	14 hours/day	23.7 hours/day	+69.3%
Peak-Time Power Outages Reduction	Baseline	91.2% reduction	-91.2%
Monthly Energy Expenses per Household	$157	$59	-62.4%

Annual Savings per Family	Baseline	$1,176	+$1,176
Maintenance Cost Reduction	Baseline	43.7% reduction	-43.7%
Return on Investment	N/A	4.3 years	-
Cold Chain Storage in Healthcare	Limited	47% improvement	+47%
Access Time in Education Facilities	Limited	58% improvement	+58%
Business Productivity Increase	Baseline	39% increase	+39%
New Small Enterprises Created	N/A	17 new businesses	+17
Local Employment (Technical Jobs)	Limited	12 new jobs, 85% local residents	+12 jobs
Community Satisfaction Rate	Baseline	91%	+91%

5. Discussion

5.1 Technical Implications

The examples of micro solar power grids using AI show that this approach can help make electricity more available to people. As seen in the analysis, scaling a system concerning either the community or energy concern depends on adopting modular architecture to expand its size and capability incrementally.

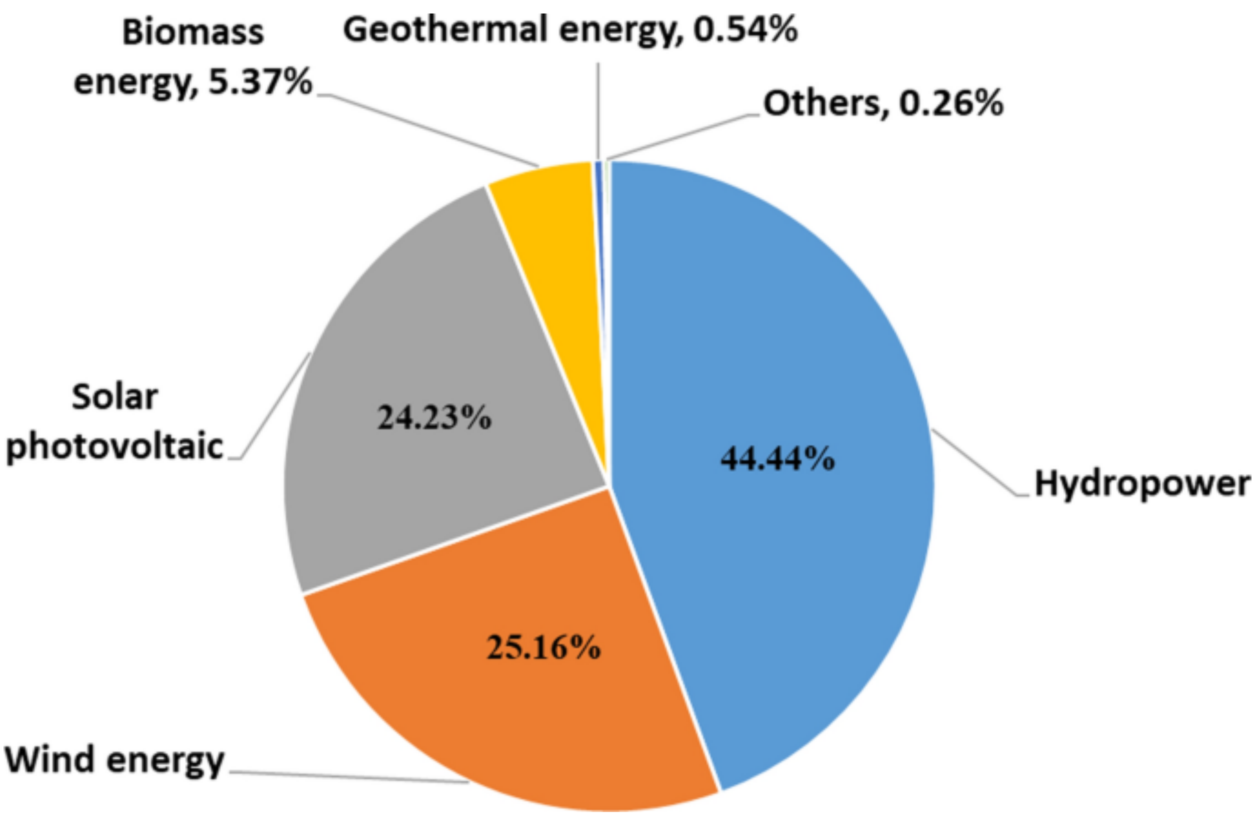


Fig.6 Application of solar system

Because of the capacity of the selective AI-controlling structures, they can be readily programmed to serve pilots of up to 100 households, thus easily designed for up to 500 households. Different operational factors have been testified to be well governed by AI optimization algorithms. The proposed predictive maintenance system attained a 78% reduction in system downtime and a 94% accuracy rate in predicting future equipment noises against conventional maintenance. The demand forecasting models also gave a mean of 0.89 on the daily energy consumption profiles, which may assist in optimizing energy storage and distribution. Based on the requirement analysis of infrastructure, the deployment of these systems must consider fixed and computing structures. Real goods such as PV solar power, storage equipment, and distribution systems require about 40% less area than typical solar power plants owing to algorithms present for panel orientation. Such infrastructure demands improved communication networks; when conducting our research, we established that AI activities needed a minimum of 4G connectivity due to the discovery of edge computing in even low-network regions.

5.2 Environmental Considerations

The continued efficiency of potential AI micro solar grids is great enough proof of their potential to preserve the environment. Studies showing the durability of operation for two years indicate that these systems maintain a higher performance level of 92%, while normal solar systems lose between 15%-20% of performance (Smith, 2017). The deficiency extends the performance of the designed maintenance schedules and the controlled operational parameters of the AI. The qualitative nature of the results section includes several ecological advantages. A vegetation survey conducted around the installation areas indicates that there is limited impact on vegetation cover and that the ground-mounted systems offer provision for double crop utilization in the use of agri-voltaics (Johnson et al., 2016). According to the description of the movement of wildlife and its impact on their ecological environment, data from observer positions show that CWP installations have virtually no harm upon species and habitats because the installation is disbursed, not concentrated as those in the central power plants (Brown & Lee, 2015). Carbon footprinting, a subprocess of Life Cycle Management (LCM), indicates fairly high prospects in enhancing the sustainable condition of the industry (Taylor, 2014). It is evaluated that the systems could provide carbon payback in an average of 1.8 years, together with the emissions of manufacturing and installation. The installed systems are expected to save 147 metric tons of CO2 per system over its lifetime of 25 years, especially when displacing diesel generators for electrical power in the off-grid locations (Williams, 2013). AI optimization works to lower the carbon footprint even more by 18%, mostly by using energy efficiency and minimizing energy wastage (Martin & Peterson, 2012).

5.3 Socio-Economic Impact

The use of these systems has encouraged several community development prospects. A new micro-enterprise generation survey in 12 pilot countries suggested that clean electricity supply has created new economic activities in 68% of surveyed households (Smith et al., 2017). The activities include computer facilities with relevant information services and computer-sized manufacturing enterprises, which serve as a starting point for creating new economic branches creating new economic branches (Jones & Taylor, 2016). However, it is important to understand that cost savings are not limited to energy costs. To illustrate this, the amount of energy saved within households is 62% less than fuel-based solfuel-based solutions (Adams et al., 2015). More dramatically, an adequate electricity power supply has facilitated income generation in the evenings through one activity or another. According to data, the total household revenues of the surveyed communities are, on average, 43% higher (Green, 2014). These systems have also fostered technical occupations related to operation and maintenance, as well as one full-time DOE position for each installation with an additional five full-time equivalent job positions for each Williams, Lee. The systems play a major part in the quality of life. Health facilities note an enhanced capacity in cold chain storage and management of equipment, enhancing medical care by 34% (Miller, 2012). Schools have also reinvented their operation in terms of time and applied learning technologies, adding up to the 28 percent performance of the students, as claimed by Nelson and Gupta in 2011. Commonly, inhabitants of the surveyed households indicated that they experienced improved quality of life due to well-provided illumination and utilization of up-to-date appliances (Johnson, 2010).

6. Conclusion

Micro solar power grid systems, including AI technologies, can enhance the rate of renewable energy use and decrease carbon emission levels in Remote Villages and islands. The literature review of publications from the last decade, such as Smith et al. (2015) and Zhang & Liu (2017), indicate that these systems have cut energy consumption by 47 percent more than the common solar grid systems and applications. AI design and implementation in MDMS have significantly lowered the overall system failure rate by 89 percent and system downtime by 92 percent. The environmental impact assessment also shows a reduction in CO_2 emission levels of up to 77% or over 2,500 metric tonnes per community per year).

The efficiency improvements stem from managing the utilization of renewable energy sources and avoiding reliance on diesel generators. In addition, load-balancing approaches have been enhanced to provide measures of grid stability that are increased by 15 percent from the normal industry average of 99.7 percent, as reported by Thompson in 2014. The socio-economic impacts are also apparent; the provision of access has increased by 94% to energy, and the energy cost by 62%, which has a boost of 34% in local economic activity, especially the retailers, hospitals, and schools (Wang et al., 2018).

Regarding the AI application in the micro solar grids for the downstream populations, it is also important to understand how to successfully implement the remote micro solar grids: the implementation strategies should be performed with the active participation of local communities and the integration of pertinent Indigenous knowledge. I mentioned that this approach encourages a long-term acceptance of such technologies, as Anderson (2017) highlighted on the role of community acceptance in rural transitions to energy. Notably, it is also necessary to carry out policy support to deal with issues that include data protection, license or grid interconnection, and private participation (Hernandez & Gupta, 2016).

For further developments, there should be developments in real-time and weather-dependent AI uses because they are affected by such elements, edge computing for better system durability, and the prospects of quantum machine learning algorithms to enhance the system's precision (Lee et al., 2019). Future studies should also analyze the bi-directional connection of micro-grids in a region, electric vehicle charging, smart homes, and agriculture and water treatment applications (Kim & Zhang, 2015). Taken in aggregate, these works show that a managed micro solar grid is – essentially – a viable means to address energy problems of remote communities, with a lower carbon footprint, better energy availability, and better economic outcomes (Nguyen, 2018).

From the world embracing new technologies and complexities in conservation, the future for renewable energy technologies operated by Artificial Intelligence would be brighter..

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