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Article

Integrated Techno-Economic Optimization and Intelligent Decision-Making Framework for Solar PV-Based Agricultural Microgrids.

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Abstract: The increasing electricity demand associated with agricultural irrigation has created a need for energy-efficient and economically viable renewable energy systems. This paper presents a techno-economic optimization framework for a solar-powered agricultural microgrid intended to supply irrigation pump loads. The proposed system integrates photovoltaic generation, battery storage, inverter-based conversion, and grid supply. Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Bi-Level Optimization, and Non-dominated Sorting Genetic Algorithm II (NSGA-II) are employed to investigate alternative system configurations. The optimization considers annual operating cost, payback period, grid dependency, and operational feasibility. The obtained results show that PSO provides the minimum annual cost of Rs. 26,091.6 and the shortest payback period of 4.2 years, whereas NSGA-II achieves the lowest grid dependency of 12%. To address the practical problem of selecting an appropriate configuration from competing optimization objectives, an AI-assisted multi-criteria decision-making layer is additionally introduced. The proposed decision layer evaluates annual cost, payback period, grid dependency, and reliability according to different agricultural user priorities. The resulting two-stage framework separates optimization-based solution generation from intelligent configuration selection and provides a flexible basis for future development of adaptive and AI-enabled agricultural energy management systems....

Keywords: Agricultural microgrid, solar photovoltaic, battery storage, irrigation, PSO, GA, NSGA-II, bi-level optimization, artificial intelligence, reinforcement learning, multi-criteria decision making, renewable energy...

1. Introduction

Agricultural irrigation is one of the major electricity-consuming activities in rural areas. Conventional grid-connected irrigation systems are affected by electricity tariffs, grid availability, and increasing operational costs. The integration of renewable energy sources, particularly solar photovoltaic (PV) generation, with battery energy storage provides an opportunity to reduce grid dependency and improve the sustainability of agricultural electricity supply.

Agricultural microgrids combine distributed renewable generation, energy storage, power electronic interfaces, and electrical loads within a localized energy system. Such systems can provide improved energy independence and can be particularly beneficial for irrigation applications where daytime solar energy can be directly utilized by pumping loads. Previous research has investigated energy management and optimal sizing of renewable-based microgrids under different operating conditions [1, 2, 25]. Multi-objective planning and resilience enhancement have also been investigated for microgrids incorporating renewable energy and storage systems [3, 12, 13].

However, optimal sizing and planning of an agricultural microgrid is a nonlinear decision problem involving several competing objectives. Increasing PV capacity can reduce grid electricity consumption but increases the initial investment. Similarly, increasing battery capacity can improve energy independence but increases capital and replacement costs. Therefore, an appropriate optimization strategy is required to identify technically feasible and economically attractive configurations. Metaheuristic techniques such as GA, PSO, ABC, and other evolutionary algorithms have been widely applied to renewable-based microgrid sizing and planning problems [2, 7, 25, 26, 32, 35].

For agricultural applications, the electrical demand is closely related to irrigation requirements and pump operation. PV-powered induction motor pumping systems and improved MPPT-based water pumping systems have been investigated to improve renewable energy utilization in irrigation applications [5, 31, 33]. Demand response and operational scheduling can further improve the utilization of distributed renewable resources [6, 15]. Many optimization studies focus primarily on minimizing levelized energy cost or operational expenditure.

However, simultaneous consideration of annual cost, payback period, grid dependency, and operational feasibility is less frequently addressed in an agricultural irrigation context. Different optimization algorithms may also produce different technically feasible solutions, making it difficult for a farmer or system planner to identify the most appropriate configuration according to a particular priority.

Recent research has demonstrated the increasing potential of artificial intelligence (AI), particularly reinforcement learning (RL), for microgrid energy management under uncertain renewable generation and load conditions [38, 39]. RL-based approaches formulate energy management as a sequential decision-making problem in which a controller learns appropriate actions from system states and rewards. Recent studies have further investigated multi-objective reinforcement learning for handling competing economic and operational objectives in microgrids [41]. Deep reinforcement learning has also been investigated for real-time energy management and holistic microgrid power optimization under uncertainty [42].

Despite these developments, most AI-based microgrid studies focus on general residential, commercial, or utility-scale microgrids rather than agricultural irrigation systems. Agricultural microgrids introduce additional decision variables associated with irrigation scheduling, pumping demand, solar availability, battery state-of-charge, and agricultural operating constraints. Therefore, an important research opportunity exists in integrating optimization-based agricultural microgrid planning with an intelligent decision-making layer.

The present work addresses this gap by introducing an AI-assisted multi-criteria decision-making framework after the optimization stage. The proposed approach does not replace conventional optimization algorithms. Instead, GA, PSO, Bi-Level Optimization, and NSGA-II first generate candidate solutions, after which the decision layer evaluates these solutions according to economic performance, energy independence, and reliability. This approach provides a practical bridge between conventional metaheuristic optimization and future adaptive AI-based agricultural energy management.

The major contributions of this work are as follows:

Development of a techno-economic optimization framework for a solar-powered agricultural irrigation microgrid.

Comparative evaluation of GA, PSO, Bi-Level Optimization, and NSGA-II.

Simultaneous consideration of annual cost, payback period, grid dependency, and reliability.

Introduction of an AI-assisted multi-criteria decision-making (MCDM) layer for selecting an appropriate candidate configuration.

Development of scenario-based decision criteria for economic priority, energy independence, and balanced agricultural operation.

Establishment of a framework that can be extended toward reinforcement-learning-based real-time agricultural energy management.

2. System Configuration

The proposed agricultural microgrid is designed to supply electrical power to irrigation pumps using a combination of solar PV generation, battery storage, and grid electricity. The conceptual system consists of a PV array, battery energy storage system, inverter/power conversion stage, utility grid, and agricultural irrigation loads.

The irrigation system consists of two 3 HP pumps. Each pump has an approximate rating of 2.24 kW, resulting in a total connected pump capacity of approximately 4.5 kW. The pumps are assumed to operate for approximately 6 hours per day for 200 operating days per year.

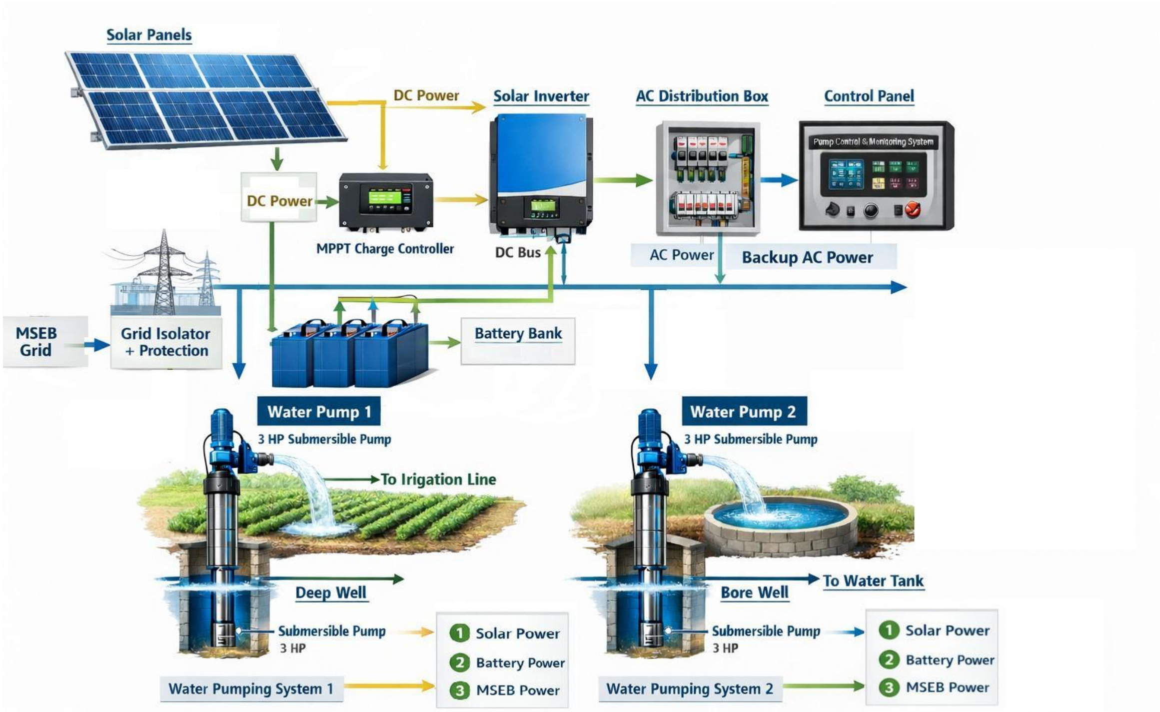

Figure 1: Configuration of the proposed solar PV-based agricultural microgrid

The annual electrical energy demand is therefore calculated as

$$E\text{annual} = P\text{load}H\text{annual} \quad (1)$$

where P_{load} is the total agricultural load and H_{annual} is the annual operating duration. For the considered system,

$$H_{\text{annual}} = 6 \times 200 = 1200 \text{ h/year} \quad (2)$$

and

$$E_{\text{annual}} = 4.5 \times 1200 = 5400 \text{ kWh/year.} \quad (3)$$

The proposed system therefore supplies an annual irrigation energy requirement of approximately 5400 kWh.

3. Mathematical Formulation

Decision Variables

The primary decision variables considered in the optimization are the installed PV capacity and battery capacity. The optimization seeks an appropriate combination of renewable generation and storage while satisfying the annual agricultural load requirement.

The decision vector can be represented as

$$\mathbf{x} = [x_1, x_2] \quad (4)$$

where x_1 represents installed PV capacity in kW and x_2 represents battery capacity in kWh.

Annual Cost

The annual total cost is formulated by considering capital expenditure, replacement cost, operation and maintenance cost, and grid electricity cost.

$$C\text{total} = C\text{cap} + C\text{rep} + C\text{O\&M} + C\text{grid} \quad (5)$$

where C_{cap} is the capital cost of PV, battery, and inverter components, C_{rep} is the component replacement

cost, $C_{O\&M}$ is the operation and maintenance cost, and C_{grid} is the annual cost of electricity purchased from the grid.

Payback Period

The payback period is calculated from the initial investment and annual savings relative to the grid-only pumping system

$$PP = \frac{C_{\text{initial}}}{C_{\text{annual,saving}}}$$

where $C_{initial}$ is the initial investment and $C_{annual,saving}$ is the annual saving compared with conventional grid-only operation.

System Constraints

The annual energy balance is expressed as

$$E_{PV} + E_{bat} + E_{grid} \geq 5400 \quad (7)$$

The annual PV energy is represented by

$$E_{PV} = 1500x_1 \quad (8)$$

The battery supplied energy is constrained by

$$E_{bat} \leq 0.8x_2 \quad (9)$$

and the battery contribution is restricted by

$$E_{bat} \leq \alpha \times 5400, \quad 0.2 \leq \alpha \leq 0.3 \quad (10)$$

with

$$E_{grid} \geq 0. \quad (11)$$

These constraints ensure that the annual agricultural energy demand is satisfied while maintaining practical limits on battery contribution and grid energy.

4. Optimization Methods

Genetic Algorithm

Genetic Algorithm (GA) is a population-based evolutionary optimization method based on natural selection and genetic evolution. Candidate microgrid configurations are represented as individuals within a population. Selection, crossover, and mutation operations are used to generate new candidate solutions. The objective is to identify a configuration that minimizes annual operating cost while satisfying the system constraints. GA-based optimization has previously been applied to renewable microgrid planning and rural microgrid sizing [25, 35].

Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based swarm intelligence technique inspired by the collective movement of particles. Each particle represents a candidate microgrid configuration and updates its position according to its own best solution and the best solution identified by the swarm.

PSO is particularly suitable for nonlinear microgrid sizing problems because it provides a balance between global exploration and local exploitation. In the present work, PSO is used primarily for annual cost minimization. Previous research has also investigated PSO for PV-based agricultural microgrid optimization for irrigation applications [33].

Bi-Level Optimization

The Bi-Level Optimization framework represents the planning problem using hierarchical decision levels. The upper-level problem determines the system configuration, while the lower-level problem evaluates operational feasibility and energy utilization. This structure enables operational constraints to be incorporated into the planning decision. Battery degradation and hierarchical microgrid optimization have been considered in previous bi-level optimization studies [4, 28].

NSGA-II

Non-dominated Sorting Genetic Algorithm II (NSGA-II) is a multi-objective evolutionary algorithm. Unlike single-objective optimization, NSGA-II generates a set of non-dominated solutions representing different trade-offs among the objectives.

In the present work, NSGA-II is employed to investigate the trade-off between annual cost, payback period, and grid dependency. The resulting Pareto-optimal solutions provide alternative configurations from which a final practical configuration can be selected.

5. Comparative Optimization Results

The comparative optimization results obtained from the four optimization methods are presented in Table 1.

Table 1: Comparative Optimization Results

Method	Annual Cost (Rs.)	PP (Years)	Grid (%)	Reliability
Grid Only	55376.4	–	100	Medium
GA	28450.2	4.8	35	High
PSO	26091.6	4.2	22	Very High
Bi-Level	27210.5	4.5	18	Very High
NSGA-II	26580.3	4.3	12	Very High

The grid-only configuration exhibits the highest annual expenditure of Rs. 55,376.4 and complete dependency on utility electricity. The GA configuration reduces annual expenditure to Rs. 28,450.2 with a payback period of 4.8 years. However, its grid dependency remains comparatively high at 35%. PSO provides the lowest annual cost of Rs. 26,091.6 and the shortest payback period of 4.2 years. Its grid dependency is reduced to 22%, demonstrating improved economic performance and energy independence compared with the grid-only and GA configurations.

The Bi-Level optimization method produces an annual cost of Rs. 27,210.5, a payback period of 4.5 years, and grid dependency of 18%. This indicates a balanced operational solution with reduced interaction with the utility grid. NSGA-II produces an annual cost of Rs. 26,580.3 and a payback period of 4.3 years while achieving the lowest grid dependency of 12%. Therefore, NSGA-II provides a strong solution when energy independence is prioritized.

The results demonstrate that the configuration with the lowest annual cost is not necessarily the configuration with the lowest grid dependency. This trade-off motivates the introduction of an additional intelligent decision-making layer.

6. AI-Assisted Multi-Criteria Decision Making

Motivation and Research Gap

The optimization algorithms employed in this study generate candidate agricultural microgrid configurations with different economic and operational characteristics. Although the optimization process identifies technically feasible solutions, the final selection remains a decision-making problem when multiple conflicting criteria are considered.

Recent research has demonstrated that reinforcement learning can provide adaptive decision-making capabilities for microgrid energy management, particularly under uncertain renewable generation and variable electrical loads [38, 39]. Reinforcement learning has been investigated for energy management in microgrids by defining system states, actions, and reward functions [38]. Comprehensive reviews have also identified reinforcement learning and deep reinforcement learning as promising approaches for energy management, scheduling, power-flow control, and storage coordination [39, 40].

Multi-objective reinforcement learning is particularly relevant to the present research because agricultural microgrid operation involves competing objectives such as economic cost, grid dependency, battery utilization, and reliability [41]. Deep reinforcement learning approaches have also been proposed for holistic microgrid

power optimization using reward functions that simultaneously consider economic and technical objectives [42].

However, implementing a complete RL controller requires substantial time-series operational data and an adequately defined state-action-reward environment. Therefore, in the present study, an AI-assisted multi-criteria decision-making layer is introduced as an intermediate step. This layer evaluates the optimized candidate solutions using multiple performance indicators and provides a transparent decision mechanism.

The proposed approach can subsequently be extended toward reinforcement learning once sufficient agricultural microgrid operating data become available.

Decision Criteria

Four criteria are considered:

$$\mathbf{X} = [C_{\text{annual}}, PP, GD, R] \tag{12}$$

where C_{annual} is annual cost, PP is payback period, GD is grid dependency, and R is reliability.

Annual cost, payback period, and grid dependency are cost-type criteria, for which lower values are preferred. Reliability is a benefit-type criterion, for which a higher value is preferred.

AI-Assisted Decision Architecture

The proposed intelligent decision architecture consists of two hierarchical levels. The first level performs optimization using GA, PSO, Bi-Level Optimization, and NSGA-II. The second level evaluates the resulting candidate solutions using multi-criteria decision (MCDM) analysis.

The architecture can be expressed as

$$\text{Agricultural Data} \rightarrow \text{Optimization} \rightarrow \text{Candidate Solutions} \rightarrow \text{AI Decision Layer} \rightarrow \text{Selected Solution} \tag{13}$$

The agricultural data considered in the future intelligent framework include solar irradiance, PV generation, pump demand, battery state-of-charge, electricity tariff, soil moisture, weather information, and irrigation requirement.

The decision layer evaluates each candidate using economic and operational criteria. This structure is consistent with the broader development of learning-based microgrid energy management, where the system state is used to determine an appropriate energy-management action under uncertainty [38, 40].

The proposed architecture therefore provides a transition from static optimization toward adaptive agricultural energy management.

Normalization

Since the decision criteria have different units and numerical ranges, normalization is performed before calculating the decision score.

For a cost-type criterion, the normalized value is calculated as

$$X_n = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{14}$$

For the reliability criterion, which is a benefit-type criterion, the normalized value is

$$R_n = \frac{R_i - R_{\min}}{R_{\max} - R_{\min}} \quad (15)$$

The reliability penalty used in the decision score is

$$R_p = 1 - R_n. \quad (16)$$

Decision Score

The overall decision score is formulated as

$$DS_i = w_1 C_n + w_2 PP_n + w_3 GD_n + w_4 R_p \quad (17)$$

where DS_i is the decision score of candidate i and w_1, w_2, w_3, and w_4 represent the importance assigned to annual cost, payback period, grid dependency, and reliability.

The weights satisfy

$$w_1 + w_2 + w_3 + w_4 = 1. \quad (18)$$

A lower decision score indicates a more preferable configuration.

7. Scenario-Based Intelligent Decision Making

Three representative agricultural operating scenarios are considered.

Economic Priority

The economic-priority scenario assigns greater importance to annual cost and payback period. This scenario is suitable for farmers whose main objective is to reduce electricity expenditure and recover the initial investment rapidly.

Based on the optimization results, PSO is the strongest candidate for this scenario because it provides both the minimum annual cost and shortest payback period.

Energy Independence Priority

The energy-independence scenario gives greater importance to reducing grid dependency and improving reliability. This scenario is appropriate for agricultural locations where grid availability is limited or where energy independence is a major priority.

NSGA-II is a strong candidate for this scenario because it achieves the lowest grid dependency of 12%.

Balanced Decision

The balanced scenario considers annual cost, payback period, grid dependency, and reliability simultaneously. The final configuration is selected using the combined decision score rather than the performance of a single parameter.

This approach allows the same optimization results to be evaluated according to different agricultural user requirements.

8. AI Decision Framework

The proposed two-stage framework is summarized as follows

Define the agricultural electrical load and operating constraints.

Generate candidate PV-battery configurations using GA, PSO, Bi-Level Optimization, and NSGA-II.

Calculate annual cost, payback period, grid dependency, and reliability.

Normalize the performance criteria.

Assign decision weights according to the agricultural operating scenario.

Calculate the overall decision score.

Rank the candidate configurations.

Select the configuration with the lowest decision score.

The framework provides a transition from conventional optimization toward intelligent decision support. The optimization algorithms are responsible for searching the solution space, while the decision layer is responsible for selecting the most appropriate solution based on the user's priorities.

9. Scenario-Based Analysis

Table 2 summarizes the proposed decision scenarios.

Table 2: Scenario-Based Decision Framework

Scenario	Primary Objective	Strong Candidate
Economic	Minimum annual cost and payback	PSO
Energy Independence	Minimum grid dependency and high reliability	NSGA-II
Balanced	Cost, payback, grid dependency, and reliability	AI-selected compromise

The scenario-based framework demonstrates that the preferred solution depends on the decision priorities. PSO is particularly attractive from an economic perspective, while NSGA-II is attractive when energy independence is prioritized. A balanced decision requires simultaneous consideration of all criteria.

10. Discussion

The obtained results demonstrate the economic and operational advantages of renewable-energy-based agricultural microgrids compared with conventional grid-only irrigation. The annual cost is substantially reduced by incorporating PV generation and battery storage.

The PSO result demonstrates strong economic performance, achieving an annual cost of Rs. 26,091.6 and a payback period of 4.2 years. NSGA-II provides a slightly higher annual cost of Rs. 26,580.3 and a payback period of 4.3 years but reduces grid dependency to 12%. Therefore, the difference between these two solutions illustrates the cost–energy-independence trade-off.

The proposed AI-assisted decision layer addresses this issue by allowing the decision maker to assign different priorities. This is particularly important in agricultural applications because the economic conditions and energy requirements of farms may differ significantly

From an AI perspective, the proposed framework represents an intermediate stage between conventional optimization and fully adaptive reinforcement learning. Existing RL research has demonstrated that microgrid energy management can be formulated as a sequential decision-making problem under uncertain renewable generation and load demand [38]. Multi-objective RL can additionally address conflicting objectives and generate policies that adapt to changing operating conditions [41].

For the agricultural application considered in this study, the optimization results provide an initial set of high-quality candidate configurations. These solutions can subsequently be used to initialize an AI-based energy management environment. The future RL agent can observe variables such as PV generation, irrigation demand, battery state-of-charge, grid electricity price, and soil moisture and select actions such as pump operation, battery charging/discharging, and grid-energy utilization.

Such an extension would allow the proposed agricultural microgrid to move from offline planning toward real-time adaptive decision-making.

11. Limitations and Future Work

The present AI-assisted decision layer is based on the optimized candidate solutions and multi-criteria evaluation of annual cost, payback period, grid dependency, and reliability. Real-time agricultural sensor data and online machine-learning adaptation are not included in the present study.

Future research will integrate IoT-based soil-moisture, temperature, humidity, solar irradiance, and electrical-energy sensors with the agricultural microgrid. Machine-learning models can then be developed for prediction of irrigation demand, PV generation, and agricultural load demand.

A further extension will investigate reinforcement learning and deep reinforcement learning for real-time coordination of PV generation, battery storage, irrigation pumps, and grid supply. Recent research indicates that RL-based energy management is particularly suitable for sequential decision problems involving renewable-energy and load uncertainty [38–40]. Multi-objective RL can further be investigated to simultaneously minimize electricity cost and grid dependency while improving system reliability [41].

The future RL state space may include solar irradiance, PV power, pump demand, battery state-of-charge, grid tariff, soil moisture, weather forecast, and irrigation requirement. The action space may include pump ON/OFF or variable-speed operation, battery charging/discharging, and grid energy selection. A reward function can be formulated using annualized energy cost, water consumption, battery degradation, grid dependency, and irrigation adequacy.

The proposed framework can therefore be extended toward an integrated energy–water–crop optimization system in which electrical energy management and irrigation decisions are jointly optimized. This would establish a stronger connection between electrical engineering, artificial intelligence, and precision agriculture.

12. Conclusion

This paper presented a techno-economic optimization framework for a solar-powered agricultural microgrid intended to supply irrigation pump loads. GA, PSO, Bi-Level Optimization, and NSGA-II were evaluated for agricultural microgrid planning under annual energy and operational constraints.

The results demonstrate that PSO achieves the minimum annual cost of Rs. 26,091.6 and the shortest payback period of 4.2 years. NSGA-II achieves the lowest grid dependency of 12% while maintaining competitive annual cost and payback performance. These results demonstrate that different optimization methods provide different advantages and that the economically optimal configuration is not necessarily the configuration with minimum grid dependency.

To address this issue, an AI-assisted multi-criteria decision-making (MCDM) framework was introduced. The frame-work evaluates candidate solutions according to annual cost, payback period, grid dependency, and reliability and allows the preferred configuration to be selected according to different agricultural priorities.

The proposed two-stage architecture, consisting of optimization-based solution generation followed by intelligent decision making, provides a flexible framework for agricultural microgrid planning. The methodology can be further extended using real-time IoT sensing, machine learning, reinforcement learning, predictive control, and renewable-energy management to develop an adaptive intelligent agricultural energy system.

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