Uncertainty Stochastic–Fuzzy Management Model for Minimization of Fuel Consumption, Battery Degradation, and Operating Cost in Power System

Stella Isioma Monye[1], Imhade Princess Okokpujie[1], Aderonke O. Akinwumi[3], Remilekun R. Elewa[4], Snow Ngozi Monye[5],

[1,2,3,4]Department of Mechatronics, Industrial and Production Engineering, Afe Babalola University, Ado Ekiti, Nigeria.

[5]Department of Information Communication and Technology, University of Delta, Agbor, Nigeria.

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ABSTRACT

This study developed a computational prototype to compare four energy-management strategies in a simplified diesel-electric hybrid energy system: Dynamic Programming, Fixed Rules, conventional Fuzzy Logic, and a scenario-weighted stochastic–fuzzy heuristic. The simulation examined six synthetic operating scenarios representing normal operation, renewable generation variability, high demand, and grid or weather disturbances. Ten runs were conducted per scenario, producing 240 controller-run observations. Performance was assessed using fuel consumption, operating-cost proxy, battery degradation-cost proxy, estimated carbon dioxide emissions, reliability, and execution time. Under the assumed conditions, Fixed Rules achieved the lowest mean fuel consumption (152.57 g) and operating-cost proxy (0.1677). Dynamic Programming recorded mean fuel consumption of 210.93 g, compared with 233.72 g for Fuzzy Logic and 232.75 g for the stochastic–fuzzy heuristic. Relative to Fuzzy Logic, the stochastic–fuzzy heuristic produced marginal reductions in fuel consumption, operating-cost proxy, and estimated emissions; however, it did not outperform Fixed Rules or Dynamic Programming. The findings indicate that integrating scenario-weighted fuzzy decisions does not guarantee improved energy-management performance. Limitations of the study include illustrative system parameters, a heuristic rather than a complete multi-period stochastic optimizer, simplified battery degradation and emissions models, and unequal terminal battery-state constraints. However, the results represent synthetic simulation evidence for this investigation, not validation against the original experimental system.

Keywords: Stochastic Optimisation, Fuzzy Logic, Hybrid Energy Systems, Energy Management, Monte Carlo Simulation, Dynamic Programming, Fuel Consumption.

INRODUCTION

Dynamic Programming, Fixed Rules and Fuzzy Logic are among the approaches used in energy-management applications. Dynamic Programming evaluates decisions across a planning horizon to identify an optimal sequence under a defined mathematical model. Fixed Rules use predetermined operating conditions to determine control actions, while Fuzzy Logic applies linguistic variables, membership functions and inference rules to make decisions under imprecise conditions. Although these strategies provide useful control mechanisms, their performance depends on the operating characteristics, model assumptions and control parameters of the energy system. As renewable energy resources are integrated into hybrid energy systems, energy-management strategies that can help lower the fuel use, operating costs, and system reliability are needed. The unpredictability of renewable energy generation, electricity consumption, grid access, and battery performance can impact energy scheduling and decisions. The choice of a suitable energy-management technique is crucial to operate a power system efficiently and sustainably Kumar et al., (2026). Amer et al., (2024) proposed an innovative energy management system for hybrid renewable power station containing

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battery energy storage system and diesel generator. The authors incorporated the costs of battery degradation due to charge depth and battery life to bring long-term battery costs to the real time cost of operation.

The optimization problem was presented in the framework of mixed integer linear programming in which the goal was to minimize operating costs, costs of battery degradation and pollutant gas emissions. In proposing an Optimization-based energy management system for grid-connected photovoltaic/battery microgrids under uncertainty, Molu et al., (2023) addressed the problem of energy management over a 24-h period, and simulated a model using MATLAB R2022a software, employing state flow analysis and linear programming methods to minimize the total variable electricity price before and after islanding. There are a few solutions to energy-management problems, such as Dynamic Programming, Fixed Rules and Fuzzy Logic. Dynamic Programming is used to systematically optimize decisions over a planning horizon, whereas fixed rules will give simple control based on pre-determined conditions Feng et al., (2025). Fuzzy Logic provides flexible decision-making by linguistic rules and membership functions. The effectiveness of these methods may be system dependent, parameter dependent, compute dependent, and can depend on the amount of uncertainty in the operating conditions.

For this purpose, this study suggests the combination of an existing energy-management method based on Fuzzy Logic and stochastic optimisation. The uncertainties can be incorporated into the model by using probability-weighted scenarios in the stochastic optimisation and the expected operating costs can be minimized. Fuzzy Logic can aid with the rule-based control decisions. The costs of integrating the operational costs, grid electricity costs, battery degradation costs and emissions will be optimized together in the proposed framework. It will be assessed using fuel consumption, operating cost, emissions, reliability, unmet energy demand and computational time in comparison to fuel management strategies already in place. The goal is to determine if the hybrid of stochastic optimisation and Fuzzy Logic can enhance energy-management decisions in the presence of uncertainty in the operating conditions. The integrated framework is still proposed and will need to be tested in a future simulation and compared in order to be judged.

LITERATURE REVIEW

Data Interoperability

In energy production, data interoperability is one of the main information systems management skills that facilitate the consistent exchange and interpretation of data between heterogeneous software applications, industrial equipment, databases, and operational platforms (Gopstein et al., 2021). In the era of the digital monitoring, artificial intelligence and connected control systems, interoperability is a key factor to coordinate information among production and distribution activities, particularly in energy industries (European Commission, 2024a). Operational environments may, however, be fragmented due to differences in data formats, communication protocols, system architectures, and information standards, which can hinder timely information sharing (United Nations Economic Commission for Europe [UNECE], 2025). Beyond the technical aspects, interoperability necessitates similar interpretations, data structures, and protocols for data exchange, which are crucial for successful integration (Couto et al., 2024).

Common information models and interoperability standards can enable different systems to communicate with one another without losing the meaning of the operational measurements and control signals in electricity production and smart-grid operations (National Institute of Standards and Technology [NIST], 2021). This standardisation can enhance the accessibility of trusted information on production status for the management of monitoring equipment and for coordination of energy resources and decision making between different organisations (European Commission, 2024b). However, if organisations employ an old infrastructure, different vendor-specific technologies and varying data-governance mechanisms (Vellore et al., 2026), interoperability efforts could be limited. These constraints can cause communication delays and lead to a lack of "system view" on interconnected facilities by production managers (Mwinuka et al., 2026). Therefore, interoperability needs to be addressed on a broader level than just technical and software interfaces, encompassing technical, semantic, organisational and governance aspects (European Commission, 2026).

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

The European energy data-exchange reference architecture also highlights the need to exchange information business-process independent, meaning that various data-exchange partners can share the information without needing to have the same internal systems (Couto et al., 2024). In this context, the interoperable data spaces could be a promising approach to make information exchange trustworthy while still enabling organisations to maintain control over their data and the way it's used. At the same time, recent reviews have also pointed to the interconnectedness of data quality, discoverability, sharing arrangements, privacy, and cybersecurity as key elements of energy data governance that should be tackled when integrating production information (Pourmirza et al., 2026). Moreover, open standards and open-source solutions can help to lower the reliance on proprietary interfaces, and ensure compatibility in digital infrastructure between energy organisations (United Nations Economic Commission for Europe [UNECE] 2025).

Furthermore, the EU's wider digitalization programme focuses on secure digital solutions and collaboration between energy and technology actors as the key pillars of a more connected energy system (Publications Office of the European Union, 2024). Operational level, enhanced data interoperability can enhance production resilience by facilitating quicker information sharing, better coordination of response efforts and visibility into the interactions between energy resources and assets (Vellore et al., 2026). While the tools and technologies are also interoperable, the success of their implementation depends on other factors, including the incentives for organizations, regulatory considerations, data sharing policies, and cybersecurity concerns, which can limit information exchange (European Commission, 2024a). Therefore energy companies must be governed to define the ownership of data, access rights, common data definitions, quality standards, and accountability for shared data (European Commission, 2026). Studies on energy-system digitalization also suggest that data fragmentation and gaps in the data can hinder real-time coordination and adversely affect the effectiveness of data-driven operational decisions (Mwinuka et al., 2026). Therefore, further studies are required to assess interoperability based on measurable metrics like data exchange success rates, semantic consistency, latency of information, integration costs and recovery performance after systems disruptions as shown in figure 1 (Gopstein et al., (2021).



Figure 1: Interoperability across measurable Indicators (Gopstein et al., 2021).

Decision Integration

Decision integration, refers to the organizational and technological ability to integrate information from operational, managerial and analytical systems into coherent decisions relating to energy production. There has been a recent study on energy management systems that provides a proof of the significance of incorporating

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forecasting, optimization, and operational control in energy systems with complex energy assets operating under variable supply and demand conditions (Zhu et al., 2025). With the growing decentralization of production, the need for decision-making coordination between generation units, storage units and control systems is growing in importance Kudzin, (2025). But, the work of information systems alone can lead to contradictory information, delayed alerts, or conflicting recommendations for production managers, which can make it more difficult to coordinate action (Babaei et al., 2025). Coordinating the different energy-management controllers (one supervisor and one local controller) is also necessary for the decision integration: the decisions made by the different levels of operation should be compatible with the production goals. Simulation based EMCs involve the use of these controllers in virtual environments to analyse their performance, optimise their settings and look into potential applications. Bakare et al., (2024) classifies the various EMCs according to their domains, giving a comprehensive understanding of their functionalities, applications and effectiveness across various sectors and scenarios as shown in figure 2.

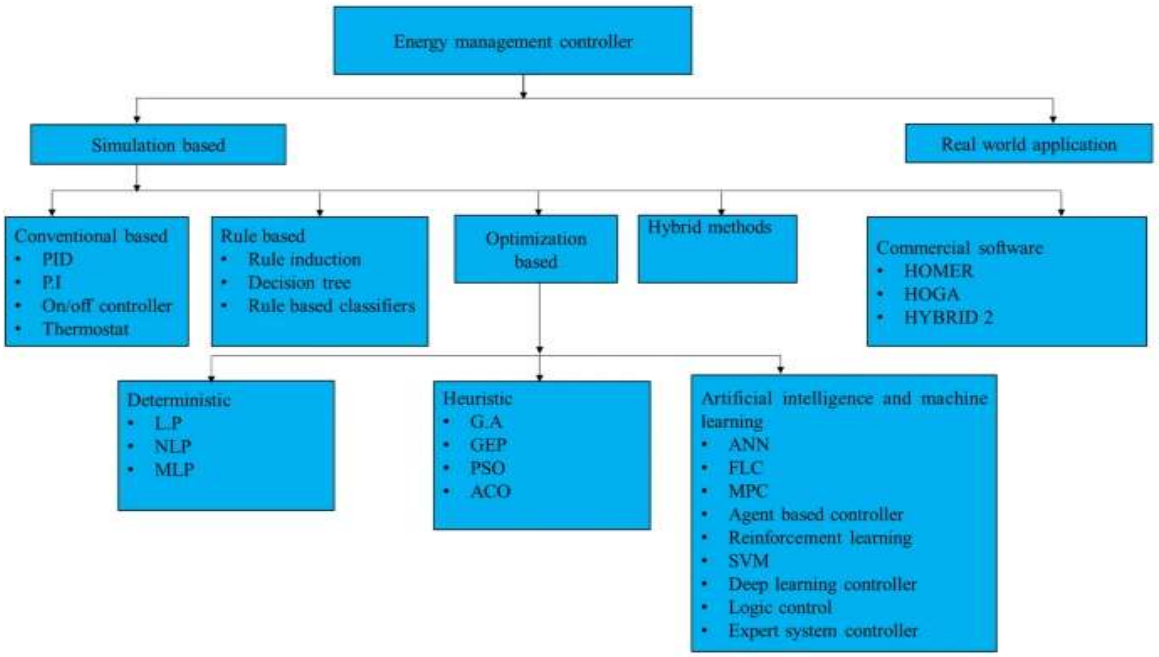

Figure 2: Various Energy Management Controller Categories Bakare et al., (2024)

Energy management in microgrids is a complex task. To make it work, we need systems that can coordinate different energy sources. These systems use forecasts, constraints, and control strategies to keep everything running smoothly. Researchers are looking into using deep learning to make decisions in real-time, as it can handle a lot of complex information. Another approach is to share information across organizations, connecting operational knowledge and supply chains. This way, energy-system tools can talk to each other and validate constraints. Before we deploy new decision-support systems, we test them in simulated environments to see how they work. There are different strategies for managing energy, including optimization, rule-based control, and learning-based methods. These strategies help us deal with uncertainty and trade-offs in power plants that use renewable energy. In practice, we often combine rule-based control with other methods to optimize performance. We can also use machine learning to generate or optimize rules. Some researchers are even using fuzzy logic to handle uncertainty problems. By using these approaches, we can create more efficient and reliable energy systems. For example, we can use simulated testing to assess control strategies and dispatch decisions. This helps us identify potential issues before we deploy new systems. Additionally, combining different energy management strategies can help us address uncertainty and operational trade-offs. Overall, the key to successful energy management is to use a combination of approaches and to test them thoroughly before deployment. This way, we can create energy systems that are efficient, reliable, and effective.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

Table 1: Comparison of Energy Management Strategies in Energy Systems Feng et al., (2025).

Strategy Type	Advantages	Disadvantages	Application
Based on Rules	Deterministic rules	High real-time performance	Local sub-optimality
	Fuzzy control	Moderate optimization	Moderate computational demands
Optimization-based	Instantaneous optimization	Moderate priority over global optimization	Limited application scope
Global Optimization	Low real-time performance	Achieves global optimum	High computational demands
Intelligent Control	Self-adaptive dynamic programming	Dynamic adaptability	Moderate computational demands
	Deep reinforcement learning		

Research on intelligent control strategies for microgrids similarly highlights the role of coordinated control and optimisation in improving energy-system operation, although implementation depends on system configuration and operating requirements (Nkambule et al., 2025). Despite these developments, decision integration should not be equated with full automation because managers must still evaluate conflicting objectives, regulatory requirements, risk tolerances, and the reliability of recommendations (Maraey et al., 2025). Future research should evaluate decision integration through measurable indicators such as decision latency, forecast-to-action time, cross-system consistency, decision accuracy, and recovery time following production disruptions, enabling clearer assessment of its relationship with energy-production resilience.

Operational Governance

Operational governance focuses on policies, responsibilities, control mechanisms, and accountability arrangements that guide how information systems support energy production and operational activities. Recent research on digital transformation in energy systems emphasizes that governance must be considered alongside technology, data management, and cybersecurity to ensure that digitalization supports dependable operations (Pourmirza et al., 2026). Effective governance is particularly important when energy production depends on interconnected information systems because unclear authority, inconsistent procedures, and fragmented responsibilities can undermine coordinated operations (Losada-Agudelo & Souyris, 2024). Operational governance should establish clear decision rights, system ownership, reporting obligations, and escalation procedures across technical and managerial levels (Ofgem, 2025).

Operational governance must also define the boundaries between corporate information technology (IT) and operational technology (OT), particularly where enterprise applications interact with industrial control systems responsible for physical production processes (Stouffer et al., 2023). In electricity networks, formal cybersecurity governance is essential because compromised digital systems can affect operational reliability, interconnected infrastructure, and the continuity of electricity services (European Commission, 2024). The U.S. Department of Energy's Cybersecurity Capability Maturity Model provides a structured approach for assessing organisational cybersecurity practices, identifying capability gaps, and prioritizing improvements across IT and OT environments (U.S. Department of Energy, n.d.). Similarly, the North American Electric Reliability Corporation's Critical Infrastructure Protection standards establish requirements covering security management, personnel training, incident response, information protection, and recovery planning for relevant bulk electric system assets (North American Electric Reliability Corporation).

The ISA/IEC 62443 standards series provides another governance-oriented foundation by addressing the cybersecurity lifecycle of industrial automation and control systems and promoting cooperation between operational and information technology functions (International Society of Automation [ISA], 2025). These security arrangements should be supported by explicit risk-management processes that account for the safety, availability, reliability, and performance requirements of industrial environments (National Institute of Standards and Technology [NIST], 2023). Beyond cybersecurity, operational governance requires structured management of energy performance so that production objectives, operational responsibilities, monitoring procedures, and continuous improvement activities remain aligned (International Organization for

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

Standardization [ISO], 2018). Governance also extends to the management of physical and digital production assets, because asset-related decisions must balance performance, risk, expenditure, and organizational objectives throughout the asset lifecycle (ISO, 2024). For regulated energy organizations, data assurance procedures further establish expectations for the completeness, accuracy, timeliness, and reporting of information submitted to regulatory authorities (Office of Gas and Electricity Markets [Ofgem], 2026).

At the data-management level, the proposed IEEE P3836 project illustrates the growing emphasis on common principles for data acquisition, storage, exchange, sharing, and governance within energy digitalization systems (Institute of Electrical and Electronics Engineers Standards Association [IEEE SA], 2025). A related IEEE P3846 project addresses data-governance methods under limited-data conditions, including situations involving communication interruptions, missing information, or measurement errors in power-dispatching environments (IEEE SA, 2025). These initiatives highlight the need for governance procedures that specify how incomplete or unreliable information is identified, validated, documented, and handled before it influences operational activities. Organisational governance is equally important when digitalization programmes involve multiple departments, technology providers, and energy-sector institutions, because unclear coordination can produce duplicated investments and inconsistent architectural decisions (Ofgem, 2025). Evidence from information systems management in Nigeria's energy sector also identifies strategic alignment, digital infrastructure, data governance, and workforce capacity as relevant considerations for obtaining organisational benefits from management information systems (Babatunde et al., 2025). In addition, the systematic review of industrial energy management by Odinaka (2026) highlights the importance of connecting performance indicators, governance arrangements, and implementation practices when integrating energy-management systems with Industry 4.0 analytics.

Operational governance should therefore be assessed not only by the existence of policies but also by how effectively those policies are implemented, monitored, audited, and revised as production conditions change. Research on data governance in operations and supply-chain management identifies a need to address governance challenges arising from operational complexity rather than concentrating exclusively on enterprise-level technical controls (Data governance in operations and supply chain: A literature review, 2026). This perspective is particularly relevant to fragmented energy-production environments, where accountability for information quality, system availability, access permissions, and incident response may be distributed across different organisational units. Consequently, future studies should operationalise governance using measurable indicators such as policy compliance, audit coverage, incident-response time, access-control effectiveness, completeness of operational records, and closure rates for identified governance deficiencies.

Fuzzy logic is useful in renewable hybrid power-plant energy management because it can represent uncertainty through linguistic variables and fuzzy rules without requiring an exact mathematical model of every operating condition Feng et al., (2025). However, its main limitation is that it does not inherently model the probability, temporal evolution, or statistical dependence of uncertain events such as fluctuating solar irradiance, wind speed, electricity demand, and equipment failures.

Stochastic Integration with Fuzzy Logic

Integrating stochastic modelling with fuzzy logic can combine fuzzy reasoning about imprecise information with probabilistic analysis of random events. While Feng et al., (2025) used Monte Carlo simulation to generate multiple possible solar, wind, demand, and equipment-availability scenarios, this study proposes stochastic optimisation to evaluate the consequences of these scenarios for dispatch, storage, and operating costs.

The rule-based control strategy includes:

(1) Rule base: a collection of all predefined "premise-action" rules, typically expressed in the form of IF-THEN or IF-THEN-ELSE.
(2) Input sensors: real-time sensors that collect environmental or system state data to serve as the premise judgment criterion for rules.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

(3) Inference engine: A component that matches the rules in the rule base based on current input data, triggering corresponding actions or decisions. Common inference methods include forward chaining and backward chaining.
(4) Actuators: components that execute specific operations based on triggered rules, such as switching devices or adjusting parameters.

The stochastic approach provides a mathematical framework for modelling and managing the random variations associated with renewable energy generation, electricity demand, energy storage, and equipment availability. Unlike conventional rule-based control, which primarily relies on predefined IF–THEN conditions, stochastic modelling explicitly represents uncertainty through probability distributions, random variables, and possible operating scenarios. In renewable hybrid power plants, this approach can be integrated with fuzzy logic to combine probabilistic uncertainty modelling with linguistic reasoning about imprecise operational conditions.

The stochastic model can incorporate chance-constrained optimisation to maintain a specified level of power-supply reliability by requiring that electricity demand be met with a predefined probability. This approach enables the energy-management system to balance operating costs against reliability requirements under uncertain renewable generation and demand. For example, Ouanes et al. (2025) demonstrated that joint chance constraints can produce more robust reserve and dispatch decisions in a renewable-powered mini-grid, albeit with a modest increase in operating costs. Also, conditional value at risk (CVaR) can be incorporated into the objective function to quantify and manage the financial or operational consequences of adverse scenarios, complementing expected-cost optimisation with an explicit measure of tail risk Jodeiri-Seyedian & Veysi, (2025).

To integrate stochastic optimisation with the rule-based control architecture, real-time sensor measurements are supplied to both the inference engine and the stochastic decision module. The inference engine evaluates predefined fuzzy or conventional IF–THEN rules, while the stochastic module uses forecasts and probabilistic scenarios to evaluate feasible control actions under uncertainty. A supervisory controller then coordinates the two components, selecting actions that satisfy equipment constraints, operational priorities, and specified risk limits. The actuators implement these decisions by adjusting battery charging and discharging, switching generation units, or modifying controllable loads. The practical value of this integration is consistent with Habibi et al. (2024), whose simulation study combined stochastic energy management, fuzzy decision-making, and optimisation to improve the economic and renewable-energy performance of a microgrid.

METHODOLOGY

The investigation used a computational simulation design involving the implementation and comparison of alternative energy-management strategies. The preliminary implementation was developed in Python using numerical computation and data-processing procedures. The simulation uses a synthetic operating profile to generate electrical demand and variable renewable energy contributions. The experiment considers four strategies: Dynamic Programming, Fixed Rules, conventional Fuzzy Logic and a preliminary stochastic–fuzzy heuristic. Each controller is evaluated against the same generated demand and renewable-energy profiles within a given replicate. Six operating scenarios and ten repeated random-seed runs per scenario were used, resulting in 240 controller-run observations. The simulation is an illustrative benchmark.

The prototype represents a simplified diesel-electric hybrid system with an electrical demand, a variable renewable contribution, an engine-generator and a battery energy-storage component.
The operating parameters are presented in Table 1.

Table 1. Parameters Used in the Preliminary Simulation

Parameter	**Assumed value**
Simulation time steps	24

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

Time-step duration	1 minute
Battery nominal capacity	2.0 kWh
Initial battery state of charge	75%
Minimum state of charge	20%
Maximum state of charge	90%
Maximum engine output	3.0 kW
Charging efficiency	94%
Discharging efficiency	94%
Fuel-consumption model coefficient	340 g/kWh
Fixed engine fuel term	65 g/h
Fuel-cost proxy	0.001 cost units/g
Battery degradation-cost proxy	0.08 cost units/kWh throughput
Unmet-demand penalty	100 cost units/kWh
Emission factor proxy	3.16 g CO_2/g fuel
Number of repeated runs	10 per scenario

The simulation generates different renewable-energy and demand profiles using random-number generation. A common random seed is applied across the four controllers within each replicate to ensure that they encounter the same generated profile.

The uncertain operating condition was represented by:

$$\xi_t = \{D_t, R_t\}$$

Where:

D_t represents electrical demand at time t

R_t represents renewable energy contribution at time t

For the full stochastic formulation, a set of possible operating scenarios was generated as:

$$S = \{1, 2, \ldots, N_s\}$$

with scenario probabilities as:

$$\sum_{s=1}^{N_s} p_s = 1$$

The expected operating cost is expressed as:

$$\min_u \sum_{s=1}^{N_s} p_s \left(C_s(u, \xi_s)\right)$$

where u represents the operational decisions, P_s is the probability of scenario s, and C_s is the total operating cost under that scenario.

The battery operation used as a simplified state-of-charge model is represented as:

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

$$SOC_{t+1} = SOC_t - \frac{P_{dis,t}\Delta t}{E_b \eta_{dis}}$$

Battery discharge is represented as:

$$SOC_{t+1} = SOC_t + \frac{P_{ch,t}\Delta t \eta_{ch}}{E_b}$$

Where

SOC_t represents battery state of charge

$P_{dis,t}$ represents battery discharge power

$P_{ch,t}$ represents battery charging power

E_b represents battery capacity

η_{dis} and η_{ch} represent discharge and charge efficiencies

Δt represents the simulation time interval
And the battery state-of-charge constraint was represented as:

$$SOC_{\min} \leq SOC_t \leq SOC_{\max}$$

Dynamic Programming controller

Dynamic Programming was implemented using backward recursion over a discretized battery state-of-charge grid and engine-power decision grid. At each time step, alternative engine-power decisions were evaluated against their immediate operating cost and estimated future cost.

The general recurrence was calculated using equation as:

$$J_t(SOC_t) = \min_{u_t} [C_t(SOC_t, u_t) + J_{t+1}(SOC_{t+1})]$$

Where J_t represents the minimum estimated cost from time t, and u_t represents the engine-power decision.

The Fixed Rules controller used predetermined state-of-charge thresholds and demand-deficit conditions to determine engine output. The control logic increased engine output when battery state of charge was low and adjuste4d engine operation according to the difference between demand and renewable contribution. This method represents a conventional rule-based baseline. The Fuzzy Logic controller used battery state of charge and the difference between electrical demand and renewable energy contribution as inputs. Membership-like functions represent low battery state, high demand deficit and other operating conditions. A controller combined the resulting rule activations to produce an engine-power command. The controller evaluates fuzzy decisions under three illustrative renewable-energy conditions: low, nominal and high renewable contribution. The resulting decisions are combined using the assigned scenario weights:

$$u_t = 0.25u_{low,t} + 0.50u_{nominal,t} + 0.25u_{high,t}$$

Performance indicators

The following indicators were calculated by the implementation:

Table 2: Indicators Summary

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

S/N	Indicator	Equation
1	Fuel Consumption	$F_{total} = \sum_{t=1}^{T} F_t$
2	Fuel Consumption Rate	$F_{rate} = \frac{F_{total}}{E_{demand}}$
3	Operating-cost proxy	$C_{proxy} = C_{fuel} + C_{battery} + C_{unmet}$
4	Battery degradation-cost proxy	$C_{battery} = E_{throughput} c_{deg}$
5	Emissions proxy	$E_{CO_2} = F_{total} EF$
6	Supply reliability	$R(\%) = \left(1 - \frac{E_{unmet}}{E_{demand}}\right) \times 100$

RESULTS

The simulation was successfully implemented using four energy-management controllers across six operating scenarios. Ten repeated runs were conducted for each scenario, giving 60 observations per controller and 240 observations across all four methods. The simulation generated fuel-consumption, operating-cost proxy, battery-throughput degradation-cost proxy, emissions proxy, unmet-energy demand, reliability, final battery state of charge and execution-time outputs. The mean for the fuel consumption from the simulation is depicted in table 3.

Table 3. Mean Fuel Consumption Summary from the Simulation

Energy-management strategy	Mean cumulative fuel consumption (g)	Standard deviation (g)
Dynamic Programming	210.93	30.04
Fixed Rules	152.57	14.35
Fuzzy Logic	233.72	31.75
Preliminary Stochastic–Fuzzy	232.75	30.97

The results indicate that Fixed Rules recorded the lowest mean cumulative fuel consumption of 152.57 g, followed by Dynamic Programming at 210.93 g. Conventional Fuzzy Logic recorded 233.72 g, while the stochastic–fuzzy heuristic recorded 232.75 g. The proposed stochastic–fuzzy controller achieved a reduction of approximately 0.42% relative to conventional Fuzzy Logic:

The Fixed Rules recorded the lowest mean operating-cost proxy, while the preliminary stochastic–fuzzy controller recorded a mean of 0.2379. Its operating-cost proxy was approximately 0.50% lower than conventional Fuzzy Logic as shown in table 4.

Table 4. Operating-Cost Proxy Summary

Strategy	**Mean operating-cost proxy**	**Standard deviation**
Dynamic Programming	0.2129	0.03
Fixed Rules	0.1677	0.0177

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

Fuzzy Logic	0.2391	0.0322
Preliminary Stochastic–Fuzzy	0.2379	0.0313

The Dynamic Programming recorded the lowest battery degradation-cost proxy, followed by the stochastic–fuzzy controller. The stochastic–fuzzy approach recorded a lower throughput-based degradation proxy than conventional Fuzzy Logic as illustrated in table 5.
Table 5. Battery Degradation-Cost Proxy

Strategy	**Mean degradation-cost proxy**	**Standard deviation**
Dynamic Programming	0.00201	0.00025
Fixed Rules	0.01508	0.00348
Fuzzy Logic	0.00541	0.00093
Preliminary Stochastic–Fuzzy	0.00518	0.00105

The Fixed Rules recorded the lowest emissions proxy because it also recorded the lowest fuel consumption. The stochastic–fuzzy controller recorded approximately 0.42% lower emissions than conventional Fuzzy Logic as depicted in table 6. The emissions values were calculated using a factor of 3.16 g CO_2 per gram of fuel.

Table 6: Mean Emissions Proxy Summary

Strategy	**Mean emissions proxy (g CO_2)**	**Standard deviation**
Dynamic Programming	666.55	94.93
Fixed Rules	482.14	45.36
Fuzzy Logic	738.57	100.34
Preliminary Stochastic–Fuzzy	735.49	97.87

DISCUSSIONS

i. The simulation showed differences in fuel consumption among the four controllers. Fixed Rules recorded the lowest mean fuel consumption, while Dynamic Programming achieved a lower fuel consumption than conventional Fuzzy Logic and the preliminary stochastic–fuzzy heuristic. The stochastic–fuzzy controller achieved only a marginal improvement over conventional Fuzzy Logic. These findings suggest that the performance of an energy-management strategy is influenced by its control structure, parameter settings and operating conditions. 5.2 Operating costs and battery management
ii. The operating-cost proxy results followed a pattern similar to the fuel-consumption results because fuel expenditure was an important component of the assumed cost formulation. Fixed Rules achieved the lowest operating-cost proxy, whereas the preliminary stochastic–fuzzy controller recorded a slightly lower value than conventional Fuzzy Logic. The battery degradation-cost proxy also indicated differences in battery energy throughput among the controllers. 5.3 Environmental performance
iii. The emissions estimates reflected the differences in fuel consumption because emissions were calculated using a constant assumed fuel emission factor. Fixed Rules recorded the lowest emissions proxy, while the stochastic–fuzzy controller produced a marginally lower estimate than conventional Fuzzy Logic. This finding suggests that the fuel consumption pattern influenced the emissions calculation.
iv. The computational results showed that Dynamic Programming required more execution time than the rule-based and fuzzy approaches. The stochastic–fuzzy controller also required additional computation relative to conventional Fuzzy Logic because it evaluated multiple renewable-energy conditions. This illustrates a potential trade-off between computational complexity and the ability to consider uncertain operating conditions. 5.5 Performance under renewable energy variability

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue XI November 2026

CONCLUSION

This study developed and executed a preliminary computational prototype for comparing Dynamic Programming, Fixed Rules, conventional Fuzzy Logic and a scenario-weighted stochastic–fuzzy control heuristic in a simplified diesel-electric hybrid energy system. The simulation considered six operating scenarios and ten repeated runs per scenario, generating 240 controller-run observations. The results showed that Fixed Rules achieved the lowest mean fuel consumption of 152.57 g and the lowest operating-cost proxy of 0.1677 under the assumed simulation conditions. Dynamic Programming recorded a mean fuel consumption of 210.93 g, while conventional Fuzzy Logic and the preliminary stochastic–fuzzy heuristic recorded 233.72 g and 232.75 g, respectively. The stochastic–fuzzy controller achieved reductions relative to conventional Fuzzy Logic in fuel consumption, operating-cost proxy and estimated emissions, but did not outperform Fixed Rules or Dynamic Programming. These findings demonstrate the importance of comparative evaluation rather than assuming that hybrid controller integration automatically improves system performance. However, the implementation remains a synthetic prototype, and the stochastic–fuzzy component has not yet been developed into a complete multi-period expected-cost optimizer. Further work must incorporate the original hybrid-system parameters, validate the powertrain and battery models, enforce equivalent operational constraints and evaluate the convergence and computational performance of the complete optimisation framework. Such validation is necessary before the proposed approach can be considered an empirically established improvement for hybrid energy management.

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