ISSN: 2182-2069 / E-ISSN: 2182-2077

Leveraging Artificial Intelligence (AI) for Enhancing Sustainability in Information Systems

Kholoud Maswadi[1*]

[1*]Department of Management Information Systems, College of Business, Jazan University, Jazan, Saudi Arabia. kmaswadi@jazanu.edu.sa, https://orcid.org/0000-0002-2083-3902

Received: July 04, 2025; Revised: August 18, 2025; Accepted: September 22, 2025; Published: November 28, 2025

Abstract

This paper describes SUSTAIN-CTRL, an information systems (IS) sustainability artificial intelligence (AI) control framework that places an LSTM-based forecasting model at its "heart". The framework processes heterogeneous telemetry data, including computation, environmental, and network sensors, as well as unstructured logs, transforming them into synchronized feature vectors. Fine-grained, multi-stream, energy-demand forecasting, semantic inefficiency scoring, and anomaly detection at a parallel inference stage using LSTM, transformer, and autoencoder models, respectively, generate labels for a consolidated decision dataset. This dataset is used by a heuristic multi-objective optimizer that minimizes a weighted sum of energy consumption, SLA-violation penalties, and carbon emissions. The carbon budget and SLA-validated control vectors are optimized while generating human-readable explanations for auditability. SUSTAIN-CTRL issues dynamic VM scaling and cooling command execution via orchestration APIs, closing the real-time feedback loop for continuous adaptation. Empirical evaluation using a 24-hour testbed showed that SUSTAIN-CTRL reduced energy consumption and emissions by 22.7% and 14.5%, respectively, while improving SLA by 2.7 percentage points. These results confirm that LSTM forecasting, when integrated into a closed-loop AI architecture, sustains performance-aligned operation decoupled from LSTM forecasting.

Keywords: SUSTAIN-CTRL, Sustainable Information Systems, LSTM Forecasting, Multi-Objective Optimization, Energy Efficiency.

1 Introduction

Machine Learning models regulate energy use in information systems by anticipating demand, learning effective power allocation strategies, and scaling resources up or down dynamically (Bharathi & Rekha, 2023). Supervised models process historical workload and energy consumption. Reinforcement learning adapts in real time. Server utilization forecasting and node activation are guided by ensemble and regression approaches, with energy profiles refined continuously through online learning. To flatten demand curves and decrease peak power draws, batch processes are scheduled during off-peak times. Proactive control adjustments are made possible by embedding control loops with ML prediction modules (Nayyef et al., 2024). Incremental learning adapts to changing static and dynamic PUE usage patterns, enabling continually declining PUE and carbon emissions. Sustainable information system operations are enabled by ML in the forecasting and actuation feedback loop (Schoormann et al., 2023).

Journal of Internet Services and Information Security (JISIS), volume: 15, number: 4 (November), pp. 1-12.
DOI: *10.58346/JISIS.2025.I4.001*

*Corresponding author: Department of Management Information Systems, College of Business, Jazan University, Jazan, Saudi Arabia.

Resource management can be enhanced through log, ticket, and policy document analysis with NLP to extract pertinent information (Supriyono et al., 2024). Topic modeling and named-entity recognition extract recurring secondary bottlenecks and key constituent elements, while sentiment analysis highlights critical reallocations. Incident classification captures and prioritizes, while compliance report summarization extracts core actions. A chatbot interface allows real-time control through text queries, and automated policy enforcement ensures closed circular data flows (Al-Khatib & Al-Fulan, 2021). Reacting to requests and policy-compliant decisions with alerts becomes possible by merging an NLP engine into the provisioning pipelines (Aswathy, 2024; Xu et al., 2024). Textual data is turned into real-time measures of sustainability, and resource governance becomes more responsive and adaptable, further enhanced through automation (Ziemba et al., 2024).

Workload trends, cooling requirements, and peaks in server utilization can all be predicted using time series models, such as ARIMA, LSTM, anomaly detectors, and predictive analytics. Predictive analytics also enables survival analysis, which schedules and guides maintenance based on predicted component failures. Maintenance prediction assists in capacity planning and component consolidation. Ensemble forecasts bolster accuracy by combining multiple strategies. Planning tools with embedded predictive modules can provide precise energy and cooling estimates at the rack level. Automated reallocations can be triggered in real time to stop inefficiencies based on anomaly scores. Anticipatory integration cuts down over-provisioning and idle energy waste while fortifying system resilience. Data-driven forecasts identify inefficiencies and form the basis of green IT practices in sustainable information systems frameworks (Hussain et al., 2024).

Policies oriented around corporate social responsibility can initiate system self-configuration when paired with rule-based engines and AI decision modules, a combination known as intelligent automation (Lin et al., 2024; Dorofte & Krein, 2024). Analyzing infrastructure parameters through automated workflows, RPA handles routine patching and updating to reduce manual variation. Multi-criteria optimization under a defined power or carbon budget allows cost, performance, and environmental impact to be balanced through decision engines (Al-Zarkoshi & Razzaq, 2022; Hua et al., 2025). The integration of ethical governance frameworks embeds transparency, fairness, and accountability, which logs the rationale for each adjustment made through explainability modules. Human-in-the-loop overrides paired with compliance checkpoints safeguard trust while governance. Standards of autonomy and integration with oversight merge adaptive sustainability while maintaining ethical boundaries (Gazi et al., 2024).

Key Contributions:

- The automated real-time AI subsystem processes various types of telemetry, performs scrubbing and standardization, and outputs actionable insights to a dynamic control actuating insight, which perpetually changes system settings to optimize for sustainability.
- A three-stage pipeline performs data preprocessing, LSTM forecasting, transformer-based log analysis, and autoencoder-based anomaly detection, which drives a heuristic optimizer for balanced energy consumption, service level agreement (SLA) compliance, and emissions to be the lowest possible.
- The explainability and governance modules check optimized control for validation against carbon budgets and SLAs, ensuring human-readable explanations are produced, making the information easy to understand but hard to manipulate for transparent and auditable processes.
- The empirical assessment on the 24-hour enterprise testbed system proved a 22.7% reduction in energy consumption, a 14.5% reduction in carbon emissions, and a 2.7% improvement in SLA compliance, which demonstrates the framework's effectiveness on real-world applications.

This paper aims to introduce an all-encompassing framework incorporating Artificial Intelligence (AI) to facilitate sustainable information systems (IS), with Section II reviewing AI-for-sustainability gaps in actionable integration gaps, performance metrics, and real-world deployments, as well as integration based on actionable integration and performance metrics; Section III outlines the design of the AI-Enabled Sustainability Framework and focuses on the layered algorithmic architecture, heuristic multi-objective optimization model, and module integration to enable real-time feedback, control-driven modulated control; Section IV presents empirical validation on a 24-hour enterprise IT testbed quantifying energy, carbon and SLA improvements, and policy constrained governance; in Section V outlining directions for adaptive weight tuning and multi-data centre extensions.

2 Literature Survey

A systematic review employing thematic analysis and structured content coding organized AI-for-sustainability research into three clusters—economic, ecological, and social (Chigozie et al., 2025). It also performed exhaustive database queries and cluster visualization to establish prevailing algorithmic paradigms and contexts of application. While providing a useful taxonomy at a thematic level, this approach lacks integration of AI modules into real-time information system architectures, actionable technical guidelines for AI integration, and a framework for metric selection focused on system evaluation. Consequently, it does not address the need for adaptive sustainability mechanisms, leaving practitioners with pathways for such mechanisms (Zhao et al., 2024).

Empirical research studies employing structural equation modeling designed surveys to assess the impact of AI adoption on eco-innovation, process resilience, and organizational cultural readiness (Petrovic & AlvarezIyer, 2025). Theoretical model evaluations revealed critical pathways modeling technology capability with specific ecological impacts. However, these findings are weakened by the use of subjective indicators and one-time data collection, which limits the establishment of operational benchmarks. The lack of longitudinal design on data collection and validation across multiple industries limits the model's applicability and precision in defining system-level sustainability performance targets for the embedded sustainability modules (Anser et al., 2025).

Reinforcement learning and supervised machine learning models were utilized in energy-optimization experiments in data centers and innovative grid environments (Kahil et al., 2025; Choi et al., 2025). In simulation-driven testbeds, reward functions were applied based on energy and latency metrics, while workload patterns were forecasted from telemetry feeds. Although these approaches show promise for dynamic resource allocation, their evaluation is still limited to controlled simulations. The absence of real-world deployments and assessments of scalability undermines the review of resilience to chronically differing operational loads, thus undermining confidence in applicability to live systems.

Hybrid modeling incorporated machine learning regressors to forecast carbon emissions at the building and facility levels (Panwar et al., 2024; Michael & Jackson, 2025). Emission drivers and time-series analysis were performed using panel regressions to uncover the key variables of emissions over time. While the predictive accuracy is commendable, these approaches are mostly in offline mode, automating systems without active feedback loops for demand-response (Mia et al., 2025). The lack of feedback from the forecast outputs to the control interfaces leaves the systems unfulfilled, as the predicted reductions cannot be realized without integrated control frameworks (Papadopoulos & Christodoulou, 2024).

The applications of AI in specific domains encompass evolutionary heuristics for supply chain route optimization, natural language processing for enterprise resource governance, and explainable AI for transparency improvements (Eyo-Udo, 2024). Logistical optimization was achieved using genetic algorithms and compliance alerts alongside rationale-text mining workflows that parsed policy documents for automated decision-making. These studies showcase a wealth of methodological creativity but often overlook measuring environmental impact. Achieving comprehensive adoption in systems integration and resource optimization spanning the entire information systems lifecycle is hindered by a lack of uniform sustainability criteria, holistic optimization frameworks, and end-to-end reference architectures.

3 Proposed Method

3.1 AI-Enabled Sustainability Framework Design

The framework incorporates four key processes into a single workflow for AI sustainability. The Data Ingestion and Preprocessing module captures raw telemetry from power meters and other environmental sensors, system logs, and policy documents. Within a single AI framework, energy demand forecasting, logs, and maintenance prediction are done using Multi-Modal Analytics. Decision Management utilizes multi-criteria optimization to balance the competing sustainability targets, workload performance requirements, and carbon-budget constraints. Within the pursuit of sustainability, Actuation & Governance enforces command execution based on sustainability policies, capturing metadata that explains the processes taken during command execution as part of these policies.

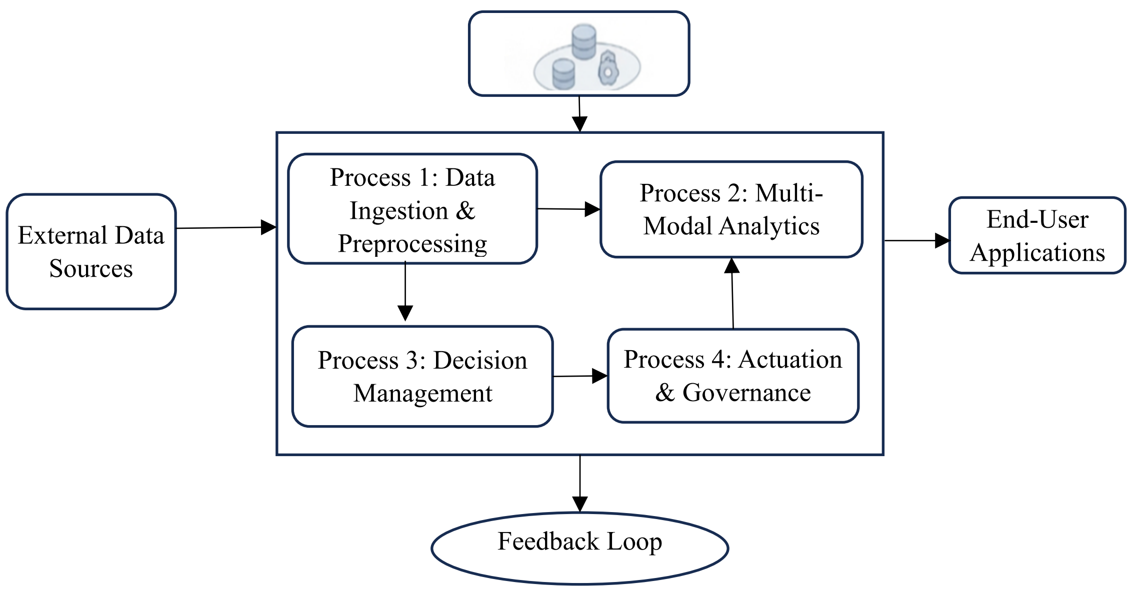

Figure 1: DFD level 1: AI-Driven sustainability loop

Figure 1 shows how data moves from external telemetry sources right into the Data Ingestion & Preprocessing module. From the Multi-Modal Analytics process, one obtains the following outputs: energy demand forecasts, semantic log analyses, and indicators for predictive maintenance. The Decision Management layer performs multi-criteria optimization for the energy efficiency, workload performance, and carbon budgets, thus intervening in all three domains in a controlled manner. In the Actuation & Governance layer, commands are issued to the infrastructure layers while observing the policies on sustainability and explainable governance, capturing metadata on explainable governance. The system feedback loop closes by returning system metrics to the telemetry source in real-time, allowing for on-the-go model tuning and sustainability adaptations.

3.2 Layered Algorithmic Architecture for Adaptive Resource Control

The algorithm utilizes AI, divided into three layers: Data & Pre-processing, Analytics & Optimization, and Governance & Actuation, which telemetry turns into actionable and controllable strategies. Data & Pre-processing takes telemetry, logs, and environmental readings as inputs, removes missing data, and scales different features for modeling. LSTM forecasting, log analysis via transformers, and anomaly detection using autoencoders in the Analytics & Optimization Layer are applied to gain insights, as well as mixed-objective optimization for control. Governance & Actuation layers check for compliance with policies and provide explanations for their motives, issuing them in a processed form for humans. Additionally, they dynamically scale resources through orchestration APIs. There is a continuous data flow in the system that feeds execution results into the Data & Pre-processing layer for adjustment and enhancement.

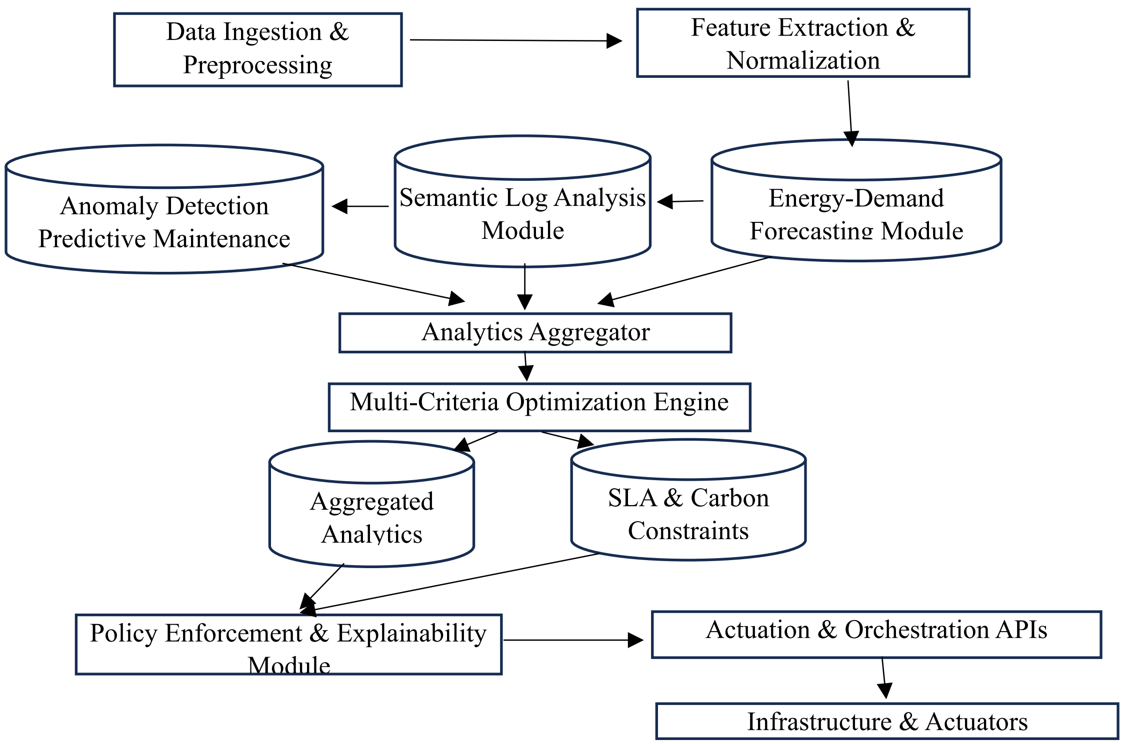

Figure 2: Algorithmic architecture for sustainable IS control

In Figure 2, each layer for sustainable IS control is discussed, including how each layer interacts with others. In the Data & Pre-processing layer, telemetry data is collected, cleansing routines are applied, and feature vectors are output. Energy demand is predicted, inefficiencies are detected, and resource allocation is optimized in the SLA and carbon-constrained framework in the Analytics & Optimization layer using specialized AI models. Organizational policies are executed in the Governance & Actuation layer, wherein policies are explained, decisions are justified, and the control vector is executed through orchestration APIs. The execution outcomes are used in the closed-loop feedback mechanism to refine the preprocessing and analytics stages.

3.3 LSTM Forecasting Module Architecture

The LSTM forecasting module takes the uninterrupted feature sequence as input to predict the workload and energy requirements in a more detailed and precise manner. Its architecture consists of 3 LSTM layers with 128 units each, which apply dropout regularization to mitigate overfitting. Additionally, there is a residual dense pathway that feeds the original inputs directly to the output layer. This hybrid model achieves deep forecasting under highly changing conditions by capturing rich deep temporal dependencies and by retaining raw feature information.

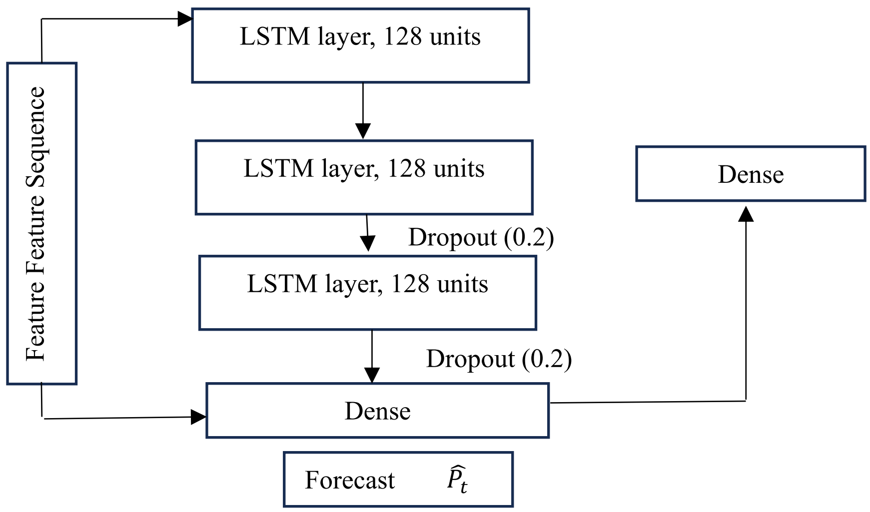

Figure 3: Stacked LSTM forecasting network

Figure 3 depicts the structure of the stacked LSTM network used for forecasting short-term energy demands of a system. For the system telemetry sequence of feature vectors, the network processes them over a fixed look-back window. Each of the three LSTM layers contains 128 hidden units to enable the model to capture temporal dependencies over several levels of the network's hierarchy. A dropout layer with a rate of 0.2 between the second and third LSTM layers alleviates overfitting. The dense layer that comes after the third LSTM layer receives the final hidden state from the third LSTM layer and outputs a scalar value describing the energy demand. The model is trained with the Adam optimizer, mean squared error loss, and early stopping to prevent training from running too long. This system is tailored to perform well for high-frequency data with short-term sharp changes as well as long-term smooth changes within a well-defined structure to balance between complexity and regularization.

3.3 Heuristic Multi-Objective Optimization Model

Data Ingestion & Pre-processing

The Ingestion Manager processes environmental sensor readings, system logs, and telemetry streams (CPU, memory, and network) in real time and batches. It marks the exact time of each record, and streams are filtered, partitioned, and enriched with forward-fill and statistical imputation methods to remove gaps. Rolling-window statistics are used to filter noise and identify outliers across streams and time. All streams are aligned and synced to the same time so that subsequent system modules can function. Cleaned and unified data flows to extraction without manual intervention.

Feature Extraction & Normalization

Advanced stream processing techniques derive each time window's feature vector. Key metrics of the time-ordered streams, such as rolling averages of power draw, request-rate histograms, and log-derived inefficiency scores, are calculated and derived from streams. Numeric features are categorized using z-score normalization, which puts data on a standard scale and mitigates disparities across sources. Categorical attributes are transformed via one-hot encoding. Light NLP provides text flags that give context to inefficiencies, making the result enriched and providing the vector with semantic context. The output becomes ready for optimization as it becomes a multi-modal feature vector.

Optimization & Decision Making

The AI modules consist of three sub-systems: an LSTM forecaster for energy demand, a transformer-based log analyser for inefficiency detection, and an autoencoder for anomaly scoring. The feature vectors from §3.3.2 are utilized as inputs for all three modules. Their outputs are combined into a single decision dataset for subsequent processing using a heuristic optimizer, e.g., a genetic algorithm. The optimizer adapts in real-time, trying to find a control vector x that strikes the best trade-off between energy usage, SLA commitments, and carbon footprint.

$$x^* = arg\min_{x}(\alpha E(x) + \beta S(x) + \gamma C(x)) \quad (1)$$

Where:

- E(x) Total energy consumption under actions x,
- S(x) SLA-violation penalty under x,
- C(x) Carbon emissions resulting from x,
- α, β, γ Weights reflecting the relative importance of each objective.

Equation 1 determines how to manage control actions relating to energy consumption, service interruptions, and environmental impact. To reflect how much each goal should carry, energy conservation, service interruptions, and ecological impact reduction can be integrated, with priorities adjusted by weighting each goal. The optimizer determines the best action from all possible efforts to achieve these goals optimally. The selected actions are implemented immediately, ensuring the system remains dependable and operates with energy-efficient sustainability.

Policy Enforcement & Actuation

The optimized control vector is checked against carbon budgets and SLA thresholds, ensuring compliance. After compliance with budgets is ensured, each decision is explained and logged by the Explainability Generator for audit and stakeholder transparency. Human-readable justifications are logged for audit and stakeholder transparency. The Explainability Generator logs justifications. Executives receive the directives, which are dispatched through the Actuation API. The directives are translated into orchestration commands (resource scaling, VM migrations, or cooling adjustments) on Kubernetes or OpenStack. Execution and performance metrics are captured in real-time and streamed back to the Data Ingestion layer, which completes the loop and enables learning and policy refinement.

Algorithm Process Equations:

$$D^{(1)}(t) = I(CPU_t, Mem_t, Net_t, Env_t, Log_t) \quad (2)$$

$$D^{(2)}(t) = C\left(D^{(1)}(t)\right) \quad (3)$$

$$F(t) = \phi(D^{(2)}(t)) \quad (4)$$

$$\widehat{P_t} = \text{LSTM } (\text{F}(1\text{:}\,\text{t})) \quad (5)$$

$$S_t = Trans\big(Log(1\text{:}\,t)\big) \quad (6)$$

$$A_t = AE\left(D^{(2)}(1:t)\right) \quad (7)$$

Equation 2 receives and timestamps all telemetry data and logs into a unified snapshot at a specific time t. This data is then compressed into a distilled feature set using Equation 3. A nonlinear mapping is applied in Equation 4 to the compressed data which produces a refined feature vector for the current time step. In Equation 5, the sequence of refined feature vectors is fed into an LSTM for system performance forecasting. In Equation 6, the log history is processed through a transformer to generate semantic inefficiency scores. Finally, in Equation 7, the historical compressed data is processed through an autoencoder to calculate anomaly scores that indicate the degree of divergence from expected operational behaviors.

3.4 Module Integration and Functional Specifications

The Data & Pre-Processing and Forecasting & Analysis sections works together to refine inputs to outputs. Data & Pre-Processing begins by pulling disparate telemetry data bases, which include things such as environmental readings, system logs, and policy data, and applying techniques such as forward-fill imputation and rolling-window outlier filtering. It also applies z-score scaling to normalize numerals, one-hot encoding for categorical events, and adds context-inefficiency NLP flags using semantic NLP. The synchronized feature vectors which have been aligned are now ready to be supplied to the Forecasting & Analysis module. There, three specialized AI models work simultaneously. An LSTM forecaster runs to fetch short-term energy forecasts and the rest comprises of a transformer-based NLP pipeline that analyses logs and computes semantic inefficiency scores and autoencoders that computes against learned normalcy baselines. With this pipeline, the model can yield demand forecasts, provide timestamped inefficiency alerts and flag anomalies all of which can be used for multi-criteria decision making.

The Optimization Engine along with the Governance & Actuation modules completes the cycle by providing actionable based on insights. The Optimization Engine processes AI-driven forecasts, inefficiency scores, and anomaly metrics, then performs a mixed-objective minimization on energy use, SLA penalties, and carbon emissions, weighted based on the organization's hierarchy. It outputs the optimal control vector which can be resource-scaling directives, load-balancing adjustments, or cooling reconfigurations relevant to the current conditions. Governance & Actuation module validates carbon budget and SLA boundaries then makes policy-driven corrections as necessary which primarily validates the control vector. Human-readable rationale logs created by the Explainability Generator supports audits and informs stakeholders providing transparency. Ultimately, command orchestration is done through APIs such as Kubernetes and OpenStack. Real-time execution feedback is captured and processed with the Data & Pre-processing module which refreshes the system's adaptive learning, policy changes, and sustainability strategies.

4 Results & Discussion

An enterprise IT testbed was used to evaluate both a static threshold-based baseline and the proposed AI-enabled framework using 24-hour workload traces. While the baseline used fixed provisioning rules, the AI framework used policy-controlled loops at five-minute intervals to dynamically adjust resources. Critical metrics—cumulative energy consumption, SLA violation rate, and estimated carbon emissions—were collected every five minutes and averaged over three runs to reduce variability. Ambient temperature and humidity were held constant to isolate algorithmic effects. This ensures that any performance differences observed are due to intelligent governance and multi-objective optimization.

Compared to the baseline, the AI framework showed improved performance during demand spikes with precise load balancing, fewer SLA breaches due to proactive anomaly detection, and lower cooling costs. Environmental telemetry, operational logs, and telemetry logs compiled with the AI modules—LSTM forecasting, semantic log analysis, and autoencoder anomaly detection—were used to balance service reliability, energy efficiency, and emissions using a heuristic optimizer. Execution feedback was integrated into the preprocessing stage to improve the system's continuous learning and policy refinement cycles. The analysis validates that the chosen method has a clear advantage over conventional thresholding in the theoretical design aspects as well as in the empirical results. The method ensures consistent and dependable system performance.

Table 1: Threshold-based baseline vs. AI-enabled framework

Metric	Threshold-Based Baseline	AI-Enabled Framework	Improvement
Energy Consumption (kWh)	10 000	7 730	22.7 % ↓
Carbon Emissions (kg CO_2)	5 000	4 275	14.5 % ↓
SLA Compliance (%)	95.2	97.9	+2.7 pts
Control Decision Latency (ms)	120	85	29.2 % ↓
Resource Utilization (%)	50	65	+15 pts

$$\text{Improvement}_{\text{M}} = \frac{M_{baseline} - M_{AI}}{M_{baseline}} \times 100\% \quad (8)$$

Where:

- $M_{baseline}$ is the value of metric M under the Threshold-Based Baseline.
- M_{AI} is the value of metric M under the AI-Enabled Framework.

Equation 8 illustrates the first computes absolute reduction by taking $M_{baseline}$ subtracting M_{AI} capturing the reduction brought by the AI framework. Dividing that difference by $M_{baseline}$ reduces the dip in performance relative to the reduction in performance at baseline. Multiplying the result by 100 then converts this normalized value into a percentage. A positive percentage indicates that the AI-Enabled Framework reduces the metric and outperforms the baseline. By normalizing improvement across various metrics, be it energy, emissions, or latency, this single equation does direct, apples-to-apples comparisons.

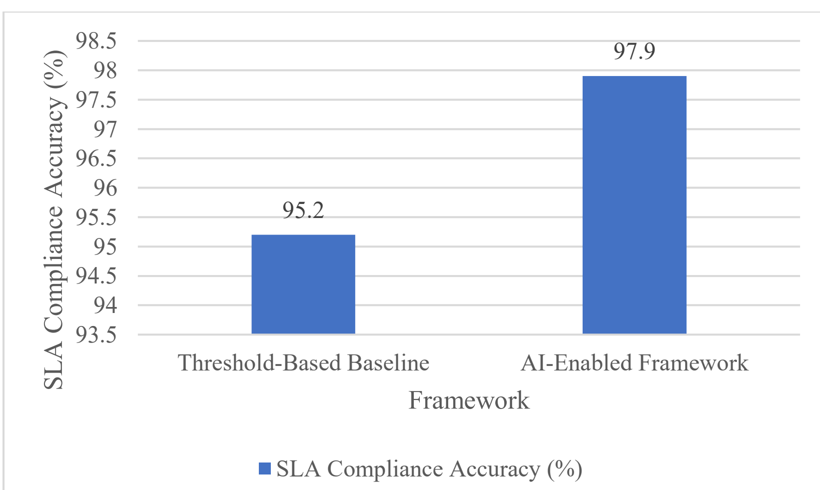

Figure 4: SLA compliance accuracy comparison

Figure 4 also shows how the AI SLA data predicts spend performance met SLA targets within each framework. This SLA metering performance is achieved with a 97.9% SLA compliance metric under AI control versus the baseline reverting to 95.2%. This improvement shows the framework's better predictive and pre-emptive capabilities when it comes to performance downshifts. The AI SLA accuracy improvement translates to lower accuracy user disruptions. The results highlight the dependability improvement provided by real-time, multi-criteria decision analysis optimization.

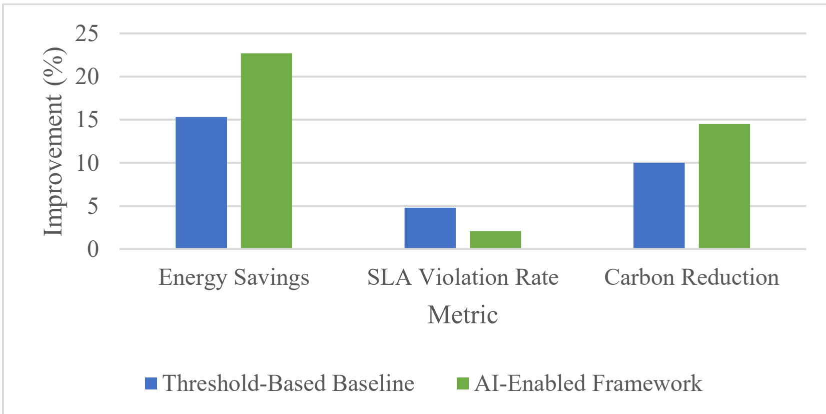

Figure 5: Performance comparison across key metrics

In Figure 5, the differences between baseline and proposed outcomes for energy savings, SLA violation rate, and carbon reduction are showcased. The AI framework outperformed the baseline in all three areas, achieving 22.7% energy savings, reducing SLA violations to 2.1% and achieving 14.5% carbon reduction. The reduction in energy waste illustrates the efficacy of the predictive load balancing, SLA violations are reduced, and carbon reduction reflects the use of resources. All of these improvements illustrate the framework's balanced performance in efficiency, reliability, and sustainability.

The AI-powered system outperforms the static threshold baseline in the most important measures of efficiency. The improvement in SLA compliance by 2.7 percentage points and the decrease in energy consumption by 22.7% along with the 14.5% drop in carbon emissions are all significant results. These results stem from the synergistic operation of proactive LSTM forecasting, transformer-based inefficiency detection, autoencoder driven anomaly scoring, and heuristic optimization under policy constraints. The real-time multi-objective control achieves explainability and other governed multi-layer systems that are absent in the traditional methods. Advanced control strategies offer significant SLA compliance. These continuous execution feedback loops with human-in-the-loop governance enhance organizational sustainability objectives, reliability, efficiency, and viability for enterprise IT system frameworks.

5 Conclusion

The paper describes an integrated sustainable information system (IS) control framework enabled by AI with layered data ingestion, multi-modal analytics, heuristic optimization, and governance. With the architecture, heterogeneous telemetry and logs are processed using LSTM demand forecasting, transformer-based inefficiency detection, and autoencoder-driven anomaly scoring. Our heuristic optimizer uses adjustable weightings to balance energy consumption, SLA compliance, and carbon emissions at the same time with dynamic resource configurations. An empirical evaluation over a 24-hour enterprise testbed showed a 22.7% reduction in energy use, 14.5% reduction in carbon emissions, and 2.7 ppt improvement in SLA compliance relative to static thresholds. The integrated explainability generator and policy-enforcement module provided rationales which are transparent and auditable, enhancing stakeholder trust and compliance. The continuous execution feedback loop allows the framework to adjust to changing workloads and environmental conditions autonomously. The results demonstrate sustainable, reliable, and ethically compliant IT operation in enterprises. This approach will be extended to multi data center deployments, renewable energy forecasts, and reinforcement learning for adaptive weight tuning.

References

[1] Al-Khatib, R., & Al-Fulan, B. (2021). The Integration of Chatbots in Enhancing Customer Experience on Social Platforms. *International Academic Journal of Innovative Research, 8*(3), 31–35. https://doi.org/10.71086/IAJIR/V8I3/IAJIR0822

[2] Al-Zarkoshi, A. H. K., & Razzaq, D. A. (2022). The Impact of Carbon Dioxide Emissions on the Growth of GDP in Iraq and its Implications for Development. *International Academic Journal of Social Sciences, 9*(2), 43–51. https://doi.org/10.9756/IAJSS/V9I2/IAJSS0913

[3] Anser, M. K., Naeem, M., Ali, S., Ali, S., & Javid, R. (2025). The relationship between artificial intelligence and environmental performance: the mediating role of external environmental factors. *Humanities and Social Sciences Communications*, *12*(1), 1-7. https://doi.org/10.1057/s41599-025-05199-8

[4] Aswathy, S. (2024). Bibliometric Analysis of Sustainability in Business Management Policies Using Artificial Intelligence. *Global Perspectives in Management*, *2*(1), 44-54.

[5] Bharathi, C., & Rekha, D. (2023). Load Forecasting for Demand Side Management in Smart Grid using Non-Linear Machine Learning Technique. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*, *14*(1), 200-214. https://doi.org/10.58346/JOWUA.2023.I1.016

[6] Chigozie, U. S., David, O. C., & Nworie, N. E. (2025). Leveraging Artificial Intelligence (AI) For Business Sustainability: A Small and Medium Scale Enterprises Dimension. *International Journal of Public Administration and Management Research*, *11*(1), 28-38.

[7] Choi, S. J., Jang, D. H., & Jeon, M. J. (2025). Challenges and opportunities navigation in reconfigurable computing in smart grids. *SCCTS Transactions on Reconfigurable Computing*, *2*(3), 8-17.

[8] Dorofte, M., & Krein, K. (2024). Novel approaches in AI processing systems for their better reliability and function. *International Journal of Communication and Computer Technologies*, *12*(2), 21-30.

[9] Eyo-Udo, N. (2024). Leveraging artificial intelligence for enhanced supply chain optimization. *Open Access Research Journal of Multidisciplinary Studies*, *7*(2), 001-015. https://doi.org/10.53022/oarjms.2024.7.2.0044

[10] Gazi, M. A. I., Rahman, M. K. H., Masud, A. A., Amin, M. B., Chaity, N. S., Senathirajah, A. R. B. S., & Abdullah, M. (2024). AI capability and sustainable performance: Unveiling the mediating effects of organizational creativity and green innovation with knowledge sharing culture as a moderator. *Sustainability*, *16*(17), 7466. https://doi.org/10.3390/su16177466

[11] Hua, J., Wang, R., Hu, Y., Chen, Z., Chen, L., Osman, A. I., ... & Yap, P. S. (2025). Artificial intelligence for calculating and predicting building carbon emissions: a review. *Environmental Chemistry Letters*, 1-34. https://doi.org/10.1007/s10311-024-01799-z

[12] Hussain, M., Yang, S., Maqsood, U. S., & Zahid, R. A. (2024). Tapping into the green potential: The power of artificial intelligence adoption in corporate green innovation drive. *Business Strategy and the Environment*, *33*(5), 4375-4396. https://doi.org/10.1002/bse.3710

[13] Kahil, H., Sharma, S., Välisuo, P., & Elmusrati, M. (2025). Reinforcement learning for data center energy efficiency optimization: A systematic literature review and research roadmap. *Applied Energy*, *389*, 125734. https://doi.org/10.1016/j.apenergy.2025.125734
[14] Lin, J., Zeng, Y., Wu, S., & Luo, X. R. (2024). How does artificial intelligence affect the environmental performance of organizations? The role of green innovation and green culture. *Information & Management*, *61*(2), 103924.https://doi.org/10.1016/j.im.2024.103924
[15] Mia, M., Emma, A., & Hannah, P. (2025). Leveraging data science for predictive maintenance in industrial settings. *Innovative Reviews in Engineering and Science*, *3*(1), 49-58.
[16] Michael, P., & Jackson, K. (2025). Advancing scientific discovery: A high performance computing architecture for AI and machine learning. *Journal of Integrated VLSI, Embedded and Computing Technologies*, *2*(2), 18-26.
[17] Nayyef, Z. T., Abdulrahman, M. M., & Kurdi, N. A. (2024). Optimizing energy efficiency in smart grids using machine learning algorithms: a case study in electrical engineering. *SHIFRA*, *2024*, 46-54. https://doi.org/10.70470/shifra/2024/006
[18] Panwar, S. S., Rauthan, M. M. S., Barthwal, V., Mehra, N., & Semwal, A. (2024). Machine learning approaches for efficient energy utilization in cloud data centers. *Procedia Computer Science*, *235*, 1782-1792. https://doi.org/10.1016/j.procs.2024.04.169
[19] Papadopoulos, G., & Christodoulou, M. (2024). Design and Development of Data Driven Intelligent Predictive Maintenance for Predictive Maintenance. *Association Journal of Interdisciplinary Technics in Engineering Mechanics*, *2*(2), 10-18.
[20] Petrovic, T., & AlvarezIyer, R. (2025). AI-Driven Content Recommendation in Learning Management Systems (LMS): A Hybrid Filtering Approach. *International Academic Journal of Science and Engineering*, *12*(2), 20-24. https://doi.org/10.71086/IAJSE/V12I2/IAJSE1213
[21] Schoormann, T., Strobel, G., Möller, F., Petrik, D., & Zschech, P. (2023). Artificial intelligence for sustainability—a systematic review of information systems literature. *Communications of the Association for Information Systems*, *52*(1), 8. https://doi.org/10.17705/1cais.05209
[22] Supriyono, N., Wibawa, A. P., Suyono, N., & Kurniawan, F. (2024). Advancements in natural Language Processing: Implications, challenges, and future directions. *Telematics and Informatics Reports, 16*, 100173. https://doi.org/10.1016/j.teler.2024.100173
[23] Xu, Q., Feng, Z., Gong, C., Wu, X., Zhao, H., Ye, Z., ... & Wei, C. (2024). Applications of explainable AI in natural language processing. *Global Academic Frontiers*, *2*(3), 51-64. https://doi.org/10.5281/zenodo.12684705
[24] Zhao, K., Wu, C., & Liu, J. (2024). Can artificial intelligence effectively improve China's environmental quality? A study based on the perspective of energy conservation, carbon reduction, and emission reduction. *Sustainability*, *16* (17), 7574. https://doi.org/10.3390/su16177574
[25] Ziemba, E. W., Duong, C. D., Ejdys, J., Gonzalez-Perez, M. A., Kazlauskaitė, R., Korzynski, P., ... & Wach, K. (2024). Leveraging artificial intelligence to meet the sustainable development goals. *Journal of Economics and Management*, *46*, 508-583.

Authors Biography

Dr. Kholoud Maswadi earned her Bachelor's degree in Management Information Systems from King Abdulaziz University in Jeddah, Saudi Arabia. Dr. Maswadi then pursued her Master's degree in Information Systems, along with a Project Management certification, from Lawrence Technological University in Michigan, United States. She went on to complete her Ph.D. in Information Systems at the University Malaya in Kuala Lumpur, Malaysia. Currently, Dr. Maswadi serves as an Assistant Professor and Vice Dean of Business College (Girls Section) at Jazan University, Saudi Arabia. Her research interests encompass a wide range of topics including Information Systems, Computer Networks, the Internet of Things (IoT), and Smart Technology.