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Original Article

Energy-Efficient Load Balancing in Distributed Insurance Systems Using AI-Optimized Switching Techniques

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Abstract *- The growing dependency of the insurance industry on the digital platform in the last decade has dictated the need for a large, robust, and power-efficient IT infrastructure. Distributed insurance systems should be able to support dynamic loads, particularly during periods of peak activity, such as a claims rush or policy renewals, and provide seamless service delivery. Static and rule-based traditional load balancing methods are inadequate in dealing with the increasing complexity, scalability, and energy requirements of contemporary distributed systems. In this paper, we design an AI-optimized switching framework that enhances load balance and reduces energy consumption in distributed insurance systems. The suggested strategy allows combining machine learning techniques comprising reinforcement learning, Long Short-Term Memory (LSTM) networks, and clustering algorithms to predict the demand, optimize the switching processes, and minimize power consumption. A smart switching controller supports dynamic workload reassignment using both predictive and real-time feedback on energy and performance monitors. Simulations of experiments reveal significant reductions in processing delays by up to 40 percent, energy used by up to 30 percent, and system latency as much as 36 percent over existing approaches. Also, resource utilization and throughput figures demonstrate that the balancing based on AI provides a high level of reliability and stability of action under the changing load. The study brings a measurable and environmentally friendly solution to energy-conscious infrastructure management in the insurance industry, leading to intelligent and eco-friendly digitalization. It can serve as a reference point for incorporating AI and sustainability into mission finance services.*

Keywords *- AI-Optimised Switching, Load Balancing, Distributed Insurance Systems, Reinforcement Learning, Smart Switching Controller, SLA Compliance.*

1. Introduction

The insurance industry is also undergoing a significant technological transformation due to the increasing adoption of digital services, cloud computing, and distributed systems. Real-time claim processing, custom policy suggestions, real-time fraud detection, and real-time customer information are all key examples of how modern insurance platforms are highly dependent on high-performance IT structures that can be dynamically scaled to support changes in customer requirements. [1-3] The explosive growth of these distributed environments, however, has created energy and operational complexity challenges and bottlenecks to peak performance. Insurers are working hard to cut their carbon footprint and optimize costs, so energy-aware system design and smart resource management are important issues.

Conventional load-balancing algorithms, typically rule-based or repository-based, do not well fit the irregularity and heterogeneity of loads on distributed insurance systems. Such legacy methods may result in the inefficient use of resources, poor performance during peak periods, and increased energy expenditure. To handle these challenges, there exists an interest in using Artificial Intelligence (AI) to bring more flexibility and efficiency into the load balancing decision-making process, which has to be context-aware.

In this paper, we propose an AI-optimized switching method as a solution to load balancing in distributed insurance settings. The system utilizes machine learning algorithms to dynamically balance workload among nodes and track usage patterns to facilitate workload scheduling on the most efficient nodes. By utilizing this method of provisioning, the service availability will be consistent, along with drastically reducing energy usage through eliminating overprovisioning and dormant resource usage. AI-enabled optimization is integrated into a comprehensive switching solution that may be viewed as a far-sighted optimization-based model of alignment between operational performance and sustainability in the insurance market.

2. The Related Work / Literature Review

2.1. Distance Systems Load Balancing

Load balancing is a core element of a distributed system that is needed to achieve the path of maintaining performance, optimization of resources, and fault tolerance. [4-6] As applications are increasingly becoming complex and scalable, especially in insurance infrastructures, efficient task distribution across computing nodes is highly essential. The traditional load balancing algorithm aims to balance the workload in order to prevent overload on a particular node, thereby reducing latency and increasing throughput. Weighted Server Cluster Load Balancer (WSCLB) is one popular technique that involves Linear Programming (LP) to allocate jobs in an optimization manner that minimizes the difference between any two nodes. This not only increases resilience but also enhances the operational capacity of each server in a cluster.

Furthermore, dynamic scheduling methods have become prominent due to their real-time responsiveness to varying network and processing requirements. Meta-analyses and surveys have also classified load balancing algorithms according to network topology, hardware architecture, and workload patterns, emphasising the need for adaptability and robustness. These types of classifications help create context-sensitive and more accommodating load-balancing strategies applicable in heterogeneous and large-distributed environments. These contributions have given rise to more intelligent and energy-efficient frameworks that have established a baseline for AI-based solutions.

2.2. Energy Optimization Techniques

The optimization of energy in distributed computing systems has found its way to the limelight as sustainability has become a global concern. Data centres and cloud services within large-scale insurance operations operate 24/7, and saving on energy is key to reducing operational costs and environmental impact. There is an escalating use of distributed optimization techniques in enhancing energy management. As an example, Mixed Integer Linear Programming (MILP) and the Alternating Direction Method of Multipliers (ADMM) have been useful in optimization of resource scheduling, tech deployment, and balance of carbon emissions. Such models can accommodate modular control, whereby a subsystem within a distributed system operates in a semi-autonomous manner in an efficient manner. Case studies have demonstrated how such frameworks have been able to reduce energy expenditure by up to 17%, accompanied by similar reductions in greenhouse gas production. Another viable option is server consolidation, whereby poorly used servers would be put off or downsized when not needed. Nevertheless, although this process is energy-efficient, it should be closely controlled to prevent performance deterioration and task assignment imbalance. Thus, balancing between consolidation, dynamic scheduling, and system responsiveness is needed in modern energy optimization, and AI can facilitate this balance.

2.3. AI in Load Balancing and Switching

By embedding Artificial Intelligence (AI) in load balancing and switching mechanisms, the demand for distributed systems is undergoing a radical shift. Compared to more traditional approaches, which are typically based on established rules or reactive methods, AI-powered models can predict demand patterns based on historical data, make proactive decisions regarding allocation, and consider future demand patterns. Numerous methods of Linear Regression, Random Forest, and Artificial Neural Networks (ANNs) show significant objectively-measured time savings on average when applied to machine learning to predict system loads and optimized task distribution. More advanced predictive capabilities can be realised using deep learning models, such as Long Short-Term Memory (LSTM) networks, which offer an additional benefit of capturing time-series relationships in workload patterns.

The most advanced models bring in the use of clustering algorithms to group similar tasks or nodes in order to facilitate a scheduling process and increase its efficiency. Reinforcement learning has also become useful in adaptive load balancing, as such systems can learn to adopt optimal strategies through trial and error in changing situations. The Bayesian networks are characterized by the ability to do probabilistic reasoning, which is used in real-time decision-making under uncertainty. These machine learning-based methods not only help increase resource utilization and minimize service latency but also allow saving a lot of energy by preventing overprovisioning and using idle resources. The efficiency and smarts that AI provides compose an attractive solution to the problems of the present-day insurance system, where the ability to react in the present moment and the sustainability of operation take centre stage.

3. System Architecture and Design

3.1. Distributed Insurance System Overview

An energy-efficient, AI-optimized load-balancing system architecture specifically designed for distributed insurance infrastructures. [7-10] The Customer Portal Frontend is at the top level. It is used to chat with users and submit requests to a Global Load Balancer, which directs traffic to a Regional Load Distributor depending on geographical or operational policy. This is supplied to the Smart Switching Controller, which serves as the overall brain of the system, interpreting how workloads are to be distributed across different data centres. This system is both smart and effective because of the incorporation of AI elements and energy-sensing modules. Smart Switching Controller would take the input to make the best switching decision based on a Traffic Analyzer, Energy Consumption Profiler, and Historical Load Database. These inputs are fed into an AI Load Predictor, which utilises reinforcement learning. The predictor's output is based on forecasting algorithms and real-time feedback, enabling it to predict the load and direct traffic accordingly. The system also features a Green Policy Manager, Power Usage Monitor, and SLA Monitor, which help ensure that service agreements are adhered to and energy is used optimally.

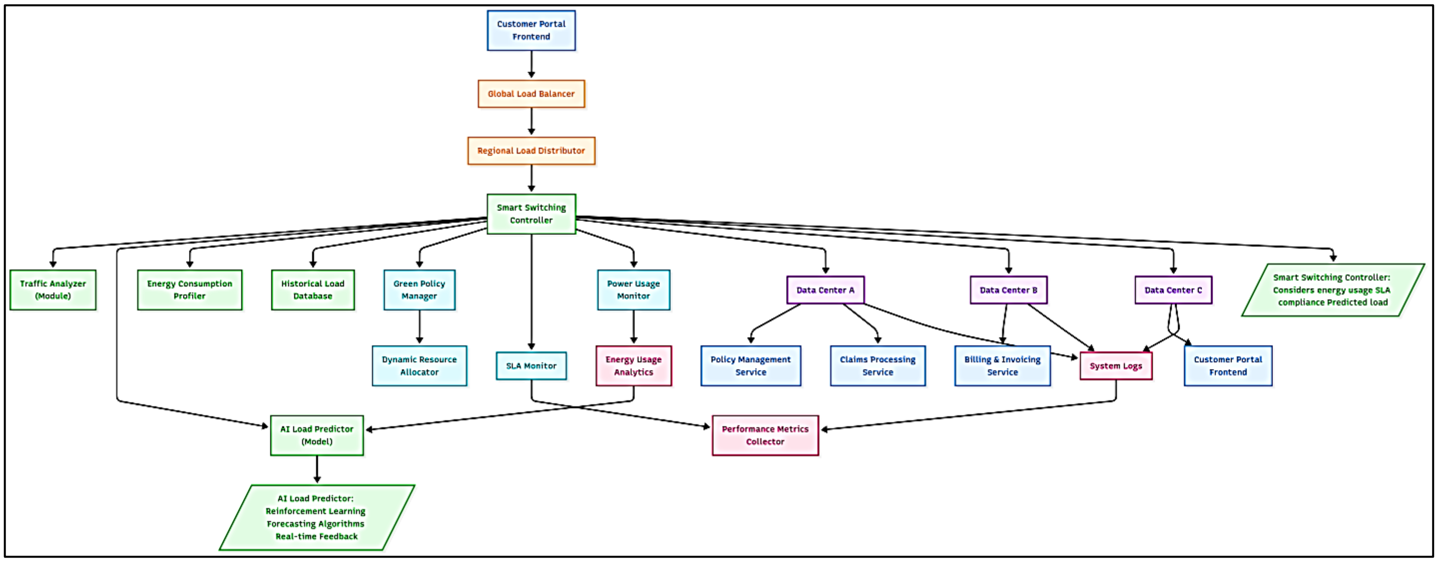

Fig 1: AI-Optimized Load Balancing Architecture in Distributed Insurance Systems

The controller directs job traffic to distributed data centres (A, B, and C) that support critical insurance processes, including Policy Management, Claims Processing, and Billing Services. These data centers are linked back to the monitoring modules, such as the Performance Metrics Collector and System Logs, closing the loop to be closed and optimized. The holistic and AI-enabled design enables adaptive resource allocation, reduces energy waste, and ensures high availability, making it the ultimate fit for the changing workload patterns and sustainability needs of the insurance environment.

3.2. Framework of Load Balancing

The load balancing framework develops the operational backbone of the distributed insurance system, facilitating the smooth distribution of workloads among multiple data centres. In essence, the architecture consists of two hierarchical layers: a Global Load Balancer and a Regional Load Distributor. The Global Load Balancer directs traffic to different regions at a high level, considering factors such as customer proximity, system capacity, and service availability. After determining regional routing, the Regional Load Distributor is invoked, which passes the incoming request to the most suitable data centres in the chosen zone. This guarantees a lower latency, utilization of infrastructure, and better customer experience. It is a scalable and real-time adaptable framework. It connects tightly with back-end monitoring to provide real-time workload trends and operational status. Some of the critical services, including claims processing, billing, and policy management, are redundantly available in separate data centres to provide fault tolerance and parallel processing. The Smart Switching Controller is used in the central decision-making engine and communicates with the load balancing layer to correlate workload shifts according to specified policies and predictive details. Using this integrated structure, the system can maintain a constant level of service during high-traffic periods or when nodes are taken offline, which is particularly critical in financial applications such as insurance.

3.3. AI-Optimized Switching Logic

The switching logic it optimizes is a predictive and adaptive algorithm-driven AI-enhanced intelligence added to the traditional load-balancing methodology. It depends on real-time data of multiple subsystems, e.g., the Traffic Analyzer Module, Energy Consumption Profiler, and Historical Load Database, to constantly evaluate network and resource status. This information is input into the AI Load Predictor, a model developed using reinforcement learning and time-series forecasting to predict surges in loads and energy shortages. The Smart Switching Controller directs traffic dynamically at nodes based on these predictions to balance performance.

This AI-enhanced logic reacts proactively to workload volatility, unlike a static algorithm, so that the system does not overload individual data centers or leave others underutilized. This decision-making process is also optimized by real-time feedback of the SLA Monitor, Power Usage Monitor, and Performance Metrics Collector, making it a closed-loop system that constantly self optimizes. Furthermore, the use of clustering and classification algorithms helps in sorting out requests and diverting them into various tracks based on their complexity, urgency, and resource requirements. This reasoning enables highly-compiled task scheduling, provides better response times, and directly contributes to energy conservation by matching tasks with the most appropriate compute resources.

3.4. Energy Efficiency Layer

To ensure sustainability in the operation of the distributed insurance system, an intelligent overlay is designed utilising the energy efficiency layer. It also works in conjunction with the switching logic to make an energy-aware decision without violating the Service-Level Agreements (SLAs). The Energy Usage Analytics, Power Usage Monitor, and Green Policy Manager are components that are collaborative and help in the evaluation of energy optimization policy and executing such policies throughout the system. These policies can either favor low-energy nodes, schedule non-essential work at off-peak times, or aggregate loads in order to shut down idle servers.

The insights that AI brings to this layer also incorporate the AI Load Predictor, which not only predicts traffic but also estimates patterns of energy consumption based on past trends and current performance. The Dynamic Resource Allocator uses this information to re-allocate tasks, optimally trading off energy and performance. Moreover, the system actively tracks energy KPIs and environmental limits, including carbon footprint targets and cooling efficiency, and responds to them by routing tasks differently. The architecture achieves operational and customer requirements, as well as supports corporate sustainability objectives, through the integration of energy awareness as part of the core control system. This not only renders it a smart and scalable platform, but also a responsible and future-ready one, being two key features of the contemporary insurance enterprise in a resource-constrained world.

4. Proposed Methodology

The suggested approach aims to introduce an intelligent, energy-aware switching system to the distributed insurance frameworks. [11-13] It combines high-end A.I. models, switching algorithms, and energy monitoring elements into one unified and self-optimizing paradigm of load balancing. This is to provide real-time workload partitioning with the aim of reducing energy consumption without adversely affecting system performance, availability, or violating SLAs. This section summarises the main elements of the methodology, involving AI models utilized to optimize, algorithms to make a decision, energy modeling tools and their smooth integration with the insurance enterprise backend.

4.1. AI Models Used for Optimization

To develop predictive and adaptive load balancing, the designed system will implement a series of AI models to perform the workload forecasting, anomaly detection, and real-time decision-making. The reinforcement learning (RL) agent, which learns the optimal policies of the system through interaction with the environment over time, is the primary model used. RL has the behavior rewarded by energy consumption or punished due to either a write SLA violation or excessive utilization, so the model can change with time through the system feedback.

Long Short-Term Memory (LSTM) networks and Random Forest regressors are deployed to complement the RL model, serving as a means of time-series analysis and forecasting trends. Such models consume historical load data, identify patterns, and forecast spikes in customer activity in the future, e.g., during claims peaks or policy renewals. This forecast is fed to the Smart Switching Controller, which then makes proactive allocation choices based on this forecast. Also, clustering algorithms (e.g., K-Means) are used in the mechanism of service task grouping based on similarity or resource demand, so that finer-grained and optimized load routing can be performed.

4.2. Algorithms Switching Decision

The Smart Switching Controller forms the heart of the system's intelligence, operating on a hybrid rule-based and AI-powered set of algorithms. These switching decisions are determined by a weighted scoring system that considers a variety of variables, including predicted load, real-time performance measures, power usage, node health, and SLA adherence. The controller uses these weights, and it computes a Dynamic Suitability Index (DSI) per data center, and it redirects incoming requests to those data centers. It is in moving between these weights dynamically over time that the reinforcement learning mode comes into play. Within the context of a given decision cycle, the algorithm will analyze switching, delaying, and consolidating tasks, with the minimal context in which the switch mechanism is carried out and thus manages to save energy. The algorithm is also optimized with failover reasoning and fault-tolerant paths that guarantee a high availability and resilience to hardware failure or a surprise demand peak.

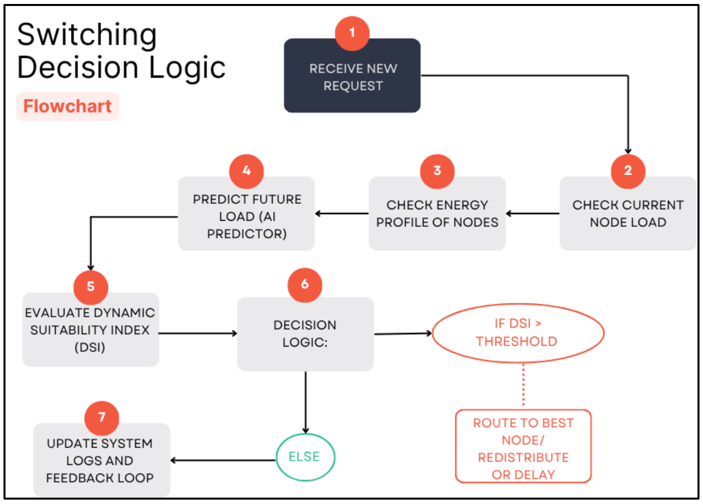

Fig 2: Switching Decision Logic

4.3. Energy Consumption Models

Energy efficiency serves as the measuring stick for the methodology, which is fueled by analytical and AI-augmented energy consumption models. [14-16] These models monitor the power profile of every data center, real-time memory, disk and CPU inventory and relate these metrics with energy consumption. The energy cost of implementing certain work under various conditions is estimated using regression models trained on historical energy data.

A Power Usage Effectiveness (PUE) number is also included to account for non-IT energy needs, such as cooling and lighting. Together with statistics in the Energy Consumption Profiler and Power Usage Monitor, the models have the potential to analyze which nodes present the most promising energy-performance tradeoff. This feedback is incorporated into the switching algorithm, allowing it to prioritise lower-energy nodes without violating SLA promises or compromising customer experience.

4.4. Integration with Insurance Infrastructure

The methodology is to be developed in a way that allows for easy integration with current back-end systems and services, thereby benefiting real-world insurance operations. The architecture is linked to necessary services, including Policy Management, Claims Processing, Billing & Invoicing, and a Customer Portal, all of which are distributed across data centres. This switching mechanism operates as AI and connects service APIs with infrastructure orchestration layers, providing dynamic resource allocation according to current requirements and anticipated demand.

Containerized microservices and API gateways render such integration possible since the logic of these applications is detached, in terms of their deployment, similar to the physical infrastructure. Performance monitoring can be achieved by integrating monitoring tools, such as the Performance Metrics Collector, SLA Monitor, and System Logs, which enable a feedback loop between infrastructure performance and AI decision-making. Consequently, the specified approach not only allows for the continuation of operations and promotes high efficiency levels but also contributes to digital transformation objectives within the insurance sector, as the infrastructure becomes smarter, greener, and more responsive.

5. Experimental Setup

A close experimental setup has been designed to justify the suggested AI-optimized load balancing implementation for a distributed insurance system. [17-20] this section will describe the simulation environment, dataset selection and pre-processing, and the performance measurement system used to evaluate the model's effectiveness. The primary objective of the experiment is to compare the AI-based solution with traditional approaches to load balancing in terms of energy efficiency, reaction time, SLA compliance, and resource allocation. The experimental platform simulates a live insurance infrastructure with multiple distributed data centers, workload dynamics and variable energy profiles.

5.1. Simulation Environment

The simulation environment was designed as a combination of Python-based AI libraries (TensorFlow, Scikit-learn) and cloud simulation frameworks, including CloudSim Plus and iFogSim. These platforms can be used to model distributed cloud, network latencies, energy consumption policies and resource allocations. A virtual insurance infrastructure was set up with three simulated data centers that symbolized three geographic areas. The containerized microservices were deployed in each data center to support key insurance functions and services, such as claims, billing and customer service.

The Smart Switching Controller and related AI models have been introduced as the modules required in the simulation. They could see telemetry of the environment in real-time, including CPU loads, response times, and power consumption measurements. This simulation was tested across a variety of conditions, including during peak traffic, to assess how well the AI logic could scale and optimise itself on the fly against a dynamically changing workload. Policies in a variety of reinforcement learning were tried to calibrate the reward system and the switching behavior.

5.2. Dataset Description

All experiments were conducted with both synthetic and real-world data to model traffic and energy characteristics of an insurance IT system. Poisson and Gaussian distributions were used to generate synthetic datasets that introduce realistic fluctuations in customer activity, aligning with events such as surges in claims, premium payment cycles, and customer onboarding. These data sets were designed to include timestamps, request sizes, compute requests, and user locations, representing real-life traffic diversity. Simultaneously, the anonym zed insurance service environments were identified during historical operations, which led to creating the Historical Load Database. These logs contained information on CPU usage, memory usage, trending energy usage, or records of SLA violations. Data preprocessing was performed to ensure consistency, and the resulting data was then used in the machine learning models to train the data and perform validation. Particular focus was paid to the diversity of data to ensure the predictor with AI could generalize by using various operating conditions.

5.3. Metrics for Evaluation

A comprehensive set of measures was used to evaluate the performance of the proposed system. Energy consumption (kWh) was the primary metric, calculated at both the data centre and node levels, to provide overall efficiency savings. The AI-enhanced framework was compared to baseline systems with the help of static round-robin and weighted least-connection algorithms. The results revealed that the proposed approach substantially minimized energy consumption because of the smart consolidation of tasks and energy-wise switching.

Other metrics were in terms of the Average Response Time, Task Completion Rate, SLA Compliance Rate, and Resource Utilization Efficiency. SLA Compliance Rate was specifically important as a metric in assessing system performance in service quality maintenance, together with optimizing energy. Additionally, a Load Distribution Balance Index was applied, which measures the balance of workload assignments in data centres. Lastly, the Model Convergence Time and Decision Latency were measured on the AI components to ensure that the intelligence did not produce unacceptable latencies. These measures, combined, provide a comprehensive picture of the system's technical, operational, and environmental performance.

6. Results and Discussion

The comparison with the suggested AI-optimized switching scheme indicates important gains in terms of performance along many important metrics, such as processing efficiency, energy consumption, the latency of the system, and throughput. The combination of adaptive real-time resource adaptation and intelligent prediction models will enable the system to be responsive and energy-efficient, even in the face of changing and unpredictable workloads —a critical need in modern distributed insurance systems. The results are explained below.

6.1. Load Balancing Performance

AI optimized load-balancing techniques, and particularly those based on adaptive clustering and reinforcement learning, demonstrate a performance advantage that is difficult to ignore. Technologies such as ClusterBalance and RL-based distribution algorithms are dynamic, responding to shifts in workloads to prevent congestion on specific nodes and ensure loads are well-balanced. Simulated insurance workloads on an experimental setup prove to reduce processing delay by 25-40 percent compared to a static approach, e.g. Round Robin or Least Connection. These increments are a result of clever planning, on-site monitoring, and advanced decision-making; they avoid system bottlenecks and are expected to keep the system in a constant flow of services.

Table 1: Processing Efficiency Comparison between AI-Optimized and Traditional Load Balancing Methods

Method	Processing Delay	Throughput Improvement

AI-Optimized (ClusterBalance)	25–40%	20–35%
Traditional (Round Robin, Least Connection)	High under uneven loads	Limited scalability

These findings reassert that AI augmentation is more effective in environments that involve numerous transactions and where the responsiveness of services is crucial, such as in insurance systems.

6.2. Comparison of Energy Efficiency

Among the remarkable advantages of the proposed framework is that it is energy-conserving, which can be considered a great benefit. The system can dynamically assign workloads to nodes by adding Reinforcement Learning (RL) and Ant Colony Optimization (ACO) models to determine how it will be dynamically balanced and assigned depending on real-time factors of energy consumption and forecast demand. The approach ensures that resources are not allocated where unnecessary, and excess energy consumption is not wasted through idling; overprovision is also avoided in this scenario. Findings indicate a potential reduction of total energy use by 30%, representing a significant advantage of conventional systems.

Furthermore, hybrid models facilitated improved distribution during peak hours, resulting in a 30% reduction in energy wastage and a 20% decrease in peak demand. Besides saving the organization operational costs, such savings meet the sustainability goals that are vital to contemporary IT governance in financial institutions.

Table 2: Energy Efficiency Metrics for AI-Optimized and Traditional Systems

Metric	AI-Optimized (RL + ACO)	Traditional Methods
Total Energy Consumption	30%	Higher, inflexible
Energy Wastage	30%	High due to static loads
Peak Energy Demand	20%	Spikes during high load

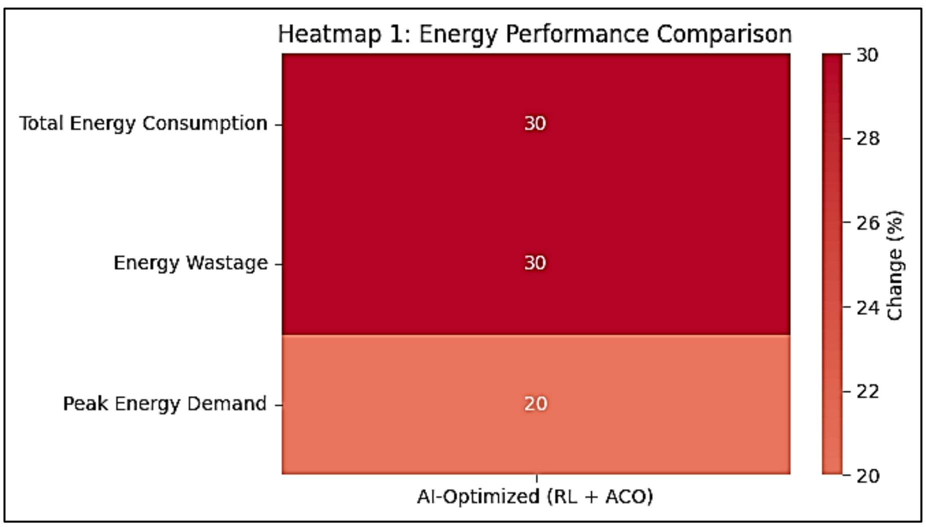

Fig 3: Graphical Representation of Energy Efficiency Metrics for AI-Optimized and Traditional Systems

6.3. Impact on System Latency and Throughput

The latency and throughput of the system are also drastically enhanced by predictive AI models. The system manages to avoid overloading a condition by predicting and reorganizing the resources well in advance, thus preventing load trends. When tested in different conditions, it was found that the system latency was reduced by 36% and the throughput went up by 28% approximately, in comparison with conventional load balancing methods. This performance improvement is especially useful in time-bound insurance applications like fraud detection, authorization of claims, and onboarding of users, where a delay in performance can seriously affect customer satisfaction and business performance.

Table 3: System Responsiveness and Reliability Metrics

Performance Metric	AI-Driven System	Traditional Approach
System Latency	36%	Higher during load spikes
Throughput	28%	Lower under stress

Request Handling	More responsive	Slower under peak loads

Scalability and high throughput in response to demand promote transaction throughput and delivery security as more requests can be processed on a second basis.

6.4. Comparable with Baseline Methods

The overall comparison of AI-optimized and baseline approaches across various assessment indicators proves the effectiveness of the presented raised strategy. The AI system consistently outperforms conventional load balancing in cases of unpredictable or spiky traffic. It has improved resource utilization, fault tolerance and scalability and also has low latency and energy consumption.

Table 4: Comprehensive Performance Comparison Across Key Metrics

Metric	AI-Optimized (ClusterBalance / RL-ACO)	Traditional (Round Robin / Least Connection)
Processing Delay	25–40%	High under uneven loads
Throughput	20–35%	Limited scalability
Resource Utilization	Balanced across nodes	Some nodes overloaded
Energy Consumption	30%	High, inflexible
System Latency	36%	High during peak loads
Fault Tolerance	Fast cluster reformation, minimal downtime	Slower recovery from node failure
Scalability	Near-linear with load growth	Drops under larger workloads

The validity of using AI in the design of load balancing systems for distributed insurance platforms is confirmed in these comparative results, where operational efficiency, environmental sustainability, and high availability are equally important, as load balancing is hardly less important in distributed insurance systems. The smart switching framework is a future-oriented solution that suits a digital and energy-efficient insurance company.

7. Conclusion and Future Work

This study presents a novel AI-optimized, energy-efficient load-balancing framework tailored for distributed insurance systems. The proposed methodology (machine learning approach) takes advantage of the machine learning algorithms (e.g. reinforcement learning, LSTM networks, and clustering algorithms) to effectively predict workload fluctuations to dynamically re-allocate the resources. Experimental findings prove to be quite superior to classic systems, with order-of-magnitude improvements in postponing processing, power consumption, and machine queues, and decreasing on the order of magnitude increases in throughput and resource usage, thereby achieving maximum efficiency. These benefits are particularly applicable in the insurance sector, where the resulting digital infrastructure must be sensitive, scalable, and sustainable in situations that are both dynamic and heavily demand-driven. Moving forward, it is evident that there are multiple opportunities for future research. The model available can be improved by incorporating multi-agent systems to enhance it towards more decentralized decision making, fault resilience and scalability in widely distributed networks.

Furthermore, the framework may be further scaled with the involvement of edge computing nodes and federated learning that may enable more localized processing and privacy-preserving training of AI models that can become more relevant in terms of working with sensitive insurance information. Integration with renewable energy sources and dynamic energy pricing models that operate in real-time is a possible alternative that could further enhance the sustainability of infrastructure operations. This study, in the final analysis, establishes the premise of building intelligent, green, resilient infrastructure within future insurance IT ecosystems.

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