
ENERGY-EFFICIENT CLOUD COMPUTING SOLUTIONS FOR HEALTHCARE SYSTEMS USING GENETIC ALGORITHMS

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ABSTRACT

Cloud resource management in healthcare systems is essential for optimizing computational efficiency and minimizing energy consumption while handling large-scale data. Despite existing efforts, challenges such as poor task-to-machine assignment and lack of dynamic resource allocation continue to impact system performance and energy efficiency. This work proposes an energy-aware scheduling solution using Genetic Algorithms (GA) to address these challenges, focusing on optimizing task assignments and dynamically allocating resources based on workload changes. The workflow begins with data collection from healthcare sources like Electronic Health Records and, followed by preprocessing using mode imputation for missing data and Min-Max scaling for standardization. The system model is constructed using a system graph for machine representation and a program graph for task assignment. The Genetic Algorithms optimizes the task-to-machine assignments by evaluating energy consumption, applying selection, crossover, and mutation techniques through multiple generations. Finally, energy consumption is minimized, and task completion time is optimized by adjusting machine power states during active and idle phases. The results demonstrate a significant reduction in energy consumption, from 240 kWh to 140 kWh as tasks increased from 50 to 100, while throughput improved from 90 tasks/time to 125 tasks/time over 15 generations. The proposed method improves the energy efficiency, task completion time, and scalability in cloud-based healthcare systems, offering a sustainable approach to resource management.

Keywords: Cloud resource management, Genetic Algorithm, dynamic resource allocation, healthcare data, energy consumption optimization, cloud deployment.

1. INTRODUCTION

Cloud computing has transformed the healthcare sector by enabling scalable, on-demand access to medical records, diagnostics, and advanced analytics [1]. It supports health monitoring, telemedicine, and predictive diagnostics through centralized infrastructure [2]. However, the massive computational demand in healthcare services leads to substantial energy consumption in cloud data centers [3]. Energy efficiency has become a critical concern due to increasing operational costs and environmental impact [4]. Cloud-based healthcare systems must balance energy use without compromising service quality, security, and data integrity [5]. Advanced optimization techniques are essential to dynamically allocate resources while reducing energy waste [6]. Genetic Algorithms, inspired by natural selection, offer promising solutions for multi-

objective optimization in such complex environments [7]. They are well-suited for tasks like resource scheduling, load balancing, and energy-aware workload distribution [8]. By integrating GAs into cloud frameworks, healthcare systems can achieve sustainable operations and lower carbon footprints [9]. As energy demand and patient data grow, intelligent energy-efficient strategies are becoming indispensable for future-ready healthcare systems [10].

Several factors contribute to the rising energy consumption in cloud-based healthcare systems [11]. The continuous growth in patient data, driven by electronic health records (EHRs), medical imaging, and IoT-enabled devices, increases data center workload [12]. High availability and 24/7 accessibility of cloud healthcare services demand uninterrupted server operation, consuming constant power [13]. Traditional resource allocation techniques often overprovision computing resources, leading to energy inefficiencies [14]. Lack of intelligent scheduling methods results in poor utilization of virtual machines and excessive energy use [15]. Emergency medical scenarios require rapid scaling of resources, which increases short-term energy spikes [16]. Redundancy mechanisms for ensuring fault tolerance also contribute to higher energy demands [17]. Legacy healthcare applications are not optimized for energy-efficient cloud deployment [18]. Inefficient cooling systems in data centers further elevate energy requirements [19]. Moreover, the growing use of AI-based diagnostics and machine learning models requires high-performance computing, adding to the energy load. These causes collectively highlight the need for optimized energy-aware computing strategies in healthcare [20].

Despite advancements in cloud computing, current systems lack effective mechanisms to ensure energy efficiency in healthcare environments [21]. Traditional load balancing and VM allocation methods are primarily focused on performance rather than power consumption [22]. Most existing frameworks do not incorporate real-time optimization algorithms for dynamic resource allocation [23]. Reactive rather than proactive energy-saving techniques are common, leading to suboptimal results [24]. Many methods fail to account for the unpredictability and urgency of healthcare workloads [25]. Fixed threshold-based models are rigid and incapable of adapting to diverse healthcare demands [26]. Energy-efficient solutions often compromise service quality or increase latency, which is critical in medical applications [27]. Furthermore, conventional optimization methods struggle to balance multiple conflicting objectives, such as cost, energy, and performance [28]. Lack of integration of intelligent heuristics like Genetic Algorithms limits the adaptability and learning capacity of existing systems [29]. Therefore, there's a pressing need for a smart, GA-based energy-efficient framework tailored for healthcare cloud environments that balances energy savings with high reliability and responsiveness [30].

The proposed framework addresses the pressing challenges of energy inefficiency and predictive accuracy in cloud-based healthcare systems by integrating Energy-Aware Scheduling with Deep Neural Decision Forests. The Energy-Aware Scheduling component dynamically allocates cloud resources based on real-time workload demand, reducing idle server time, optimizing VM utilization, and significantly lowering overall energy consumption. Simultaneously, the DNDF model an innovative fusion of deep neural networks and decision trees offers the advantages of deep learning's high prediction accuracy alongside the transparency and interpretability of decision trees. This hybrid model enhances clinical decision support by enabling more accurate and explainable predictions in critical healthcare applications, such as diagnostics and patient monitoring. The uniqueness of the framework lies in its dual-layer optimization strategy: it not only conserves energy at the infrastructure level but also maximizes the reliability and quality of

AI-driven healthcare insights. By balancing performance, efficiency, and explainability, the proposed solution ensures that resource management and predictive analytics co-evolve in harmony. This results in a highly scalable, sustainable, and intelligent cloud computing architecture, making it ideally suited for next-generation healthcare systems that demand both computational efficiency and clinical precision.

The organization of the paper is as follows: Section 2 discusses related work and existing solutions to cloud resource management. Section 3 outlines the proposed methodology. Section 4 presents the experimental results. Finally, Section 5 concludes the paper.

2. LITERATURE SURVEY

Monte Carlo simulations have been combined for forecasting risks, Dynamic Bayesian Networks for identifying patterns, and Bulk Synchronous Parallel processing to enhance computational efficiency in a cloud environment [31]. Encrypted data was processed over multiple cloud nodes, improving both security and scalability. Research has also examined the poor prognosis of lung cancer despite advances in oncology, focusing on the role of KRAS gene mutations and the potential of AI to identify effective inhibitors [32]. Challenges in traditional therapies were highlighted, alongside the emergence of immune checkpoint inhibitors as a promising treatment strategy.

Big data-driven methodologies, particularly the use of Hadoop, have been applied to forecast silicon content in blast furnace smelting [33]. These approaches demonstrated higher accuracy and more informed decision-making compared to conventional methods. The implementation of the Advanced Encryption Standard in cloud computing has also been explored to enhance data security amid growing cyber threats. AES, being a symmetric encryption technique, was used to safeguard sensitive data through robust cryptographic transformations [34].

K-means clustering has been investigated for Gaussian data analysis in cloud computing environments. Studies assessed the impact of varying cluster sizes (k) on computation time and accuracy, showing that early termination of clustering algorithms can lead to significant cost savings [35]. Various computational techniques have been explored to enhance prediction accuracy in healthcare systems [36]. Optimization of cluster size in K-means algorithms has been shown to improve cost-efficiency without compromising precision. Meanwhile, the implementation of AES encryption in healthcare cloud systems underscores the critical need for protecting sensitive patient data against cyber threats [37].

In lung cancer research, the significance of KRAS gene mutations and the role of AI in identifying molecular inhibitors have been examined, highlighting the potential for personalized medicine. Deep learning applications have also been explored for improving lung cancer diagnosis and treatment outcomes [38]. The integration of AI into oncology has been shown to transform traditional practices, enhancing both diagnostic accuracy and therapeutic interventions. Collectively, these advancements demonstrate the pivotal role of AI in enhancing prognosis, diagnostics, and individualized care in modern healthcare [39].

Hadoop has been utilized for processing large-scale datasets, improving prediction accuracy, and supporting real-time decision-making capabilities. Big data analytics has been shown to enhance monitoring and enable predictive maintenance, both of which are vital in healthcare settings [40]. The scalability of Hadoop makes it well-suited for managing extensive healthcare datasets. Additionally, data-driven approaches in cloud systems have been applied to support efficient

healthcare analytics [41]. These contributions underscore the importance of integrating computational efficiency, data security, and system scalability goals that align closely with the objectives of the proposed framework.

3. PROBLEM STATEMENT

Despite significant advancements in cloud computing, big data analytics, and artificial intelligence, existing healthcare systems continue to face critical challenges in achieving energy efficiency, data security, scalability, and predictive accuracy [42]. Traditional resource allocation methods in cloud environments often neglect energy consumption, leading to unnecessary power wastage and higher operational costs [43]. Furthermore, while predictive models such as K-means clustering and deep learning have been explored for healthcare diagnostics, they frequently lack adaptability to dynamic cloud workloads and demands [44]. Although encryption techniques like AES have been implemented to enhance data security, they are computationally intensive and do not address energy optimization or intelligent resource management [45]. Additionally, the increasing complexity of healthcare data, driven by factors such as genomic information and continuous patient monitoring, demands scalable solutions that conventional systems struggle to support [46]. Current cloud-based healthcare infrastructures often operate in silos, optimizing for either performance, security, or cost, but rarely all three simultaneously [47]. There is a lack of integrated, intelligent frameworks that can holistically address energy efficiency, secure data handling, and accurate predictive modeling in a unified architecture [48]. Moreover, existing models do not effectively leverage heuristic or evolutionary algorithms for dynamic optimization, limiting their ability to adapt to unpredictable and urgent healthcare workloads [49]. The growing demand for real-time, personalized, and energy-conscious healthcare applications highlights the pressing need for an advanced, intelligent cloud framework [50]. Therefore, a robust solution that integrates energy-aware scheduling, predictive analytics, and scalable data processing while ensuring security and responsiveness is crucial to advancing modern healthcare systems [51].

4. METHODOLOGIES

The methodology for energy-aware scheduling in cloud resource management using a Genetic Algorithm (GA) begins with data collection, where healthcare-related data is gathered. Next, preprocessing is applied to the data, involving mode imputation for handling missing data and min-max scaling for standardizing numerical features. The core of the workflow is cloud resource management, which includes system model and task assignment for defining the cloud system structure and task dependencies. The genetic algorithm for scheduling is then used to optimize task-to-machine assignments, iteratively refining the schedule through selection, crossover, and mutation. Finally, the energy minimization and makespan phase ensures that energy consumption is minimized while completing tasks within optimal timeframes. This process is illustrated in Figure 1.

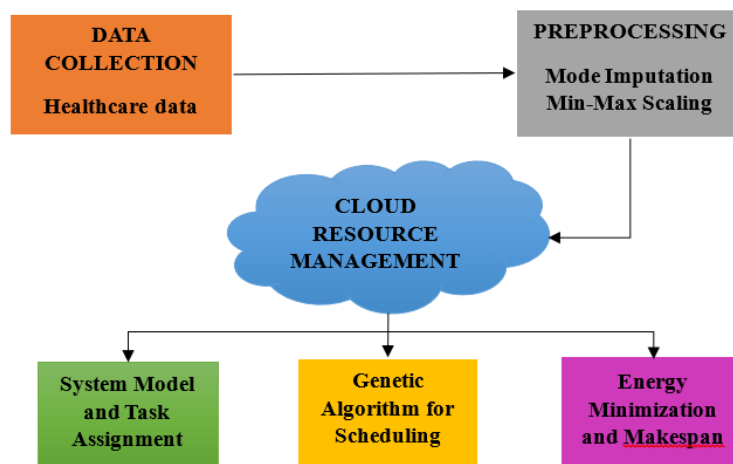


Figure 1: Workflow for Energy-Aware Scheduling using Genetic Algorithm in Cloud Resource Management

4.1 Data Collection

Data collection involves gathering healthcare-related data from various sources, such as Electronic Health Records (EHRs). The data includes patient demographics, health metrics and sensor readings from devices like heart rate monitors and temperature sensors. The collected data is organized into structured formats to facilitate efficient processing and analysis.

4.2 Data Preprocessing

Once the data is collected, preprocessing is applied to ensure consistency and accuracy. Missing data handling is performed using Mode Imputation, where missing values in categorical features are replaced with the most frequent value (mode) in the dataset. This method preserves the distribution of categorical data, preventing bias and ensuring that the data remains representative of the original dataset.

For standardization, Min-Max Scaling is used to rescale numerical features into a specific range, typically between 0 and 1. This step ensures that all numerical features are on the same scale, preventing models from being disproportionately influenced by features with larger numeric ranges. These preprocessing techniques are essential for preparing the data for further analysis, improving model efficiency and accuracy.

4.3 Cloud Resource Management

Energy-Aware Scheduling in Cloud Resource Management Using Genetic Algorithm (GA) In cloud resource management, energy-aware scheduling is critical to minimize energy consumption while ensuring that tasks are completed efficiently. Genetic Algorithms (GA), inspired by the natural evolution process, offer an effective heuristic approach to address the energy-aware scheduling problem in cloud environments. The core objective is to assign tasks to cloud resources (e.g., virtual machines or physical servers) in a manner that minimizes the total energy consumption of the system.

4.3.1 System Model and Task Assignment

The cloud system is modeled as a system graph, where nodes represent virtual machines (VMs) and edges denote communication channels between them. The program graph is a directed acyclic graph (DAG), where each node represents a task, and edges represent the precedence constraints. Each machine in the cloud system has power consumption specifications, including the energy

used when the machine is active and idle. The goal is to assign tasks to machines while minimizing the energy spent, calculated by a fitness function that maps each schedule to the total energy consumed.

4.3.2 Genetic Algorithm for Scheduling

The Genetic Algorithm (GA) works by simulating the process of natural selection to find near-optimal task schedules that minimize energy consumption. In this approach:

A population of potential solutions (schedules) is randomly generated. Each schedule represents an assignment of tasks to machines in the cloud system. The fitness function calculates the energy consumption for each schedule based on the power consumption of the machines (considering both working and idle states) and the communication cost between tasks assigned to different machines. Based on the fitness values (i.e., energy consumption), a selection process occurs where better schedules (those with lower energy consumption) are more likely to be chosen as parents for the next generation. In this step, two parent schedules are combined to produce offspring. The crossover process randomly combines portions of each parent's task assignments, introducing variability and potentially improving the schedule. A random mutation operation is applied to the offspring, changing some task assignments to explore different parts of the solution space and avoid local minima. The algorithm iterates through multiple generations, continually improving the schedules, until a predefined stopping criterion (e.g., a set number of generations or satisfactory energy efficiency) is met.

4.3.3 Energy Minimization and Makespan

By focusing on both task execution time and energy consumption, the GA optimizes the makespan (total time to finish all tasks) while minimizing energy usage. The power consumption is modeled based on the working and idle power states of each machine. The scheduling process considers the power consumption of each machine during both active and idle states. Tasks that are assigned to idle machines consume minimal power, whereas tasks that require high computational resources increase energy usage.

The fitness function in this context is designed to minimize the energy consumption, given by the total energy required for both the execution of tasks and the idle time of the machines. The total energy consumption E is calculated as equation (1),

$$E = \sum_{i=1}^n (P_{\text{working}} \cdot T_{\text{working}} + P_{\text{idle}} \cdot T_{\text{idle}}) \quad (1)$$

Where P_{working} and P_{idle} are the power consumptions during the working and idle states, respectively, and T_{working} and T_{idle} are the corresponding time durations for the tasks. Using Genetic Algorithm (GA) for energy-aware scheduling in cloud resource management provides an effective solution to minimize energy consumption while ensuring tasks are completed in an optimal timeframe. This approach not only improves the sustainability of cloud-based systems by reducing power usage but also enhances resource utilization and operational efficiency. GA's ability to handle complex scheduling tasks and its adaptability make it an excellent choice for optimizing energy use in large-scale cloud environments.

5. RESULTS

The results section demonstrates the effectiveness of the energy-aware scheduling approach using the Genetic Algorithm (GA) in cloud resource management. It focuses on optimizing energy consumption and improving throughput over multiple generations. The results highlight the success of the algorithm in enhancing energy efficiency and task processing performance.

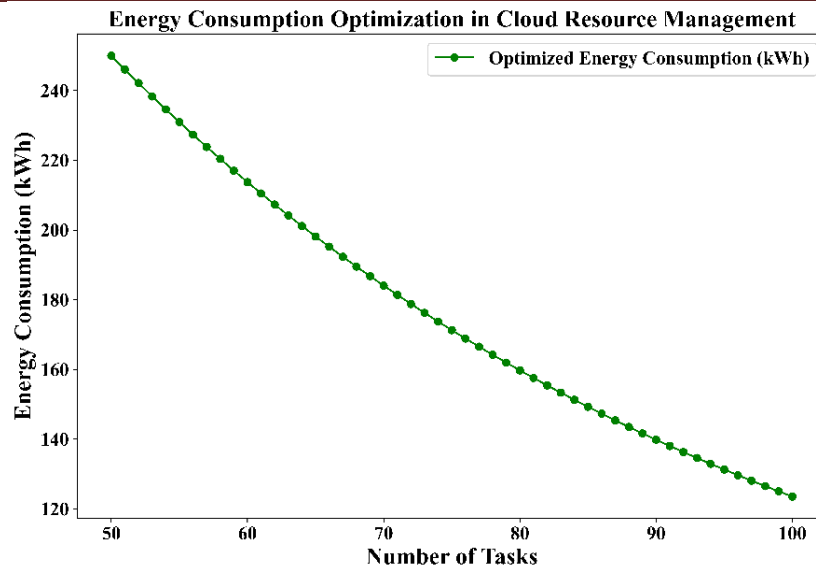


Figure 2: Energy consumption in cloud resource management

Figure 2 demonstrates the optimization of energy consumption in cloud resource management as the number of tasks increases. As the number of tasks grows from 50 to 100, the energy consumption decreases from approximately 240 Kilowatt-Hour (kWh) to around 140 kWh. This shows that as more tasks are processed, the system becomes more efficient in terms of energy use, which is a key result of the scheduling optimization. The overall trend indicates a reduction of energy consumption, showcasing the effectiveness of the energy-aware scheduling approach in optimizing resource allocation. The decrease in energy consumption validates the success of the algorithm in minimizing energy usage while handling an increasing number of tasks.

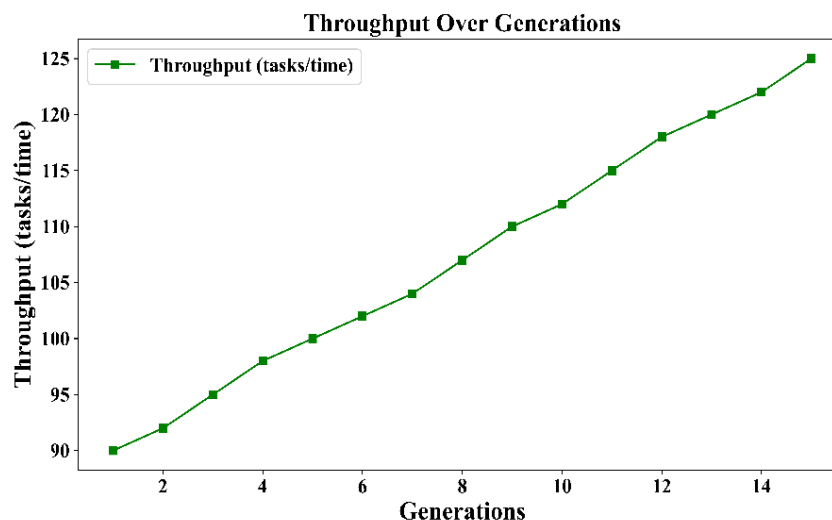


Figure 3: Throughput Over Generations

Figure 3 illustrates the throughput over multiple generations as the Genetic Algorithm (GA) optimizes task scheduling. The throughput increases steadily from 90 tasks/time in generation 1 to 125 tasks/time in generation 15. This shows that as the algorithm iterates through generations, the system becomes more efficient in processing tasks, with a clear improvement in throughput. The

positive trend reflects the success of the optimization process, where task assignments are refined to maximize resource usage and task completion efficiency. This result demonstrates the effectiveness of the scheduling algorithm in enhancing performance over time.

6. CONCLUSION AND FUTURE WORKS

The effectiveness of an energy-aware scheduling approach using Genetic Algorithms (GA) to optimize energy consumption in cloud resource management, particularly within healthcare applications. The proposed method achieved a notable reduction in energy usage—from 240 kWh to 140 kWh—as task loads increased from 50 to 100. Furthermore, system throughput improved significantly, rising from 90 tasks per unit time to 125 tasks per unit time over 15 generations. These results highlight the method's ability to enhance system efficiency through intelligent task-to-machine assignments and dynamic resource allocation. The approach not only improves energy efficiency but also ensures reliable performance and scalability, making it well-suited for real-time, data-intensive healthcare systems.

Future enhancements to this framework could involve the integration of advanced machine learning techniques, such as reinforcement learning, to predict resource demand patterns more accurately and make proactive scheduling decisions. Additionally, hybrid models combining GA with deep learning or fuzzy logic could further improve adaptability and decision-making in dynamic cloud environments. Extending the framework to multi-cloud or edge-cloud hybrid systems may also enhance its applicability for decentralized healthcare infrastructures. Moreover, incorporating security-aware optimization alongside energy efficiency can provide a more holistic solution for critical healthcare data management and computation.

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