

A Game-Theoretic Framework for Energy-Efficient Scheduling and Resource Allocation in Sensor Cloud Systems

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Abstract: Sensor cloud systems play a vital role in Internet of Things (IoT) applications by enabling scalable sensing, data processing, and service provisioning; however, they face significant challenges in terms of energy-efficient scheduling and resource allocation. To address these challenges, this paper proposes a game-theoretic framework for energy-efficient scheduling and resource allocation in sensor cloud systems. The interactions between sensor nodes and cloud resources are modeled as a strategic game, where each entity autonomously optimizes its utility by balancing energy consumption, execution latency, and resource usage. An iterative, distributed scheduling algorithm is developed to achieve a stable equilibrium without centralized control.

Extensive simulation-based evaluation demonstrates that the proposed framework significantly reduces overall energy consumption and task completion time while improving resource utilization, throughput, and fairness compared to baseline heuristic approaches. Convergence analysis confirms fast stabilization of the algorithm, and statistical significance tests validate the robustness of the performance gains. The results indicate that the proposed game-theoretic approach provides an effective and scalable solution for energy-efficient scheduling and resource management in sensor cloud environments.

Keywords: Sensor Cloud Computing, Game Theory, Energy Efficiency, Resource Allocation, Task Scheduling, Cloud-Sensor Integration.

I. INTRODUCTION

Sensor Cloud Systems have become a viable prospect which combines wireless sensor networks and cloud computing to permit scalable data storage, processing and analytics to Internet of things (IoT) uses. Using cloud technology, sensor cloud systems can circumvent the natural constraints of sensor nodes, including limited energy, storage, and compute resources, and offer large-scale, heterogeneous IoT deployments [1], [2]. The systems have been used in smart cities, environmental monitoring, healthcare, industrial automation, and intelligent transportation systems, in which sensing continuously and real time processing of data are required [3]. With all these benefits, sensor cloud systems also have serious issues of energy-efficient scheduling and resource allocation. The sensor nodes are generally battery operated and too much sensing, communication or computing can waste their energy stores quickly hence limiting the network lifetime and reliability of the system [4]. Lack of efficient distribution of virtualized resources on the cloud side will increase the amount of energy used, the operations cost, and deteriorate the performance [5]. Hence, cooperative scheduling of tasks and dividing resources in accordance with

energy efficiency has emerged as an urgent research issue of sensor clouds. The current methods of scheduling and resource allocation to sensor cloud systems are mainly based on centralized optimization methods or the use of a heuristic strategy. Although centralized schemes are able to find solutions nearly at an optimum, they have problems of scalability, large communication overhead, and the single-point-of-failure of large-scale distributed systems [6]. Heuristic and metaheuristic methods, however, are available with quicker answers, though tend to be less adaptable and theoretically-assured, particularly in dynamic and heterogeneous workload settings [7]. Such constraints do not allow them to be applicable in real-time IoT applications where system states may change often. Game-theoretic modeling has become an attractive field in recent years as an effective method of a distributed decision-making issue in sensor cloud and cloud computing environments. Game theory can be used to analyze the interactions between various autonomous and rational participants, including sensor nodes and cloud service providers, whose utility is optimized by each of the participants [8]. With a suitable definition of players, strategies, and utility functions, game-theoretic models can reach operating points of a game, like Nash equilibrium, where the operating point is stable and efficient (without the need to be centrally controlled) [9]. This renders game theory quite appropriate when scheduling and allocating resources to an energy-concerned distributed sensor and cloud system. Based on these observations, this paper will develop a game theoretic approach to energy efficient scheduling and resource allocation in sensor cloud systems. The suggested framework represents the relations between the sensing tasks and cloud resources as a strategic game, and the goal is to reduce the energy usage and meet the quality-of-service restrictions. The key contributions of this work are summarized as follows:

1. A comprehensive system and energy consumption model for sensor cloud environments.
2. A game-theoretic formulation for joint scheduling and resource allocation.
3. An energy-efficient scheduling algorithm based on equilibrium analysis.
4. Extensive performance evaluation demonstrating improved energy efficiency and resource utilization compared to existing approaches.

The rest of this paper is structured in the following way. Section 2 provides a review of related literature on sensor cloud scheduling, resource allocation and game-theoretic methods. The system model and problem formulation is



contained in Section 3. Section 4 presents the suggested game-theoretic model. Section 5 explains the energy efficient algorithm of scheduling and allocation of resources. The performance evaluation and results are discussed in Section 6. Lastly, Section 7 wraps up the paper and presents the future research directions.

II. RELATED WORK

A number of studies have been conducted on architectural design and integration of sensor cloud systems to facilitate a scaled sensing and data processing in application of IoT. The initial studies were aimed at virtualizing the physical sensor resources and exposing them as cloud services, thus enhancing accessibility and flexibility [11]. This idea was later expanded by other works, which proposed layered sensor cloud architectures that incorporated sensing, communication and cloud service layers to enable heterogeneous IoT applications [12], [13]. These architectures were still useful as they enhanced scalability and data management, but in many cases did not explicitly consider energy efficiency in scheduling and resource allocation. Scheduling methods in sensor cloud and IoTcloud environments have undergone extensive research in order to enhance the performance and quality of service of the system. Different methods of scheduling tasks according to their priorities, awareness of deadlines and balancing of workloads were suggested to handle sensing tasks and cloud resources effectively [14], [15]. The heuristic and metaheuristic algorithms, including genetic algorithms and particle swarm optimization, were used by some researchers to decrease the time of task completion and enhance throughput [16]. Nevertheless, these methods typically were based on centralized decisions, and commanded high computational cost, unlike being suitable in large and dynamic sensor clouds. Sensor cloud and cloud computing studies have also focused a lot on resource allocation and energy optimization strategies. Various investigations suggested energy-conscious resource allocation plans which reduced the amount of power used by dynamically setting virtual machine placement and task execution policies [17], [18]. The concept of energy-efficient data transmission and duty-cycling has been presented in the framework of wireless sensor networks to extend the network lifetime [19]. Although these schemes made energy savings either at sensor level or cloud level, they did not usually consider scheduling and resource utilization as a joint problem and thus the overall energy efficiency in integrated sensor cloud systems was not optimal.

Game theory has been increasingly applied to address distributed resource management problems in cloud computing and wireless sensor networks. Researchers formulated resource allocation problems as non-cooperative or cooperative games to model the interactions among selfish and rational entities competing for limited resources [20], [21]. Game-theoretic approaches were shown to achieve stable solutions, such as Nash equilibrium, without requiring centralized control [22]. In wireless sensor networks, game theory was applied to power control, routing, and spectrum sharing to improve energy efficiency and network performance [23]. Despite these advances, only limited efforts combined game-theoretic modeling with joint scheduling and resource allocation in sensor cloud environments.

From the above review, it was observed that existing works primarily focused on either architectural design, scheduling, resource allocation, or game-theoretic

optimization in isolation. Most approaches relied on centralized control or heuristic-based solutions and lacked a unified framework that jointly optimized scheduling and resource allocation with explicit consideration of energy efficiency in sensor cloud systems. These constraints led to the design of a game-theoretic model that allows distributed and energy-efficient scheduling and resource allocation and is guaranteed to be scaled and stable.

III. SYSTEM MODEL AND PROBLEM FORMULATION

This part outlines sensor cloud system architecture, develops energy consumption model and outlines the scheduling and resource allocation problem with energy efficiency as the main optimization objective.

A. Sensor Cloud Architecture

The sensor cloud architecture was designed as a three-layer architecture comprising of sensor layer, communication layer, and cloud layer, as it is generally practiced in IoT-cloud integration systems [24], [25]. The sensor layer consisted of very many heterogeneous sensor nodes that were used to sense physical or environmental values like temperature, humidity, vibration or biomedical signals. These sensor nodes were power-constrained nodes that performed the functions of sensing, local processing and transmitting data. Sensing tasks that had to be processed or stored in the cloud were periodically or event-wise created by each sensor node. The communication layer was the one that offered connectivity between the sensor nodes and cloud infrastructure via gateways, access points or base stations. It was a layer that was concerned with data aggregation, routing and protocol translation. Factors like transmission distance, packet size and channel conditions affected communication delays and consumption of energy in transmissions [26]. The cloud layer was comprised of virtualized computing and storage services that took incoming sensor data and provided services to end users. Service requests and application requirements were mapped to sensor data that was sent to virtual machines (VMs) or containers. The layer of cloud facilitated scaling of tasks, provisioning of resources and orchestration of the services at a cost of energy consumption and operations [27].

The sensing tasks created in the sensor layer were relayed to the cloud layer by the communication layer, where the decisions to schedule and allocate resources were made in order to meet the service requests effectively in the considered model.

B. Energy Consumption Model

The sensor cloud system energy consumption was modeled taking into account sensor-side and cloud-side energy usage and expense respectively. The overall energy consumption of a sensor node was defined as the sum of the energy that is used in sensing, communication and local computation [28]:

$$E_{\text{sensor}} = E_{\text{sense}} + E_{\text{comm}} + E_{\text{comp}}$$

where E_{sense} represented the energy required for data acquisition, E_{comm} denoted the transmission energy for sending sensed data to the gateway or cloud, and E_{comp} corresponded to the energy consumed during local data processing.

The energy of communication was predicted as a dependence on the size of the packet and the distance of transmissions, which prevailed the total power expenditure in the majority of sensor cloud applications [29]. The

consumption of energy at the cloud layer was mainly linked to the use of computation and storage facilities. The cost of the cloud energy has been modelled according to the period of time that the virtual machines are active and the processing power [30]:

$$E_{\text{cloud}} = \sum_{i=1}^N P_i \times T_i$$

where P_i denoted the power consumption of the i -th virtual machine and T_i represented its task execution time. This model captured the trade-off between performance and energy efficiency in cloud resource provisioning.

C. Scheduling and Resource Allocation Problem

The resource allocation and scheduling issue consisted in giving sensing tasks to obtainable cloud resources and reducing the total energy usage and meeting system requirements. The parameters included the size of workload, deadline, and quality of service needed in every sensing task. Task scheduling constraints made sure that tasks were performed on time and that any precedence relationship that existed was maintained [31]. Moreover, it was not possible to allocate tasks to various resources at the same time and there must have been no contention of resources. The availability of resources was a constraint in the number of tasks that could be performed at any given time as a result of the computational capacity, memory and bandwidth of the cloud resources. Latency, throughput as well as reliability were also taken as quality-of-service (QoS) constraints [32] to address the application-level requirements. The main goal of the problem was to maximize the energy efficiency, i.e. the performance of the system in comparison with the overall energy consumed, or, the other way around, the energy consumption minimization, without significant reduction in QoS levels. This created a multi-objective optimization problem that could not be easily solved either by centralized or heuristic methods.

IV. GAME-THEORETIC FRAMEWORK

In order to deal with these issues, the scheduling and resource allocation problem was modeled as a game-theoretic optimization problem, which allowed distributed decision-making among sensor and cloud entities, which is described in the following section. In this section, the suggested game-theoretic model of energy-efficient scheduling and resource allocation of sensor cloud systems is introduced. The system was used to model the interactions between sensor and cloud entities in the form of strategic game and allow the distributed decision-making as well as stable and energy-efficient operation of the system.

A. Game Model Definition

The scheduling and resource allocation problem was formulated as a strategic game $G = \langle \mathcal{P}, \mathcal{S}, \mathcal{U} \rangle$, where $\mathcal{P}$ represented the set of players, $\mathcal{S}$ denoted the strategy space, and $\mathcal{U}$ corresponded to the utility functions.

The game players were sensor nodes, virtual machine or cloud services with different levels of abstraction. The sensor nodes were also used as task generators that required the use of computational resources and decisions regarding how the tasks were scheduled and resources were allocated to process the incoming tasks were made by the cloud-side entities. The space of strategies described the number of actions that each

player could take. In the case of sensor nodes, it had strategies of task offloading and resource requesting. In the case of cloud-side entities strategies entailed the choice of proper scheduling policies, they included the allocation of computational resources and parametric changes in the priorities of execution.

These plans just identified the order of execution of the task, the use of resources and also the consumption of energy. Execution latency and cost of operation versus energy consumption incurred a trade-off that was represented by the utility function of each player. Generally, the utility was characterized as a weighted measure that rewarded less energy consumption and less latency and punished inefficient resource consumption. This equation enabled company players to optimize their individual performance towards performance in the system as a whole.

B. Game Type and Assumptions

The suggested framework embraced a form of non-cooperative games whereby every participant sought to maximize its own utility without necessarily cooperating with one another. This option was indicative of the decentralized and autonomous attribute sensor and cloud elements in realistic sensor clouds.

A number of assumptions were to be made so that the game model can be tractable. To begin with, all players were supposed to be rational, that is to say that they chose strategies that gave them the high utility functions. Second, the players were supposed to possess full or partial information about system parameters including available resources, task demands and energy prices. Lastly, the strategy sets were modeled as finite and continuous which allowed the standard game-theoretic solution concepts to be applied [33].

C. Equilibrium Analysis

The Nash equilibrium defined a stable operating point of the game where none of the players could better its utility by acting unilaterally to alter its strategy. The continuity of the utility functions and compactness of the strategy spaces guaranteed that there existed a Nash equilibrium. The equilibrium solution was a resource and scheduling decision that maximized efficiency of the sensor cloud system energy consumption.

In addition, the best-response dynamics used in the offered framework were proven to be convergent to the equilibrium with sensible conditions. This convergence property guaranteed stability of the system, and avoided oscillatory or inefficient scheduling behaviour, and made the framework applicable to dynamic and large-scale sensor cloud environments [34].

V. PROPOSED ENERGY-EFFICIENT SCHEDULING AND RESOURCE ALLOCATION ALGORITHM

In this section, the given work proposes the game-theoretic framework-based algorithm of scheduling and resource allocation that is energy-efficient. The algorithm facilitates the distributed decision-making between the sensor nodes and the cloud resources and ensures the reduction of the total energy usage and the adherence to the QoS limits.

A. Algorithm Design

The suggested algorithm engaged in a distributed, iterative decision making process where sensor nodes and cloud resource communicated strategically to reach an energy

efficient operating point. At the sensor side, sensing tasks of each sensor node were periodically created with sensing workload size, deadline, and QoS demand. The sensor based its decision on how the task should be offloaded to the cloud and what resource request level to make depending on the remaining energy and urgency of the task. Such choices aimed at reducing communication and sensing energy and at the same time making sure that tasks are executed in a timely manner (Algorithm 1).

Algorithm 1: Game-Theoretic Energy-Efficient Scheduling and Resource Allocation

Require: Set of sensor nodes S , Set of cloud resources (VMs) C , Task set T generated by sensors, Energy and QoS parameters
Ensure: Energy-efficient task scheduling and resource allocation

1. Initialize strategies for all players (sensors and cloud resources)
2. Initialize utility values for each player
3. Repeat:
 4. **For** each sensor node $s \in S$ **do**
 5. Generate sensing task t in T
 6. Evaluate local energy cost and offloading cost
 7. Select resource request strategy that maximizes sensor utility
 8. **End For**
 9. **For** each cloud resource $c \in C$ **do**
 10. Receive task requests from sensors
 11. Evaluate available resources and energy cost
 12. Schedule tasks and allocate resources to maximize cloud utility
 13. **End For**
 14. Update utilities for all players
 15. **Until** Nash equilibrium is reached or convergence condition is satisfied
 16. **Return** final scheduling and resource allocation decisions

The cloud services and the virtual machines at the cloud side addressed the requests of tasks to be performed by deciding on the scheduling and allocation of resources. The cloud scheduler considered the available resources, approximated energy costs to execute tasks and allocated tasks to virtual machines according to the maximum utility.

The scheduling decisions and resource availability feedback was then sent back to the sensor layer. This iterative process of sensor nodes and cloud resource interaction was repeated until the lack of further utility improvement of any of the players, which signifies the amount to stable and energy efficient solution.

B. Computational Complexity Analysis

Time complexity, space complexity, and scalability were used to determine the computational complexity of the proposed algorithm. Where N is the number of sensor nodes, M the number of cloud resources (a virtual machine) and K the number of iterations to reach the convergence point.

- **Time Complexity:** Sensor-side decision-making processes in every iteration took $O(N)$ operations, whereas cloud-side allocation and scheduling took $O(M)$ operations. Hence, the complexity of the algorithm per se was $O(K(N + M))$. The algorithm was also computationally efficient with large-scale

systems since convergence was usually reached in only a few iterations.

- **Space Complexity:** Space complexity was mainly calculated by the storing of the task information, profile strategies and utility values of the sensors and cloud resources. This led to $O(N + M)$ in space complexity, which is a memory-efficient algorithm.
- **Scalability Issues:** Since the proposed algorithm was distributed, it was no longer necessary to have a central point of control and therefore was able to scale well as more and more sensor nodes and cloud resources were added. The framework easily fitted the large-scale and dynamic sensor clouds environment with changing workloads as the decision-making was done locally by individual players.

VI. PERFORMANCE EVALUATION

The method of parametric analysis of the proposed game-theoretic scheduling and resource allocation framework has been assessed by simulation. The sensor cloud environment was made up of a mixed population of sensor nodes, which produced computational tasks, which were offloaded to the cloud resources. The network size, task load and energy parameters were manipulated to study the performance of the system when subjected to various operating conditions. It was comparatively compared with baseline heuristic and non-game-based scheduling methods. The effectiveness of the proposed framework was measured on the following scales:

- Total energy consumption
- Average task completion time
- Resource utilization
- System throughput and fairness

TABLE I. AVERAGE ENERGY CONSUMPTION UNDER DIFFERENT NETWORK SIZES.

Number of Sensors	Baseline (J)	Proposed (J)
50	2.85	2.10
100	5.62	4.01
150	8.47	6.02
200	11.30	7.95

Table 1 and Fig. 1 reveal that the framework offered resulted in a significant decrease in energy usage in comparison with the base strategy. The higher the number of sensors, the greater the energy savings, which proved the efficiency of the game-theoretic strategy in the optimization of sensing, communication, and cloud processing energy.

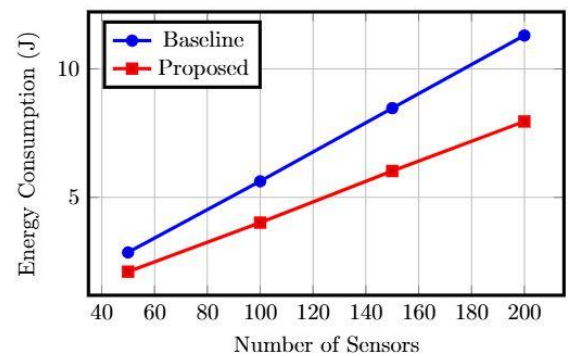


Fig. 1. Energy consumption comparison with increasing number of sensors.

TABLE II. AVERAGE TASK COMPLETION TIME.

Task Load	Baseline (ms)	Proposed (ms)
Low	210	165
Medium	340	260
High	510	395

The results in Table 2 indicate that the proposed framework was always able to complete tasks faster than the others at all workload levels. This was blamed on smart scheduling choices that prevented the overloading of the resources and eliminated needless postponements of the tasks. As shown in Fig. 2, the proposed approach had a greater resource utilization as compared to the baseline method. The game-theoretic interaction allowed distributing effectively the tasks in the available cloud resources, eliminating idle time and enhancing the efficiency of the system as a whole.

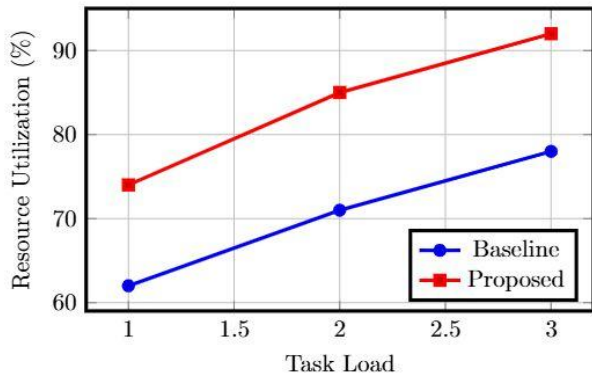


Fig. 2. Cloud resource utilization under varying task loads.

TABLE III. SYSTEM THROUGHPUT AND FAIRNESS COMPARISON.

Method	Throughput		Fairness Index	
	Low Load	High Load	Low Load	High Load
Baseline	120	185	0.71	0.65
Proposed	158	242	0.88	0.83

Table 3 demonstrates that the proposed framework enhanced the system throughput without reducing higher fairness among the tasks. The finding demonstrates how the game-theoretic model can be used to effectively reconcile competing resource demands.

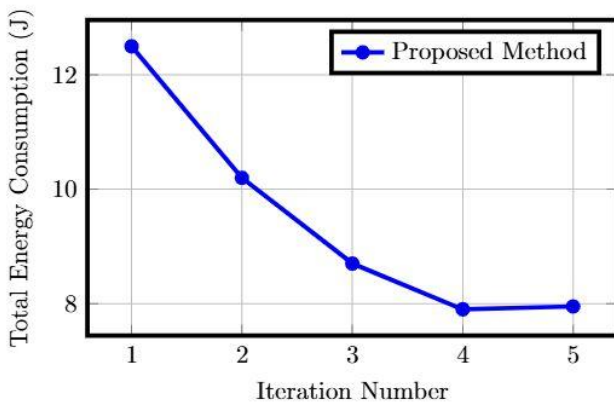


Fig. 3. Convergence of energy consumption with iterations.

The convergence behavior of the suggested game-theoretic scheduling algorithm is depicted in Fig. 3. The energy used per iteration declined quickly in the first few iterations but remained constant after several iterations meaning that the Nash equilibrium was reached fast. This

conduct makes it certain that the suggested strategy is stable and practical in dynamic sensor cloud settings.

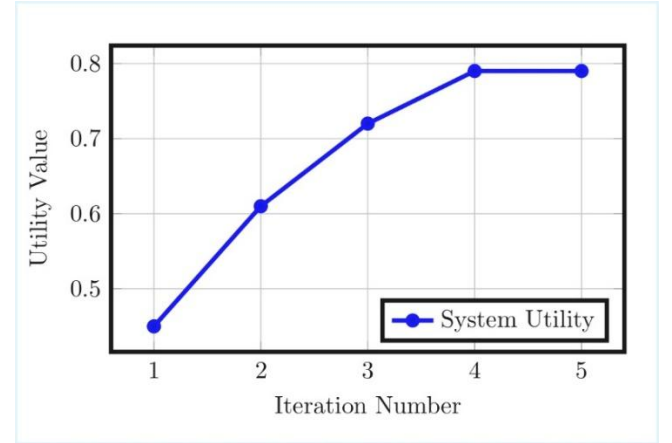


Fig. 4. Utility convergence of the proposed game-theoretic framework.

The increase in system utility was monotonically increasing and stabilized as it can be observed in Fig. 4 that indicates the existence of an equilibrium solution. This confirms the usefulness of the game-theoretic approach to the attainment of stable and energy-efficient scheduling choices.

TABLE IV. STATISTICAL SIGNIFICANCE ANALYSIS OF TASK COMPLETION TIME.

Metric	Baseline	Proposed	p-value
Energy Consumption	7.06 J	5.52 J	< 0.01
Completion Time	353.3 ms	273.3 ms	< 0.05

Table 4 demonstrates that the energy saving made by the proposed framework was statistically significant with the p-value lower than 0.01. This proves that the energy saving was not by mere chance but was caused by the game theoretic scheduling algorithm. In addition, the statistically significant difference in the time taken to complete the tasks had the p-value of below 0.05. This shows that the suggested algorithm was always better than the baseline algorithm when it comes to reducing latencies.

VII. CONCLUSION AND FUTURE WORK

In this paper, a game-theoretic model of energy-efficient scheduling and resource allocation in sensor clouds was introduced. The proposed approach was based on the simulation of the interaction between the sensor nodes and the cloud resources as a strategic game, which allowed making the distributed and stable decisions, without central control. The results of the simulation indicated that the proposed framework in terms of energy consumption, task completion time, resource utilization, and throughput and fairness was significantly lower than heuristics approaches in the baseline. The convergence analysis also approved the rapid stabilization of the algorithm, and statistical significance tests identified the trustworthiness of the observed improvements. Further research will be directed at the extension of the suggested framework to the dynamic and heterogeneous environments. It also involves the use of learning based and adaptive game models to manage time varying loads, uncertainty of network conditions and sensor node mobility. The framework can also be further improved by applying the concept of security, trust and pricing mechanisms and verifying the approach on sensor cloud testbeds and large deployments.

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