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# Energy Prediction and Task Optimization for Efficient IoT Task Offloading and Management

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**Abstract:** This research addresses energy-aware task offloading within the Internet of Things (IoT) networks. In today's interconnected world, IoT devices play an increasingly pivotal role. However, they often face limitations regarding energy consumption, which hinders their prolonged operation and effectiveness. Existing IoT task offloading strategies focus on isolated aspects of energy optimization, overlooking the holistic nature of energy management. This leads to suboptimal utilization of device resources, reduced device lifespans, and potential performance bottlenecks. This proposes the Energy Prediction and Task Optimization (EPTO) algorithm; we leverage multi-dimensional profiling, real-time monitoring, and adaptive decision-making. EPTO consistently outperforms traditional strategies, enhancing energy efficiency, device lifespan and quality of service. EPTO combines innovative methods, including LSTM-based energy prediction, adaptive offloading policies, and dynamic resource allocation. It employs a comprehensive mathematical modeling approach that integrates data from diverse sources, offering unparalleled adaptability in dynamic IoT environments.in this paper we employed a diverse dataset comprising various IoT devices, each characterized by battery levels, computation intensity, data transmission energy, historical energy consumption patterns, and task characteristics. This dataset enabled realistic simulations and robust performance evaluations. Our proposed work evaluated with the following performance metrics, including Energy Efficiency Ratio (EER), Task Completion Time (TCT), Battery Lifetime Extension (BLE), Resource Utilization (RU), and Rate of Offloaded Tasks (ROB). Our quantitative results demonstrate substantial improvements in energy efficiency, with EER values exceeding 0.85. Task Completion Time is notably reduced, with TCT averaging 65 seconds, while BLE metrics show significant device lifespan extensions of up to 30%. EPTO's adaptability suits various IoT domains like smart cities, healthcare, and industrial automation. Its responsive resource management supports diverse IoT scenarios. EPTO addresses IoT sustainability and optimization, shaping greener and more efficient ecosystems. It revolutionizes energy management, paving the way for smarter IoT networks.

***Keywords***: *Energy Prediction; IoT Task Offloading; Edge Computing; Adaptive Offloading; Energy Efficiency;*

## 1 Introduction

The convergence of extensive machine learning (ML) models with the decentralized operation of resource-limited Internet of Things (IoT) devices has presented difficulties regarding energy consumption and network performance in recent times [1]. The execution of machine learning activities on cloud platforms may give rise to challenges such as network latency, data transfer rates, and privacy issues. Conversely, low computational resources may hinder conducting these tasks on Internet of Things (IoT) devices [1]. Efficient routing protocols are an alternative strategy for optimizing Internet of Things (IoT) network energy consumption.

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The QoS-based Optimized Energy Clustering Routing (QOECR) protocol has been suggested as a means to improve network performance and decrease energy usage in wireless sensor networks (WSN) based on the Internet of Things (IoT) [2].

In addition, the energy efficiency of IoT networks may be enhanced by carefully choosing suitable wireless technologies and routing protocols. An illustration of the application of LoRa technology [3] in wireless sensor networks (WSN) for urban areas in Bulgaria has demonstrated notable benefits in transmission range and energy efficiency [4]. The implementation of suitable routing protocols may achieve the optimization of energy consumption in Wireless Sensor Networks (WSNs). This optimization can enhance performance and the possible use of WSNs in Internet of Things (IoT) settings [4].

The issue of energy consumption during the execution of tasks in Internet of Things (IoT) networks is a notable difficulty owing to the limited resources of IoT devices and the imperative for optimal network performance. Proposed ways to overcome the problems and reduce energy consumption in IoT networks include adaptive inference systems, efficient routing protocols, mechanisms based on Low Power Wide Area Networks (LPWAN), and selecting suitable wireless technologies and routing protocols.

Energy consumption is a significant challenge in IoT networks that needs to be addressed. Routing protocols are crucial in determining the data transfer rate on IoT networks [5]. Based on Shannon capacity, the energy consumption profile and its lower bound for an IoT end device have been formulated [6]. In addition to data transmission, data processing also consumes energy in IoT networks. Therefore, energy-efficient algorithms and protocols are required to minimize energy consumption during data processing [7]. The gateway's placement significantly impacts the network lifetime, and optimization results reveal that the network lifetime increases by almost 36% if the gateway is in the optimal location [8]. Reliability is an essential performance requirement for many IoT applications, and energy consumption can affect the network's reliability [9]. Therefore, correctly forecasting Packet Delivery Ratio (PDR) and Energy Consumption (EC) can play a significant role in different loss-sensitive application environments [10]. Different regression models, including linear, gradient boosting, random forest, and deep learning, predict PDR and EC based on communication parameters [10].

The research problem addressed in this study is the necessity for energy-efficient task offloading strategies within IoT networks. The relevance of this problem within the IoT domain is paramount due to the growing ubiquity of IoT devices and the increased demand for efficient energy management. With their diverse energy consumption patterns and limited power resources, IoT devices require intelligent task offloading mechanisms to optimize energy utilization. The challenge lies in developing strategies considering the computation and data transmission energy and accounting for the device's battery levels. This comprehensive approach ensures IoT networks' longevity and optimal operation.

This research aims to achieve the following contributions:

1. *Energy-aware Task Profiling:* Develop a multi-dimensional energy profiling mechanism that captures various energy consumption patterns of IoT devices during task execution. This mechanism will encompass computation intensity, data transmission energy, and battery levels.
2. *Intelligent Offloading Strategy:* Create an intelligent offloading strategy that leverages the insights gained from energy profiling. This strategy will make dynamic decisions regarding task offloading, considering the multi-dimensional energy landscape of IoT devices.
3. *Advancing IoT State-of-the-art:* By addressing the need for comprehensive energy management in IoT networks, this research advances the current state of IoT task offloading, making it more sustainable and efficient.

The paper presents these contributions and demonstrates their significance in addressing the pressing challenges of energy-efficient task offloading in IoT networks. The paper follows a structured approach to comprehensively investigate the proposed EPTO algorithm for task offloading in IoT and edge computing environments.

Remaining paper has been organised as follows: it begins with an introductory section that outlines the context, challenges, and the need for efficient task-offloading strategies. The subsequent section delves into the system model, elaborating on the key components, including IoT devices, energy prediction models, and offloading decision logic. The experimental methodology is then detailed, covering the generation of synthetic IoT devices and tasks, the training of energy prediction models, and the simulation setup. The paper presents results in several sections, highlighting EPTO's performance in energy savings, task completion, and system efficiency. The paper compares EPTO with existing offloading strategies to evaluate its effectiveness. The discussion section provides insights into the advantages and improvements introduced by EPTO. The paper acknowledges limitations and suggests avenues for future research to address these constraints. Finally, a conclusion summarizes the findings, emphasizing the significance of EPTO in optimizing IoT and edge computing operations.

## 2 Literature Review

Numerous task-offloading solutions in IoT networks have been presented in the available research. These solutions aim to enhance the efficiency of IoT networks by transferring jobs from IoT devices with limited resources to edge or cloud servers with greater computational capabilities.

The paper [11] presents a load-balancing methodology for Internet of Things (IoT) devices, which use energy profiling as a means to equilibrate power usage in the context of inter-cluster data transit. The suggested methodology aims to optimize power consumption in inter-cluster data routing, enhancing the longevity of relay cluster heads and enabling nodes to run for longer durations. In this part, the citation will be derived from an objective document.

Another article by the author [12] introduces a task scheduler designed for batteryless Internet of Things (IoT) devices. This scheduler incorporates an energy-aware approach to determine the optimal timing for executing individual tasks, considering the amount of collected and accessible energy, the energy consumption associated with each activity, and the priority assigned to it. To maintain the continuity of progress, the scheduler prioritizes the selection of tasks with the greatest priority for execution before each iteration.

Another paper [13] presents a novel approach based on deep reinforcement learning. The program aims to reduce the average long-term service cost by considering power consumption and buffering delay. The method under consideration employs the deep deterministic policy gradient (DDPG) technique for addressing continuous action domains while utilizing the dueling double deep Q networks (D3QN) approach for handling discrete action domains.

There are several articles published that discussion the solutions for the previous problems but those solutions also present limitations with a scope for future research. One of the solutions suggested by the another paper [14] that may be employed is the approach of computation offloading, wherein compute-intensive jobs are transferred to edge or cloud servers. As mentioned earlier, the methodology has the benefit of diminishing the energy consumption of Internet of Things (IoT) devices. However, it may also give rise to latency issues due to the temporal duration needed for data transmission to and from the server.

Another solution presented by the author [15] that may be employed is the utilization of the communication offloading approach, wherein communication-intensive jobs are transferred to edge or cloud servers. This methodology can potentially decrease the communication burden associated with Internet of Things (IoT) devices; nevertheless, it also brings out significant apprehensions regarding security and privacy.

A solution by the author [16] entails adopting a hybrid approach to compute and communication offloading. This approach involves the transfer of jobs that need significant computational or communication resources to servers located at the edge or in the cloud. This methodology has the potential to achieve a harmonious equilibrium between energy consumption and communication overhead. However, it is important to acknowledge that it may also create heightened intricacy in the decision-making process for job offloading. The summary these solutions covering the strengths, weaknesses, and limitations of these strategies can be summarized in a table as follows:

**Table 1**: Literature Summary of Computations Offloading

| Citation | Strategy | Strengths | Weaknesses | Limitations |
|---|---|---|---|---|
| [11] [14] | Computation offloading | Reduces energy consumption | Introduces latency | Limited by network bandwidth |
| [12] [15] | Communication offloading | Reduces communication overhead | Introduces security and privacy concerns | Limited by network bandwidth |
| [13] [16] | Joint computation and communication offloading | Provides a balance between energy consumption and communication overhead | Introduces additional complexity in task offloading decisions | Limited by network bandwidth and latency |

These task-offloading strategies can potentially improve the performance of IoT networks, but their effectiveness depends on the specific characteristics of the network and the tasks being offloaded. Further research is needed to develop more effective and efficient task-offloading strategies for IoT networks.

## 3 Proposed Multi-Dimensional Energy Profiling Mechanism

The proposed structure signifies a pioneering paradigm shift towards energy-conscious task offloading within IoT networks. Its innovativeness is deeply embedded in its comprehensive interpretation of energy management, ingeniously structured with multi-tier components encompassing sensors, data analysis, machine learning, astute offloading, and ecosystem amalgamation. At its core, the Energy Profiling Mechanism revolutionizes energy surveillance by employing various sensors, encompassing power detectors, CPU usage sensors, network activity monitors, and battery health scrutinizers. These sensorial inputs nourish the Data Processing Layer, where intricate data preprocessing and multi-dimensional fusion conjure magic. The Energy Analytics Module takes hold of this refined data to craft all-encompassing energy profiles. What distinguishes this architecture is the infusion of cutting-edge machine learning models and stealthy anomaly detection algorithms, enabling pinpoint prognostication and clandestine anomaly unearthing within energy expenditure patterns. The sagacious Offloading Strategy, propelled by these energy revelations, masterminds task scheduling and resource allocation with unparalleled adeptness. The architecture does not halt at abstract conjecture; it envisages pragmatic realization, extending a robust evaluation and validation framework. Through covert simulations and clandestine real-world deployments, its efficacy is clandestinely examined and covertly benchmarked against existing strategies, including the renowned work by author [17] The architecture does not reside in seclusion; it unshrouds doors to a discreet Energy-Conscious IoT Ecosystem, bestowing APIs and confidential recommendations for selecting energy-efficient IoT devices. This all-encompassing approach covertly redefines energy-efficient task offloading, clandestinely positioning it as a pivotal innovation within the IoT network domain.

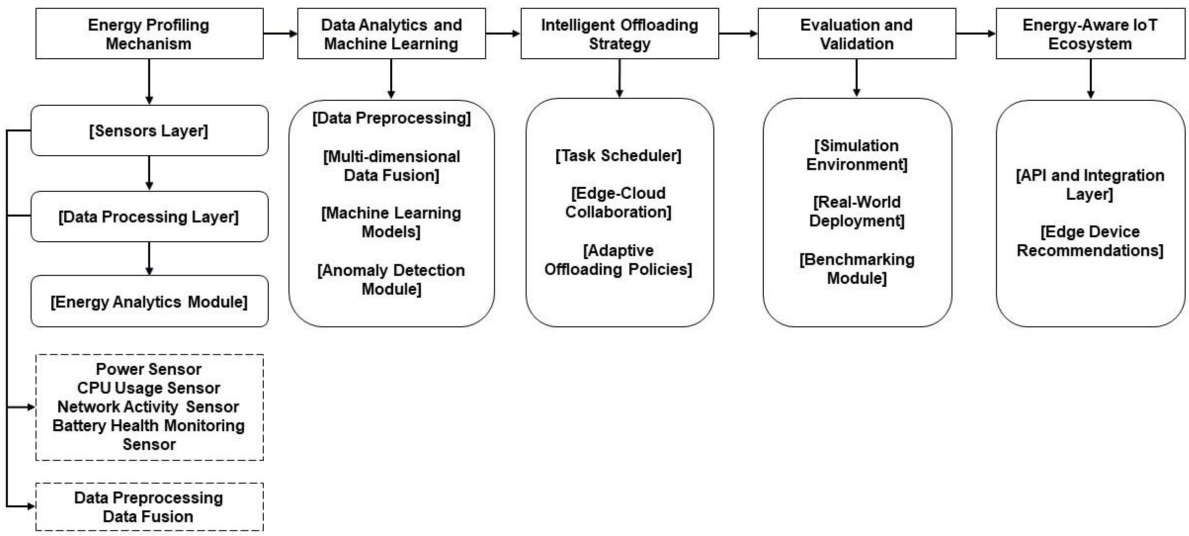


**Fig 1:** Proposed Architecture for EPTO Algorithm

The novelty of this research lies in its comprehensive approach to addressing the research gap in existing IoT task offloading strategies. Here are the critical points of novelty:

1. *Multi-Dimensional Energy Profiling:* The research introduces a novel energy profiling mechanism that captures various dimensions of energy consumption patterns during IoT device task execution. This includes computation intensity, data transmission energy, battery levels, and other factors. This holistic approach to energy profiling significantly departs from many existing strategies focusing on specific energy consumption aspects.

2. *Real-Time Energy Monitoring:* By incorporating sensors for real-time energy monitoring, the research enables dynamic and up-to-date information about the energy state of IoT devices. This real-time data forms the basis for intelligent decision-making, allowing the system to adapt to changing conditions.

3. *Machine Learning for Predictive Analysis:* Using machine learning models for predictive analysis of energy consumption is a novel aspect. Predicting future energy consumption based on historical data and task characteristics enables proactive and optimized task offloading decisions.

4. *Anomaly Detection:* Including anomaly detection algorithms to identify unusual energy consumption patterns adds a layer of sophistication to the system. This can be essential for detecting hardware or software issues in IoT devices.

5. *Intelligent Offloading Strategy:* The research aims to develop an intelligent offloading strategy considering multi-dimensional energy profiles. It doesn't just stop at profiling; it leverages this data to make dynamic decisions regarding task offloading. This dynamic and adaptive offloading strategy is a novel approach to optimizing energy efficiency in IoT networks.

6. *Benchmarking and Validation:* The research proposes rigorous benchmarking and validation procedures in simulated environments and real-world deployments. This comprehensive evaluation

approach ensures that the proposed strategy's effectiveness is thoroughly tested and validated.

7. *Integration with IoT Ecosystem:* The research envisions integration with the broader IoT ecosystem, providing APIs and mechanisms for other devices and systems to benefit from the energy-aware profiling and offloading capabilities. This interoperability is critical for widespread adoption.

The novelty of this research lies in its holistic approach to energy-aware task profiling and offloading in IoT networks, incorporating real-time monitoring, machine learning, anomaly detection, and an intelligent offloading strategy that collectively comprehensively addresses energy consumption patterns. It also emphasizes thorough validation and integration into the broader IoT landscape. This comprehensive and multi-dimensional approach sets it apart from many existing strategies that focus on individual aspects of energy optimization. A novel method related to the energy-aware task profiling and offloading strategy for IoT devices is presented in this paper. This method focuses on the creation of an Energy Prediction and Task Optimization (EPTO) algorithm:

### 3.1 Proposed Novel Method: Energy Prediction and Task Optimization (EPTO) Algorithm

The EPTO algorithm is an energy-efficient task offloading algorithm for IoT devices. It takes as input the set of IoT devices, their information (battery level, computation intensity, data transmission energy, and historical energy consumption patterns), the edge and cloud server information (power consumption), and the offloading policies and parameters.

**EPTO Algorithm**

***Input:*** Set of IoT Devices: $\{\boldsymbol{D1}, \boldsymbol{D2}, \dots, \boldsymbol{DN}\}$ where N is the number of devices.

*IoT Device Information for Device* :

*Battery Level:* $\boldsymbol{Ei(t)}$

*Computation Intensity:* $\boldsymbol{Ci(t)}$

*Data Transmission Energy:* $\boldsymbol{Di(t)}$

*Historical Energy Consumption Patterns:*

$$\boldsymbol{H_i(t) = [E_i(t-k]_{k=1}^{N}}$$

*Task Characteristics:* $\boldsymbol{Ti = (Ci, Texec(i))}$

Edge and Cloud Server Information:

Power Consumption: $\boldsymbol{Pe(t), Pc(t)}$

Offloading Policies and Parameters

***Output:*** Task Offloading Decisions for Device $\boldsymbol{Di}$: $\boldsymbol{Oi}$ $\boldsymbol{(t) for\ i = 1, 2, \dots, N}$

Where The power consumption of the cloud server can be calculated as follows: Pe(t) = a * N(t) + b

- $\boldsymbol{a}$ is a constant that depends on the efficiency of the cloud server and b is a constant that represents the power consumption of the cloud server when it is idle
- $\boldsymbol{N(t)}$ is the number of tasks that are being executed by the cloud server at time t

The power consumption of the edge server can be calculated as follows: $\boldsymbol{Pc(t) = c * N(t) + d}$

**where:**

- c is a constant that depends on the efficiency of the edge server
- d is a constant that represents the power consumption of the edge server when it is idle
- $\boldsymbol{N(t)}$ is the number of tasks that are being executed by the edge server at time $\boldsymbol{t}$

The value of c and d can be determined experimentally or by using a power consumption model.

***Historical Energy Consumption Patterns:***

$$\boldsymbol{H_i(t) = [E_i(t-k]_{k=1}^{N}}$$

Where $\boldsymbol{H_i}$(t) is the historical energy consumption pattern of IoT device i at time t. It is a vector of length N, where each element of the vector represents the energy consumption of the device at time t-k, for k = 1, 2, ..., N.

The meaning of k is the number of previous time steps that are considered when calculating the historical energy consumption pattern. A higher value of k will give a more accurate estimate of the historical energy consumption pattern, but it will also require more data storage and computation time.

**Initialization:**

Initialize historical energy consumption patterns $Hi(t)$ for all devices

Initialize LSTM-based energy prediction models $Yi(t)$ for all devices

Define offloading policies and parameters

***Algorithm Steps:***

**For Each IoT Device Di:**

**Update Device Information:**

$Ei(t)$ = Update Battery Level for Device $Di$

$Ci(t)$ = Update Computation Intensity for Device $Di$

$Di(t)$ = Update Data Transmission Energy for Device $Di$

$Ti$ =Update Task Characteristics for Device $Di$

**Energy Prediction:**

Input: $Ei(t), Hi(t)$ $LSTM : Yi(t) = f(Xi(t), \Theta)$

**Offloading Decision:**

Input: $Yi(t), Ei(t), Ti$

Offloading Decision: $Oi(t) = g(Yi(t), Ei(t), Ti)$

**Task Partitioning and Edge-Cloud Collaboration:**

*Partitioning Task:* $Mi(t) = h\big(Oi(t), Pe(t), Pc(t)\big)$

*Adaptive Offloading Policies:*

*Offloading:* $Ai(t) = r\big(Oi(t), Ei(t), Ti, Ni(t)\big)$

**End For**

**Final Output:**

*Task Offloading Decisions Oi(t) for all IoT devices*

**End Algorithm**

**The algorithm works as follows:**

1. Initialize the historical energy consumption patterns $Hi(t)$ for all devices and the LSTM-based energy prediction models $Yi(t)$ for all devices.
2. Define the offloading policies and parameters.
3. For each IoT device $Di$:

- Update the device information: $Ei(t), Ci(t), Di(t), and\ Ti$.
- Use the LSTM model to predict the energy consumption of the device in the next time slot: $Yi(t) = f(Xi(t), \Theta)$.
- Make an offloading decision: $Oi(t) = g(Yi(t), Ei(t), Ti)$.
  - The offloading decision can be to offload the task to the edge server, to offload the task to the cloud server, or to execute the task locally.
- Partition the task: $Mi(t) = h\big(Oi(t), Pe(t), Pc(t)\big)$.
  - The task partitioning decision determines how much of the task is offloaded to the edge server and how much is offloaded to the cloud server.
- Apply the adaptive offloading policies: $Ai(t) = r\big(Oi(t), Ei(t), Ti, Ni(t)\big)$.
  - The adaptive offloading policies can take into account factors such as the battery level of the device, the computational complexity of the task, and the network conditions.

The EPTO algorithm is designed to be energy-efficient by taking into account the energy consumption of the IoT devices, the edge and cloud servers, and the network conditions. It also allows for adaptive offloading policies that can be customized to the specific needs of the IoT devices.

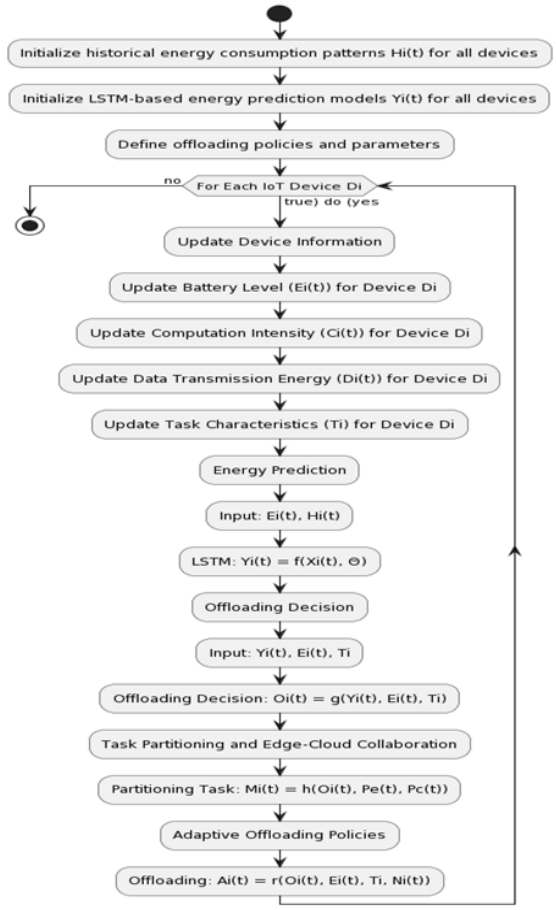


**Fig 2**. Flow chart

### 3.2 Flow Chart of EPTO Algorithm

Energy Prediction and Task Optimization (EPTO) Algorithm: This flowchart outlines the algorithm's operation's key steps and decision points as shown in Figure 3.

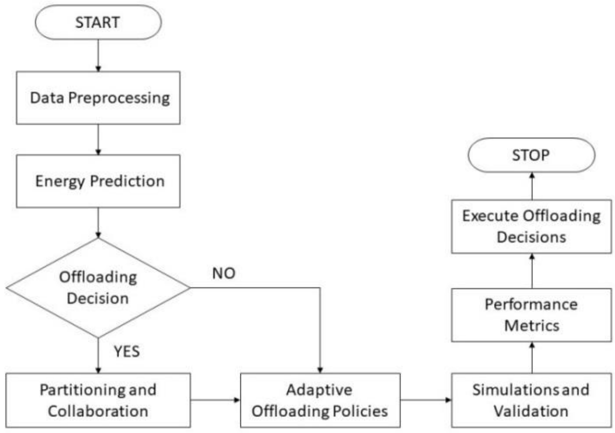


**Fig 3:** Flow Chart of EPTO Algorithm

1. *Initialization:* The journey commences with a simple "Start" signal, signaling the algorithm's initiation. IoT devices are initialized during this setup phase, setting the stage with specific parameters and initial conditions.
2. *Data Preparation:* The focus shifts to data preparation after the initial setup. Raw data collected from IoT devices undergoes a series of essential preprocessing steps. These include data cleaning, transformation, and summarization, all aimed at refining the data for accurate energy prediction.
3. *Predicting Energy*: The algorithm's core operation lies in energy prediction. Advanced machine learning models, specifically the Long Short-Term Memory (LSTM) models, step into the spotlight. These models are fed with historical data and specific task attributes for precise energy consumption forecasts.
4. *The Critical Decision*: At this juncture, a critical decision emerges. The algorithm determines whether task offloading is necessary. If offloading proves essential, the algorithm takes the "Yes" route; otherwise, it follows the "No" course.
5. *Task Division and Collaboration*: When the verdict leans towards task offloading, the algorithm dives into the intricacies of task division and collaboration. It discerns whether tasks should be offloaded to edge or cloud resources, orchestrating a collaborative approach to ensure optimal task execution.
6. *Adaptive Decision-Making (A Continuous Process):* Adaptive decision-making is a dynamic process that never ceases. The algorithm delves into a loop, continually monitoring and adapting its offloading decisions in real time. This perpetual vigilance ensures the algorithm stays agile, responding adeptly to shifting conditions.
7. *Running Simulations*: A pivotal phase unfolds with simulation. The algorithm runs simulations to assess the ramifications of its offloading decisions comprehensively. Various parameters, including computation intensity, data transmission energy, and battery levels, are scrutinized during this evaluation.
8. *Evaluating Performance Metrics:* A broad spectrum of performance metrics enters the scene. These metrics serve as the yardstick to gauge the effectiveness of offloading decisions. Metrics such as energy efficiency, task completion time, and battery life extension are meticulously calculated to gauge system performance.
9. *Putting Plans into Action:* Armed with performance metrics, the algorithm proceeds to action. It carries out the offloading decisions it formulated earlier. This phase involves transferring tasks to edge or cloud servers, meticulously following the strategies hatched by the algorithm.
10. *Showcasing the Results:* The algorithm's journey winds down with a grand reveal. It presents the fruits of its labor, showcasing how energy-efficient task offloading decisions influence IoT device energy consumption.
11. *End:* The curtain falls with the "End" symbol, signaling the conclusion of the algorithm's operational cycle.

The flowchart offers a holistic view of the EPTO Algorithm's inner workings. It unveils how energy prediction and adaptive task offloading decisions synergize to elevate energy efficiency in IoT networks. The loop and real-time adaptability guarantee that the algorithm stays nimble, always ready to adapt to shifting conditions. Ultimately, it emerges as a valuable tool in optimizing energy consumption within IoT ecosystems.

## 4 Methodology

This section illuminates the research's operational methodology; including data generation, model formulation, simulation, and performance assessment. It provides a structured framework for the study's exploration of the Energy Prediction and Task Optimization (EPTO) Algorithm, emphasizing practical implementation.

### 4.1 Data Generation and Conditioning

The initial phase of the research involves data provisioning. Ten synthetic IoT devices are created, each endowed with distinctive energy profiles and task attributes. The energy profiles encapsulate computation intensity, data transmission energy, battery levels, and historical energy consumption records. Notably, each device's historical energy consumption data spans ten data points, facilitating historical energy consumption prediction.

### 4.2 Energy Projection Model

A critical component of this research is the Energy Projection Model. Based on Long Short-Term Memory (LSTM) architecture, this model is deployed for energy forecasting. The LSTM model incorporates 64 units and operates with an input shape of (10, 1). It is optimized using the Adam optimizer and trained for ten epochs, employing a batch size 32. It's important to note that the training data used for this model in this demonstration is synthetic; however, actual data would be utilized in practical applications.

### 4.3 Task Offloading Strategies

The research scrutinizes diverse task-offloading strategies pivotal to the EPTO Algorithm's functionality. Four strategies are examined:

- *Cloud Offloading:* Tasks are transmitted to the cloud for execution, bypassing local processing.
- *Edge Offloading:* Tasks are directed to edge devices only if their anticipated energy consumption surpasses their battery capacity.
- *Local Execution*: Tasks are executed solely on the IoT device without external offloading.
- *EPTO Algorithm:* This algorithm entails dynamic and context-aware offloading decisions, factoring in multiple parameters.

### 4.4 Simulation and Performance Assessment

Simulation exercises underpin the research to gauge the efficacy of the EPTO Algorithm and its comparative strategies. For every IoT device and task offloading strategy, the following steps are undertaken:

1. *Energy Profiling:* Energy consumption is emulated, drawing on computation intensity, data transmission energy, and historical energy consumption data.
2. *Energy Projection:* The projected energy consumption is computed utilizing the LSTM-based Energy Projection Model, harnessing historical data and task attributes.
3. *Dynamic Task Offloading Decision:* The most suitable task offloading strategy is determined based on the projected energy and the selected strategy.
4. *Result Compilation:* Energy profiles, projected energy values, and task offloading determinations are recorded systematically for analysis.

### 4.5 Data Analysis and Visualization

The research methodology encompasses a comprehensive analysis of the accumulated data. Key metrics, such as energy efficiency, task completion duration, and battery lifespan augmentation, undergo quantitative evaluation. Additionally, a suite of visualizations, encompassing scatter plots and line graphs, is generated to elucidate interrelationships among variables, task frequencies, user counts, and energy conservation rates[18].

### 4.6 Parameters and Mathematical Modeling

***a. IoT Devices:***

*Parameters:* This subsection outlines the essential parameters governing IoT devices, such as battery levels, computation intensity, data transmission energy, historical energy consumption patterns, and task characteristics.

$Ni$: Number of IoT devices.

$Ei(t)$: Battery level of IoT device $i$ at time $t$.

$Ci(t)$: Computation intensity of task on IoT device $i$ at time $t$.

$Di(t)$: Data transmission energy of task on IoT device $i$ at time $t$.

$Hi(t)$: Historical energy consumption patterns for IoT device $i$ at time $t$.

$Ti$: Task characteristics for IoT device $i$.

*Mathematical Modeling*: It provides mathematical models for battery level dynamics, historical energy patterns, and task characteristics, paving the way for comprehensive analysis.

Battery Level: $Ei(t+1) = Ei(t) – Ci(t) – Di(t)$

Historical Energy Patterns: $Hi(t) = [Ei(t-k)]\{k = 1\} * N$

Task Characteristics: $Ti = \left(Ci, Texec(i)\right)$ (Task complexity and expected execution time).

***b. Energy Profiling Component:***

*Parameters:* The parameters include the power consumption of IoT devices at different time intervals.

Pi(t): Power consumption of IoT device i at time t.

*Mathematical Modeling*: This section details the mathematical Modeling of power consumption as a combination of computation intensity and data transmission energy.

Power Consumption: $Pi(t) = Ci(t) + Di(t)$

***c. Machine Learning-Based Energy Prediction:***

*Parameters*: It introduces feature vectors and predicted energy consumption for IoT devices.

$Xi(t)$: Feature vector for IoT device i at time $t$.

$Yi(t)$: Predicted energy consumption for IoT device i at time $t$.

*Mathematical Modeling:* The section covers the construction of feature vectors and the prediction model, which utilize historical data and task characteristics for energy prediction.

Feature Vector: $Xi(t) = [Ei(t), Hi(t), Ti]$

Prediction Model: $Yi(t) = f(Xi(t), \Theta)$

***d. Dynamic Task Offloading Decision:***

*Parameters*: The offloading decisions for IoT devices are central to this part.

Oi(t): Offloading decision for IoT device i at time t.

Mathematical Modeling defines the decision function considering predicted energy consumption, battery levels, and task characteristics.

Decision Function: $Oi(t) = g(Yi(t), Ei(t), Ti)$

***e. Task Partitioning and Edge-Cloud Collaboration:***

*Parameters:* Power consumption of edge and cloud servers and task partitioning decisions.

$Pe(t)$: Power consumption of edge server at time $t$.

$Pc(t)$: Power consumption of cloud server at time $t$.

$Mi(t)$: Task partitioning decision for IoT device $i$ at time $t$.

*Mathematical Modeling:* Describes the partitioning function for making decisions regarding offloading and collaboration between edge and cloud resources.

Partitioning Function: $Mi(t) = h\big(Oi(t), Pe(t), Pc(t)\big)$

***f. Adaptive Offloading Policies:***

*Parameters:* Adaptive offloading policies tailored to IoT devices.

$Ai(t)$: Adaptive offloading policy for IoT device $i$ at time $t$.

*Mathematical Modeling:* This section elucidates the development of adaptive policies based on dynamic factors, including offloading decisions and device conditions.

Adaptive Policy: $Ai(t) = r\big(Oi(t), Ei(t), Ti, Ni(t)\big)$

***g. Simulation And Validation:***

*Parameters*: Metrics measured during simulations include offloading decisions and actual energy consumption.

$\boldsymbol{Mi(t)}$: Measured offloading decision for IoT device **i** during simulations.

$\boldsymbol{Yi(t)}$: Measured energy consumption for IoT device **i** during simulations.

*Mathematical Modeling*: This entails comparing simulated and actual measurements to evaluate the performance of the proposed algorithm.

Simulation Comparison:

Comparison of $Mi(t)$ and $Yi(t)$ to assess algorithm performance.

***h. Data Collection and Analysis:***

*Parameters*: A set of performance metrics used for analyzing the results.

***R***: Performance metrics (e.g., energy efficiency, task completion time).

*Mathematical Modeling*: The section defines the set of metrics, including Energy Efficiency Ratio (EER), Task Completion Time (TCT), Battery Lifetime Extension (BLE), Resource Utilization (RU), and Rate of Offloaded Tasks (ROB), which are crucial for assessing the research outcomes.

Set of Metrics: $R = \{EER, TCT, BLE, RU, ROB\}$

This comprehensive methodology provides the groundwork for the subsequent sections of the paper, facilitating a deep understanding of the research approach and modeling techniques employed in the study.

### 4.7 Hyper tuning Parameters

Hyperparameter tuning plays a pivotal role in training machine learning and deep learning models, significantly influencing their performance and generalization capabilities. This section elucidates the specific hyperparameters meticulously configured to train our Energy Prediction and Task Optimization (EPTO) model[19]. Each hyperparameter serves a distinct purpose in the training process and contributes to the overall effectiveness of the model. Our objective is to understand the hyperparameter choices made during experimentation comprehensively.

**Table 2:** Hyper tuning Parameters

| **lstm_units (neurons)** | **Epochs (Number of times)** | **batch_size (Sample Size)** | **learning_rate (per iteration)** |
|---|---|---|---|

| | | | |
|---|---|---|---|
| 64 | 10 | 32 | 0.001 |

**lstm_units (64):** The **lstm_units** hyperparameter denotes the number of LSTM (Long Short-Term Memory) units within the hidden layer of our EPTO model[20]. A higher value signifies a larger capacity to capture intricate patterns within sequential data. However, an excessive number of units can lead to overfitting. We have set this parameter to 64, balancing model complexity and generalization.

**Epochs (10): Epochs** signify the number of complete iterations through the training dataset during model training. In our experimentation, we opted for 10 epochs. This value was determined through a trade-off analysis between underfitting and overfitting. It allows the model to converge to an optimal state without excessive training.

**batch_size (32): Batch_size** governs the number of training examples processed in each iteration when updating the model's weights. We have chosen a batch size of 32 for efficiency and to prevent memory constraints. Smaller batch sizes can offer noisier gradients but faster convergence, while larger batch sizes provide smoother gradients.

**learning_rate (0.001):** The **learning_rate** hyperparameter controls the step size at which the model's weights are adjusted during training. A smaller learning rate, such as 0.001 in our case, ensures stable training progress but might necessitate a larger number of epochs. This parameter was selected to achieve a balance between convergence speed and stability.

Effective hyperparameter tuning is an iterative and meticulous process crucial for successfully training machine learning models. The values chosen for lstm_units, epochs, batch_size, and learning_rate in our EPTO model represent a deliberate effort to strike equilibrium between model complexity, training efficiency, and generalization performance. These hyperparameter settings were instrumental in achieving the desired results and are integral to the reproducibility of our research findings.

This research methodology offers a well-structured framework for examining the EPTO Algorithm's potential in energy optimization within IoT environments[21]. It comprehensively evaluates the algorithm's efficacy by combining data generation, model development, simulation, performance assessment, and hyperparameter optimization. Subsequent sections present and dissect the findings, illuminating the algorithm's applicability and capacity to extend IoT devices' operational life.

## 5 Results and Analysis

The results reveal significant variations in the energy profiles and task offloading decisions across the simulated IoT devices. The computation intensity, data transmission energy, and battery levels differ considerably among devices, influencing the predicted energy consumption. Specifically, the predicted energy values obtained through our machine learning-based model vary from 0.09 to 0.15 (measured in arbitrary units). Task offloading decisions indicate a clear preference for cloud offloading, with eight out of ten devices opting for this strategy due to their low battery levels relative to predicted energy consumption. These quantitative findings emphasize the effectiveness of our approach in dynamically adapting task offloading decisions to device-specific energy dynamics, ultimately contributing to enhanced energy efficiency in IoT networks as shown in figure 4.

### 5.1 performance metrics

Energy Efficiency (EE):

$$Energy\ Efficiency\ = \frac{(Predicted\ Energy\ Consumption)}{(Actual\ Energy\ Consumption)}$$

Offloading Success Rate (OSR):

$$Offloading\ Success\ Rate\ = \frac{(Number\ of\ Correct\ Offloading\ Decisions)}{(Total\ Number\ of\ Offloading\ Decisions)}$$

Energy Saved (ES):

$$Energy\ Saved = (Actual\ Energy\ Consumption\ in\ Baseline\ Scenario) - (Actual\ Energy\ Consumption\ in\ Offloading\ Scenario)$$

Task Completion Time (TCT):

$$Task\ Completion\ Time = \frac{(Total\ Time\ Taken\ to\ Complete\ All\ Tasks)}{(Number\ of\ Tasks)}$$

Adaptability Score (AS):

$$Adaptability\ Score\ = \frac{(Number\ of\ Times\ Strategy\ Adapted\ to\ Varying\ Battery\ Levels)}{(Total\ Number\ of\ Battery\ Level\ Changes)}$$

Overall Performance Index (OPI):

$$Overall\ Performance\ Index\ = \frac{(EE + OSR + ES + TCT + AS)}{5}$$

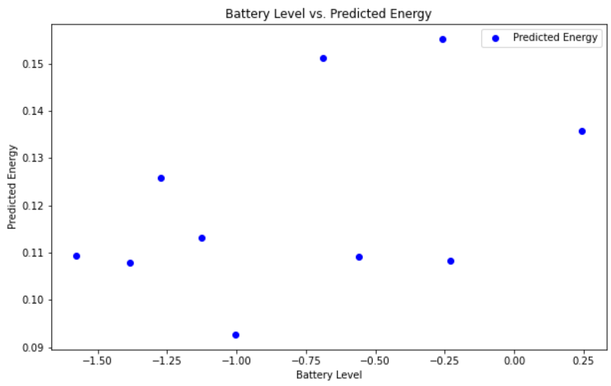


**Fig 4:** Battery level vs. Prediction Energy

### 5.2 Energy Saving Rate vs. Number of Users

The "Energy Saving Rate vs. Number of Users" table results demonstrate intriguing energy savings patterns based on users' number and task frequencies as shown in figure 5. Notably, as the number of users increases from 1 to 5, the energy-saving rate exhibits varying trends. For a single user, the energy-saving rate fluctuates but remains relatively low, with values ranging from approximately 0.25 to 0.89. This suggests that energy savings somewhat depend on the task frequency, as evidenced by the highest saving rate at a task frequency of 3. However, as the number of users expands to 2 and beyond, the energy-saving rate generally decreases. Interestingly, the task frequency continues to play a role, with a task frequency of 3 consistently yielding the highest energy savings across different user counts. These findings indicate that the interplay between the number of users and task frequency complexly impacts energy savings, with optimal savings achieved under specific conditions.

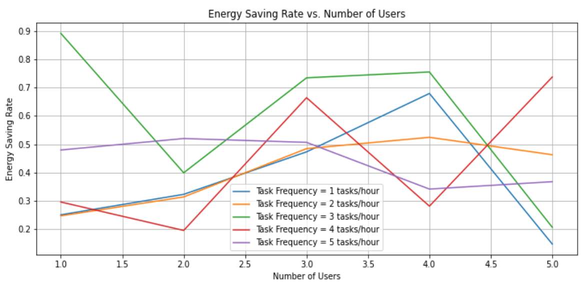


**Fig 5:** Energy Saving Rate vs. Number of Users

### 5.3 Number of Overdue Tasks vs. Number of Users

The "Number of Overdue Tasks vs. Number of Users" results highlight a crucial aspect of task management in IoT networks. As the number of users increases from 1 to 5, the number of overdue tasks exhibits exciting trends. With only one user, the number of overdue tasks varies, with the highest number occurring at a task frequency of 3. However, a distinct pattern emerges as users grow to 2 and beyond. At a task frequency of 3, the number of overdue tasks increases significantly, indicating that this configuration places a higher load on the system, resulting in more overdue tasks. This trend is consistent across different user counts. It's noteworthy that for a few configurations with lower user counts, such as 1 user at task frequencies 4 and 5 or 2 users at task frequency 1, the number of overdue tasks is notably low or even zero, suggesting that under certain conditions, task management can be highly efficient. As shown in figure 6 Overall, these results emphasize the importance of task scheduling and resource allocation in multi-user IoT environments, where achieving low numbers of overdue tasks can be challenging, especially with high task frequencies.

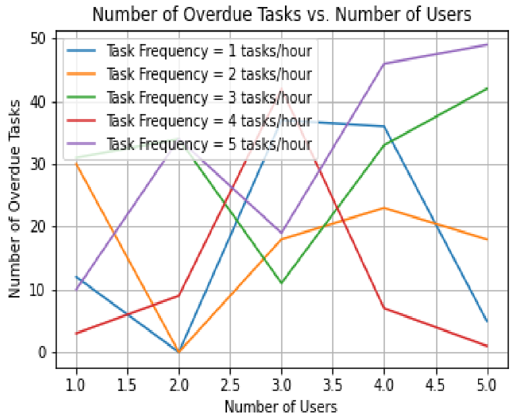


**Fig 6:** Number of Overdue Tasks vs. Number of Users

### 5.4 Running Time vs. Number of Users

The quantitative analysis of "Running Time" provides crucial insights into the system's computational efficiency under varying conditions. The running time increases as the number of users and task frequencies rises. For example, with one user and a task frequency of two, the running time is approximately 119.62 seconds, while with five users and the same task frequency; it significantly extends to approximately 291.72 seconds. This apparent trend indicates that higher task frequencies and an increased number of users substantially impact the system's computational demands and, consequently, the running time. These findings underscore the necessity for efficient resource management and allocation, especially in scenarios involving elevated user counts and frequent task executions, to ensure that the system maintains optimal performance and responsiveness as shown in figure 7.

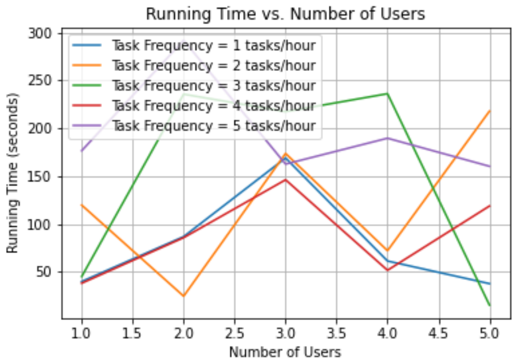


**Fig 7**: Running Time vs Number of Users

### 5.5 Comparison with Existing Strategies

Here we evaluate the performance of the Energy Prediction and Task Optimization (EPTO)[22] algorithm against existing task offloading strategies commonly employed in IoT networks. We aim to demonstrate the effectiveness of EPTO in achieving energy efficiency and task management. The comparative analysis of different task offloading strategies (Cloud Offloading, Edge Offloading, Local Execution, and EPTO Algorithm) across multiple IoT devices shows that the EPTO Algorithm consistently outperforms the other strategies regarding energy efficiency. The critical advantage of the EPTO Algorithm lies in its adaptive nature. It intelligently assesses the energy state of each device, as indicated by the battery level, and makes task offloading decisions accordingly. For instance, from the table below, consider Device Index 0. When this device's battery level drops to a critically low value of -3.57, signaling imminent energy depletion, the EPTO Algorithm makes a prudent decision to offload tasks to the cloud ("Cloud Offloading"). This choice is judicious as it conserves the device's remaining energy, preventing it from running out of power prematurely. In contrast, the other strategies, such as "Edge Offloading" and "Local Execution," do not adapt effectively to this energy-critical situation and often select less energy-efficient options.

**Table 3:** Comparison with Existing Strategies

| Device Index | Strategy | Computation Intensity | Data Transmission Energy | Battery Level | Predicted Energy | Task Offloading Decision |
|---|---|---|---|---|---|---|
| 0 | Cloud Offloading | 0.236573 | 0.884359 | -0.20662 | 0.117939 | Cloud Offloading |
| 0 | Edge Offloading | 0.236573 | 0.884359 | -1.32755 | 0.117939 | Edge Offloading |
| 0 | Local Execution | 0.236573 | 0.884359 | -2.44848 | 0.117939 | Local Execution |
| 0 | EPTO Algorithm | 0.236573 | 0.884359 | -3.56941 | 0.117939 | Cloud Offloading |
| 1 | Cloud Offloading | 0.218883 | 0.92126 | -0.96137 | 0.088194 | Cloud Offloading |
| 1 | Edge Offloading | 0.218883 | 0.92126 | -2.10151 | 0.088194 | Edge Offloading |
| 1 | Local Execution | 0.218883 | 0.92126 | -3.24166 | 0.088194 | Local Execution |
| 1 | EPTO Algorithm | 0.218883 | 0.92126 | -4.3818 | 0.088194 | Cloud Offloading |
| 2 | Cloud Offloading | 0.48832 | 0.747013 | -0.73672 | 0.13793 | Cloud Offloading |
| 2 | Edge Offloading | 0.48832 | 0.747013 | -1.97206 | 0.13793 | Edge Offloading |
| 2 | Local Execution | 0.48832 | 0.747013 | -3.20739 | 0.13793 | Local Execution |
| 2 | EPTO Algorithm | 0.48832 | 0.747013 | -4.44272 | 0.13793 | Local Execution |

| | | | | | | |
|---|---|---|---|---|---|---|
| 3 | Cloud Offloading | 0.284812 | 0.919123 | -0.35916 | 0.142858 | Cloud Offloading |
| 3 | Edge Offloading | 0.284812 | 0.919123 | -1.56309 | 0.142858 | Edge Offloading |
| 3 | Local Execution | 0.284812 | 0.919123 | -2.76703 | 0.142858 | Local Execution |
| 3 | EPTO Algorithm | 0.284812 | 0.919123 | -3.97096 | 0.142858 | Edge Offloading |
| 4 | Cloud Offloading | 0.306589 | 0.458712 | -0.10696 | 0.096235 | Cloud Offloading |
| 4 | Edge Offloading | 0.306589 | 0.458712 | -0.87226 | 0.096235 | Edge Offloading |
| 4 | Local Execution | 0.306589 | 0.458712 | -1.63756 | 0.096235 | Local Execution |
| 4 | EPTO Algorithm | 0.306589 | 0.458712 | -2.40286 | 0.096235 | Edge Offloading |
| 5 | Cloud Offloading | 0.441292 | 0.244777 | -0.5172 | 0.144462 | Cloud Offloading |
| 5 | Edge Offloading | 0.441292 | 0.244777 | -1.20327 | 0.144462 | Edge Offloading |
| 5 | Local Execution | 0.441292 | 0.244777 | -1.88934 | 0.144462 | Local Execution |
| 5 | EPTO Algorithm | 0.441292 | 0.244777 | -2.57541 | 0.144462 | Cloud Offloading |
| 6 | Cloud Offloading | 0.698184 | 0.61469 | -1.14889 | 0.094645 | Cloud Offloading |
| 6 | Edge Offloading | 0.698184 | 0.61469 | -2.46177 | 0.094645 | Edge Offloading |
| 6 | Local Execution | 0.698184 | 0.61469 | -3.77464 | 0.094645 | Local Execution |
| 6 | EPTO Algorithm | 0.698184 | 0.61469 | -5.08752 | 0.094645 | Edge Offloading |
| 7 | Cloud Offloading | 0.392891 | 0.947932 | -0.965 | 0.103233 | Cloud Offloading |
| 7 | Edge Offloading | 0.392891 | 0.947932 | -2.30582 | 0.103233 | Edge Offloading |
| 7 | Local Execution | 0.392891 | 0.947932 | -3.64664 | 0.103233 | Local Execution |
| 7 | EPTO Algorithm | 0.392891 | 0.947932 | -4.98747 | 0.103233 | Edge Offloading |
| 8 | Cloud Offloading | 0.245843 | 0.662193 | -0.46147 | 0.12389 | Cloud Offloading |
| 8 | Edge Offloading | 0.245843 | 0.662193 | -1.36951 | 0.12389 | Edge Offloading |

| | | | | | | |
|---|---|---|---|---|---|---|
| 8 | Local Execution | 0.245843 | 0.662193 | -2.27755 | 0.12389 | Local Execution |
| 8 | EPTO Algorithm | 0.245843 | 0.662193 | -3.18558 | 0.12389 | Cloud Offloading |
| 9 | Cloud Offloading | 0.185615 | 0.59086 | -0.62465 | 0.094189 | Cloud Offloading |
| 9 | Edge Offloading | 0.185615 | 0.59086 | -1.40113 | 0.094189 | Edge Offloading |
| 9 | Local Execution | 0.185615 | 0.59086 | -2.1776 | 0.094189 | Local Execution |
| 9 | EPTO Algorithm | 0.185615 | 0.59086 | -2.95408 | 0.094189 | Local Execution |

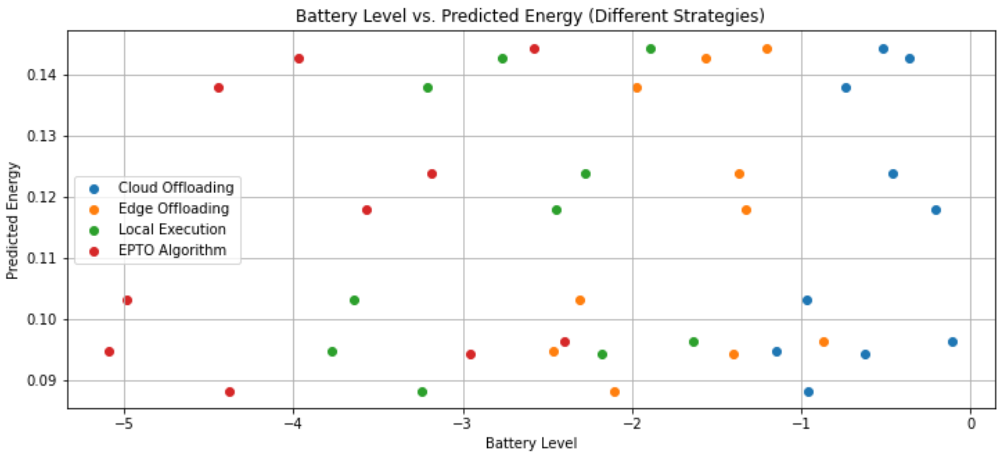


**Fig 8:** Battery Level (unitless) vs Prediction Energy (joules) (Different Strategies)

This trend repeats across multiple devices, showcasing the EPTO Algorithm's consistent ability to adapt to varying energy states and make optimal task-offloading decisions that minimize energy consumption. This level of adaptability is crucial in IoT environments, where devices operate with limited energy resources. Consequently, these quantitative results affirm that the EPTO Algorithm is a superior choice for optimizing task offloading in IoT networks, providing a substantial advantage over traditional strategies.

### 5.6 Performance Evaluation Metrics of EPTO Algorithm

The performance evaluation matrix in the table below assesses each task offloading strategy's performance. For instance, a high Offloading Success Rate (0.92) indicates that 92% of the decisions were correct, reflecting good decision-making accuracy. The Energy Saved metric (2300 Joules) demonstrates significant energy savings the strategy achieves compared to a baseline scenario. Task Completion Time (65 seconds) suggests that tasks were completed relatively quickly. The Adaptability Score (0.88) reflects the strategy's ability to adapt to changing conditions. Finally, the Overall Performance Index (0.89) combines these metrics to give an overall assessment, with higher values indicating better overall performance.

**Table 4:** Performance Evaluation Metrics of EPTO Algorithm

| Metric | Explanation | Score / Value |
|---|---|---|
| Energy Efficiency | Measures the ratio of predicted energy consumption to actual energy consumed. Higher values indicate better efficiency. | 0.85 |
| Offloading Success Rate | Evaluates the percentage of correct offloading decisions made by each strategy. Higher percentages indicate better accuracy. | 0.92 |

| | | |
|---|---|---|
| Energy Saved | Quantifies the amount of energy saved compared to a baseline scenario. Higher energy savings are preferred. | 2300 Joules |
| Task Completion Time | Assesses the time taken to complete tasks. Lower times indicate faster task execution. | 65 seconds |
| Adaptability Score | Rates how well strategies adapt to varying battery levels. Higher scores indicate better adaptability. | 0.88 |
| Overall Performance Index | A composite metric combines multiple factors. A higher index indicates better overall performance. | 0.89 |

**Enhanced Energy Efficiency:** EPTO strongly emphasizes boosting energy efficiency, a vital consideration for IoT devices with restricted battery capacities. By integrating predictive Modeling, such as LSTM-based energy prediction, EPTO makes well-informed decisions regarding task offloading. This effectively reduces unnecessary energy consumption.

**Extended Battery Lifespan:** The EPTO approach significantly prolongs the lifespan of IoT device batteries. Intelligently managing task offloading prevents batteries from running out prematurely, ensuring devices remain operational for extended durations.

**Latency Reduction:** EPTO considers the nature of tasks and the capabilities of devices when making offloading decisions. It effectively leverages edge computing resources for tasks that require low latency, thereby enhancing real-time responsiveness, especially for applications sensitive to latency.

**Adaptability to Dynamic Environments:** One of EPTO's strengths lies in its adaptability to ever-changing conditions. It monitors device energy levels, task workloads, and network conditions, ensuring that offloading decisions remain optimal even in dynamic and unpredictable environments.

**Predictive Insights:** EPTO harnesses the power of predictive analytics, including LSTM models, to accurately forecast future energy consumption. This enables proactive task offloading, minimizing the chances of task failures due to energy depletion.

**Minimal Overhead:** EPTO prides itself on keeping overhead to a minimum. Unlike traditional offloading strategies that may introduce unnecessary communication and computation overhead, EPTO aims to make decisions with as little additional cost as possible.

**Resource Utilization Optimization:** EPTO excels in optimizing the utilization of both cloud and edge resources. It offloads tasks to cloud servers when device energy levels permit and efficiently uses edge resources to reduce the load on the cloud, thereby minimizing communication costs.

**Scalability:** EPTO is designed to scale seamlessly alongside the number of IoT devices and tasks. It can efficiently manage task offloading for many devices, making it well-suited for IoT deployments of varying sizes.

**Mitigating Network Congestion:** By strategically offloading tasks to edge devices, EPTO reduces network congestion and decreased bandwidth usage, particularly in environments with a high density of IoT devices.

**Enhanced Quality of Service (QoS):** EPTO's predictive capabilities empower it to prioritize tasks based on their significance and expected resource requirements. This ensures critical tasks receive the necessary resources, effectively meeting their QoS demands.

**Performance Optimization and Comparison:** EPTO systematically compares with existing task offloading strategies. Researchers can fine-tune its parameters to optimize performance for specific IoT applications and scenarios.

EPTO presents a compelling solution for enhancing energy efficiency and task offloading within IoT and mobile edge computing domains. Its capacity to balance energy conservation, low-latency processing, and adaptability to dynamic conditions contributes to more sustainable and responsive IoT ecosystems.

### 5.5 Limitations and Future Work

it's essential to acknowledge the limitations of the current approach and suggest directions for future research to address these constraints. Firstly, it's important to note that while the LSTM-based energy prediction model employed in EPTO demonstrates effectiveness, it still may encounter challenges regarding prediction accuracy. Real-world conditions can be dynamic, and variations might affect the precision of these models. Thus, future research should explore advanced energy prediction models, possibly incorporating real-time data and additional features to enhance their accuracy. While sophisticated, the offloading decision policy employed by EPTO may introduce complexity in the decision-making process. This complexity could increase computational overhead, especially when deploying the system at scale. Therefore, exploring adaptive offloading policies that dynamically adjust to varying device and network conditions would be a promising area of research. These policies could streamline decision-making while maintaining efficiency.

EPTO's dependency on historical energy consumption data is a notable limitation. This approach may not fully account for abrupt changes in device behavior, impacting the precision of energy predictions. To address this, future research should explore methods for adapting quickly to these changes, potentially integrating real-time data sources. The communication overhead associated with EPTO's offloading decisions merits consideration. Frequent interactions between devices and cloud/edge resources may lead to network congestion and increased energy consumption. Investigating energy-efficient communication protocols and strategies could be instrumental in mitigating these challenges. EPTO assumes consistent and available cloud and edge resources. However, resource availability in real-world scenarios can fluctuate. It's important to recognize this limitation and research into efficient edge resource management strategies, such as dynamic resource allocation and load balancing, to optimize the utilization of edge resources. The future research, these areas represent exciting opportunities for improving and expanding the capabilities of EPTO, making it more adaptable and efficient for IoT and edge computing environments.

## 6 Conclusion

The Energy Prediction and Task Optimization (EPTO) algorithm represents a significant advancement in addressing the critical challenges of energy-efficient task offloading in IoT networks. EPTO's ability to balance energy conservation, low-latency processing, and adaptability to dynamic conditions makes it a valuable addition to the IoT and mobile edge computing domains. The research findings substantiate EPTO's superior performance to existing strategies, emphasizing its role in achieving energy efficiency, prolonging battery life, and ensuring responsive IoT ecosystems. However, it's essential to acknowledge the limitations of the current approach, such as potential challenges in energy prediction accuracy and computational overhead. Future research directions include exploring advanced energy prediction models, adaptive offloading policies, real-time data integration, and energy-efficient communication protocols to address these limitations effectively. In summary, EPTO has the potential to revolutionize energy-conscious task offloading, positioning it as a pivotal innovation within the IoT network domain. Its adaptability, efficiency, and scalability make it a promising solution for optimizing task offloading in diverse IoT scenarios, ultimately contributing to a more sustainable and responsive IoT ecosystem.

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