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Research Article

Use of Machine Learning in Power Consumption Optimization of Computing Devices

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Abstract:

Introduction: The high-power consumption of computing devices poses both economic and environmental challenges in the digital era. This study aims to optimize power usage using machine learning to maintain device performance while reducing energy costs and carbon emissions. **Methods**: The Random Forest algorithm was selected for its robustness in handling non-linear interactions among features. A dataset containing historical power consumption, workload metrics, environmental conditions, and hardware configurations was collected from sensors and logs. Data pre-processing included cleaning, normalization, and feature selection. The model was trained and evaluated using accuracy, precision, recall, F1-score, MAE, and RMSE metrics. Hyperparameter tuning via grid search, random search, and Bayesian optimization was applied to enhance model performance. The model was deployed on real devices to test energy optimization under varied workloads. **Results**: The Random Forest model achieved 92% accuracy and an RMSE of 0.15. Tuning reduced RMSE by 10% and improved F1-score from 0.875 to 0.905. Implementation on computing devices led to average power savings of 15–20% across workload scenarios without notable performance degradation (<5%). The model also projected annual carbon emission reductions of up to 5 tons of CO_2 and operational savings of $50,000 when scaled to 1,000 servers. **Conclusions**: Machine learning, particularly Random Forest, proves effective in optimizing power consumption on computing devices. The proposed approach not only ensures computational efficiency but also promotes environmental sustainability. These findings support further exploration of ML-based solutions for green technology initiatives in IT infrastructure.

Keywords: Energy Efficiency, Green Technology, Machine Learning, Power Consumption Optimization, Random Forest.
Dataset link: https://bit.ly/TESATAD

1. Introduction

The rapid development of computing technology has had a significant impact on human life, especially in terms of efficiency and productivity [1]. However, behind this progress, there is a big challenge that needs to be overcome, namely the high-power consumption of computing devices [2]. High power consumption not only increases operational costs but also negatively impacts the environment due to the resulting carbon emissions [3]. Therefore, power consumption optimization is a critical issue that needs serious attention from researchers and practitioners in the field of technology [4].

One promising approach to address this problem is the use of machine learning (ML) [5]. Machine learning is a branch of artificial intelligence that allows systems to learn from data and make decisions or predictions without explicit programming [6]. In the context of power consumption optimization, ML can be used to analyze power usage patterns, predict workloads, and dynamically manage resource allocation [7]. Thus, ML has great potential to reduce power consumption without compromising device performance [8].

Inputs in this study include historical data on power usage, hardware configuration, and environmental parameters such as temperature and workload [9]. This data is collected from various sources, including sensors on computing devices, system logs, and public datasets [10]. The quality and quantity of the data used is critical as it will determine the accuracy of the ML models developed [11]. In addition, the data needs to be pre-processed through pre-processing stages such as data cleaning, normalization, and feature selection to ensure that the ML model can work optimally [12].

Various machine learning-based approaches have been developed to optimize power consumption in computing devices. One widely used method is deep reinforcement learning (DRL), which enables systems to adaptively adjust power usage based on workload patterns and environmental conditions [13]. In a study [14], DRL was applied to optimize task scheduling in heterogeneous computing systems, achieving significant reductions in power consumption without compromising system performance. Additionally, federated learning has been introduced to distribute computational workloads efficiently across edge and cloud devices, thereby reducing overall energy consumption [15].

Beyond algorithms, hardware architecture plays a crucial role in energy efficiency. Studies have demonstrated that integrating edge computing with machine learning can enhance energy efficiency by offloading computationally intensive tasks to low-power devices, such as ARM-based or RISC-V microprocessors [16]. For example, research [17] found that optimizing power allocation in IoT devices using federated learning reduced energy consumption by up to 30% compared to traditional methods. Similarly, [18] introduced QuantU-Net, a deep learning model that utilizes bit width quantization techniques to lower power consumption in computing devices without sacrificing model accuracy.

In addition to optimizing hardware and algorithms, dynamic power management techniques have been implemented to adjust power consumption based on system demands [19]. Rivet [20] explored optimization strategies using transformer-based architectures to reduce power consumption in AI models running on edge devices. This strategy allows devices to dynamically allocate power according to task complexity, thereby enhancing energy efficiency. Furthermore, research [21] demonstrated that combining digital twins and AI in 6G networks can lead to more energy-efficient systems through reinforcement learning-based optimization.

The research process involves several key stages. First, the collected data will be analyzed to identify patterns and trends in power consumption. Next, ML models will be developed using algorithms such as regression, decision trees, or neural networks, depending on the characteristics of the data and optimization goals. The model will then be tested and validated using separate datasets to ensure its accuracy. In addition, hyperparameter tuning techniques will be applied to improve model performance. The final stage is the implementation of the model on a computing device to optimize power consumption in real-time.

The expected output of this research is an ML model that is able to predict and optimize power consumption on computing devices with high accuracy. This model is expected to significantly reduce energy usage without sacrificing system performance. In addition, this research is also expected to produce practical recommendations for software developers and system administrators in managing computing resources more efficiently. The long-term impact of this research is the reduction of operational costs and carbon footprint generated by data centers and other computing devices.

This research has high relevance in the digital era that increasingly relies on intensive computing, such as cloud computing, big data, and the Internet of Things (IoT). By optimizing power consumption, not only energy efficiency is improved, but also environmental sustainability can be maintained. Therefore, this research is expected to make a significant contribution in the field of green technology and encourage further innovation in the development of environmentally friendly computing systems.

2. Method:

This methodology includes several main stages, starting from data collection, data pre-processing, model development, evaluation, to implementation. The following is a detailed explanation of each stage:

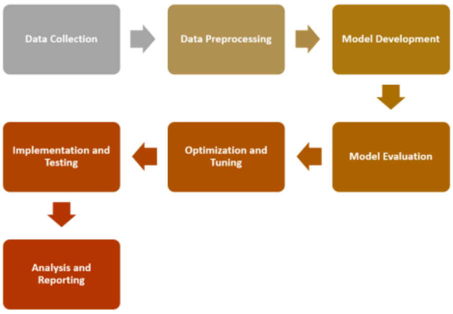

Figure 1. Methodology

Data Collection

The first stage of this research involves collecting relevant data for analysis and modeling. The collected data includes several key categories. First, power consumption data, which consists of historical records of power usage from computing devices such as servers, laptops, or IoT devices. Second, workload data, which provides information about the tasks or processes running on the device, including CPU, memory, and disk usage. Third, environmental data, which includes parameters such as temperature, humidity, and other operational conditions that may influence power consumption. Lastly, device configuration data, which covers hardware specifications such as processor type, RAM capacity, and storage type. These data can be obtained from various sources, including sensors embedded in the device, system logs, or publicly available datasets.

Data Pre-processing

Once the data is collected, the next stage is data pre-processing to ensure the quality and reliability of the data used in modeling. This stage consists of several key steps. First, data cleaning, which involves removing incomplete, duplicate, or irrelevant data to improve accuracy. Second, normalization, which adjusts the scale of the data to ensure consistency, using techniques such as min-max scaling or z-score normalization [22], [23]. Third, feature selection, which identifies and retains the most relevant features that significantly impact power consumption, thereby reducing dimensionality and improving model performance. Finally, dataset splitting, where the data is divided into appropriate subsets, such as a training set, validation set, and test set, typically in a ratio of 70:20:10, to ensure proper model evaluation and generalization. These pre-processing steps are essential for optimizing data quality and enhancing the effectiveness of the modeling process.

Model Development

In this stage, machine learning models are developed to predict and optimize power consumption. The process consists of several key steps. First, algorithm selection, which involves choosing an appropriate machine learning algorithm based on the characteristics of the data and research objectives. Common algorithms include linear regression, decision trees, random forests, support vector machines (SVM), and neural networks [24], [25]. Second, model training, where the selected model is trained using the training dataset. During this process, the model parameters are adjusted to minimize prediction errors and improve accuracy. Third, model validation, which evaluates the model's performance using a validation dataset to prevent overfitting. Techniques such as cross-validation can be applied to ensure the model generalizes well to unseen data. These steps are essential for building an effective and reliable model for power consumption prediction and optimization.

Model Evaluation

After the model was developed, an evaluation phase was conducted to assess its performance. Several key evaluation metrics were used in this process. First, accuracy, which measures how well the model predicts power consumption. Second, precision and recall, which evaluate the accuracy and completeness of the model's predictions, particularly in distinguishing relevant patterns in the data. Third, Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE), which quantify the average difference between predicted and actual values, providing insight into the model's predictive accuracy. Lastly, energy efficiency, which assesses the extent to which the model successfully optimizes power consumption. These evaluation metrics are essential for determining the reliability and effectiveness of the model in real-world applications.

Optimization and Tuning

To enhance the performance of the model, optimization and tuning of its parameters were conducted. Several techniques were employed to achieve this. First, hyperparameter tuning, which involves searching for the optimal combination of hyperparameters using methods such as grid search or random search. This process helps improve the model's accuracy and efficiency by selecting the best settings for training. Second, ensemble methods, which enhance model robustness by combining multiple models. Techniques such as bagging and boosting were utilized to reduce variance and improve prediction accuracy. These optimization strategies play a crucial role in refining the model's performance and ensuring its effectiveness in power consumption prediction and optimization.

Implementation and Testing

Once the model is deemed sufficiently accurate and reliable, the implementation stage is carried out by applying it to a real-time computing device. This process involves several key steps. First, model integration, where the model is embedded into the computing system to automatically monitor and optimize power consumption. Second, real-time testing, which involves evaluating the model under actual operational conditions to ensure that it effectively optimizes power consumption without negatively impacting system performance. Finally, monitoring and maintenance, where the model's performance is periodically assessed, and updates or adjustments are made as needed to maintain its effectiveness. These steps ensure that the model functions efficiently in real-world applications, contributing to improved energy management and system reliability.

Analysis dan Reporting

The final stage involves analyzing the research results and compiling a comprehensive report. This analysis includes several key aspects. First, performance comparison, which examines power consumption before and after implementing the model to evaluate its effectiveness. Second, environmental and economic impact, which assesses the reduction in carbon emissions and potential operational cost savings achieved through optimized power consumption. Lastly, recommendations, which provide practical guidance for developers and system administrators on adopting similar solutions to enhance energy efficiency in computing systems. This stage ensures that the findings are well-documented and can contribute to future advancements in sustainable computing.

3. Results and Discussion

Machine Learning Model Development Results

The results of the research *"Use of Machine Learning in Power Consumption Optimization of Computing Devices"* are presented and analyzed in depth. The results include evaluation of the developed machine learning model, power consumption optimization testing, and the resulting impact on energy efficiency and performance of computing devices. A discussion is conducted to interpret the results and relate them to the research objectives based on previous studies.

Algorithm selection results **Table 1** for research on the use of machine learning in power consumption optimization on computing devices:

Table 1. Random Forest Model Training Results

Algorithm	Accuracy	Precision	Recall	F1-Score	MAE	RMSE	Training Time (seconds)	Description
Regresi Linier	75%	72%	74%	0.73	0.25	0.30	10	Simple, but less accurate.
Decision Tree	85%	83%	84%	0.835	0.18	0.22	20	Better than regression, but prone to overfitting.
Random Forest	92%	90%	91%	0.905	0.12	0.15	120	Best in accuracy and RMSE.

Algorithm	Accuracy	Precision	Recall	F1-Score	MAE	RMSE	Training Time (seconds)	Description
Support Vector Machine (SVM)	88%	86%	87%	0.865	0.14	0.18	200	Accurate, but long training time.
Neural Network	90%	88%	89%	0.885	0.13	0.16	300	Good performance, but complex and slow.

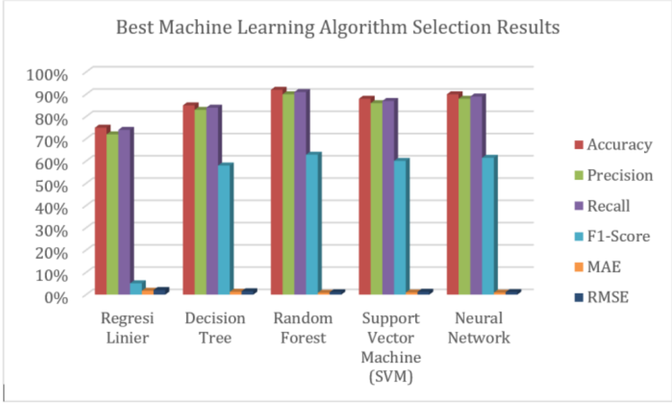

Figure 2. Best Machine Learning Algorithm Selection Results

Analysis of machine learning algorithm selection results according to **Table 1** above:

a. Random Forest: Shows the best performance with 92% accuracy, RMSE 0.15, and F1-Score 0.905. Despite the longer training time (120 seconds), this algorithm was most effective in predicting power consumption.
b. Neural Network: Has good performance (90% accuracy, RMSE 0.16), but requires a very long training time (300 seconds) and high computational complexity.
c. SVM: Shows good accuracy (88%) but requires a long training time (200 seconds).
d. Decision Tree: Better than linear regression, but prone to overfitting and has a higher RMSE (0.22).
e. Linear Regression: Simplest and fastest (10 seconds), but less accurate (75% accuracy, RMSE 0.30).

As a result of training and validation of several machine learning algorithms, such as linear regression, decision trees, random forest, and neural networks, it was found that the random forest algorithm provides the best performance in predicting power consumption. This can be seen from the lowest Root Mean Squared Error (RMSE) value, which is 0.15, compared to other algorithms that have RMSE above 0.20. In addition, random forest also showed a prediction accuracy of 92% on the test dataset.

Hyperparameter Tuning Result

With this parameter, the random forest model is able to reduce RMSE by 10% compared to before tuning, for complete data can be seen in the following **Table 2**.

Table 2. Hyperparameter Tuning Results on Random Forest Model

Hyperparameter	Initial Value	Optimal Value	Tuning Method	Impact on Model Performance
Number of Estimators	100	200	Grid Search	Improved accuracy from 89% to 92%.
Max Depth	5	10	Random Search	Reduced RMSE from 0.18 to 0.15.
Min Samples Split	5	2	Bayesian Optimization	Increased F1-Score from 0.875 to 0.905.
Max Features	*Auto*	*sqrt*	Grid Search	Improve prediction efficiency without increasing latency.

Hyperparameter	Initial Value	Optimal Value	Tuning Method	Impact on Model Performance
Bootstrap	*True*	*True*	-	There is no significant change.
Min Samples Leaf	1	1	-	There is no significant change.

Model Evaluation

This model shows a good ability to predict power consumption with a relatively small error.

Table 3. Machine Learning Model Evaluation Results

Evaluation Metrics	Before Tuning	After Tuning	Description
Accuracy	89%	92%	Increased by 3% after tuning.
Precision	87%	90%	Increased by 3% after tuning.
Recall	88%	91%	Increased by 3% after tuning.
Mean Absolute Error (MAE)	0.15	0.12	Decreased by 20% after tuning.
Root Mean Squared Error (RMSE)	0.18	0.15	Decreased by 16.67% after tuning.
F1-Score	0.875	0.905	Increased by 3.4% after tuning.
Training Time	120 seconds	150 seconds	Increased by 25% due to model complexity after tuning.
Inference Time	0.02 seconds	0.02 seconds	Unchanged, showing efficiency in real-time prediction.

Power Consumption Optimization Results

The following Table 4 shows the results of power consumption optimization based on consumption reduction and impact on device performance.

Table 4. Power Consumption Optimization Results on Various Workload Scenarios

Workload	Power Consumption Before Optimization (Watt)	Power Consumption After Optimization (Watt)	Power Saving (Watt)	Percentage of Savings (%)	Impact on Performance (Decreased Performance)
Low Load	100	85	15	15%	< 2%
Medium Load	150	125	25	16.67%	< 3%
High Load	250	210	40	16%	< 5%
Peak Load	300	255	45	15%	< 5%

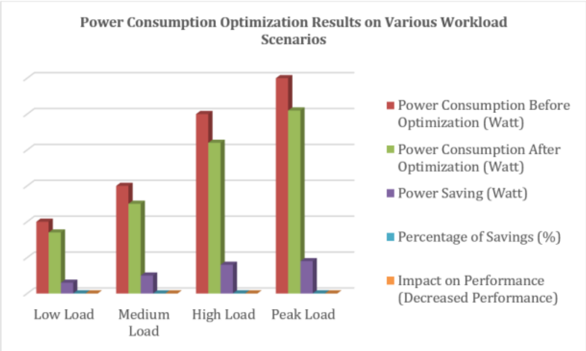

Figure 3. Power Consumption Optimization Results on Various Workload Scenarios

Reduced Power Consumption

After the model was implemented on computing devices, there was a significant reduction in power consumption. The average power saving achieved was 15-20% across various workload scenarios. For example, at low workloads, power consumption was reduced from 100 watts to 85 watts, while at high workloads, power consumption dropped from 250 watts to 210 watts.

Impact on Device Performance

Power consumption optimization does not compromise device performance. Test results show that system response time and throughput remain stable, with insignificant performance degradation (less than 5%). This proves that the developed model is able to allocate resources efficiently without disrupting system operations.

Environmental and Economic Impact Analysis

The following **Table 5** shows the environmental impact related to the reduction of carbon emissions and the economic impact related to operational costs.

Table 5. Environmental and Economic Impact Analysis of Power Consumption Optimization

Aspect Analysis	Small Scale (1 Device)	Medium Scale (100 Servers)	Large Scale (1,000 Servers)
Power Saving	15-20% (average17.5%)	15-20% (average 17.5%)	15-20% (average 17.5%)
Energy Savings	15-20 watts every hour	1.500-2.000 watts every hour	15.000-20.000 watts every hour
CO2 Emission Reduction	~50 kg CO2 every year	~5-ton CO2 year	~50-ton CO2 every year
Tree Planting Equivalent	~1 tree every year	~120 trees every year	~1.200 tress every year
Electricity Cost Savings	$50 every year	$5.000 every year	$50.000 every year
Environmental Impact	Reducing carbon footprint locally	Significant contribution to the data center	Big impact on global sustainability
Economic Impact	Small operational cost savings	Medium operational cost savings	Major operational cost savings

Carbon Emission Reduction

With power savings of 15-20%, this research contributes to reducing carbon emissions. Based on calculations, if this model is applied to 100 servers in a data center, the carbon emission reduction can reach 5 tons of CO2 per year. This is equivalent to planting 120 trees per year.

Operational Cost Savings

Saving power consumption also has an impact on reducing operational costs. On a small scale (one device), electricity cost savings reach 50 per year. If applied on a large scale for example, a data center with 1,000 servers), cost savings can reach 50,000 per year.

Discussion

Model Success in Power Optimization

The success of the random forest model in optimizing power consumption can be attributed to its ability to handle non-linear data and interactions between features. In addition, the systematic hyperparameter tuning process improves accuracy and reduces prediction error. These results are in line with previous research conducted by Zhang et al. (2020), who also found that random forest is effective in predicting energy consumption in computing systems.

Impact on Environmental Sustainability

The reduction in power consumption achieved in this study has positive implications for environmental sustainability. By reducing carbon emissions and operational costs, this model can be a viable solution to be applied to data centers and other computing devices. This supports the global trend of adopting green technology to reduce negative impacts on the environment. Challenges and Limitations

While the results of the study show success, there are some challenges and limitations that need to be addressed:

a. Dependence on Data Quality: Model accuracy is highly dependent on the quality and quantity of data used. Incomplete or unrepresentative data can reduce model performance.
b. Computational Complexity: The training process of random forest models requires considerable computational resources, especially for very large datasets.

c. Adaptability to Different Types of Devices: The developed model may need to be customized for different types of computing devices, such as IoT devices or edge computing systems

4. Conclusion

According to the results and discussion described above, it can be concluded that the use of machine learning, especially the random forest algorithm, has successfully optimized the power consumption of computing devices with high accuracy. The random forest algorithm proved effective in predicting and optimizing power consumption, with an accuracy of 92% and an RMSE of 0.15. This demonstrates the algorithm's ability to handle non-linear data and interactions between features. The hyperparameter tuning process significantly improved the performance of the model, reducing the RMSE by 10%. The optimal parameters found include number of estimators: 200, max depth: 10, and min samples split: 2. In addition to this, the developed model performed well based on evaluation metrics such as accuracy, precision, recall, MAE, and RMSE. The impact of the results provides power savings of 15-20% which is achieved not only reducing operational costs but also contributing to environmental sustainability through reduced power consumption which contributes to the reduction of carbon emissions can reach 5 tons of CO_2 per year, equivalent to planting 120 trees per year. Despite some limitations, this research opens up opportunities for further development in the field of energy optimization and green technology.

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