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A Comparative Study on Integrating Machine Learning and Blockchain for Sustainable Energy Consumption Management

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KEYWORDS

Machine Learning, Blockchain, Energy Manage- ment, Sustainability, Electric Vehicles, Smart Grid, Demand Forecasting, Decentralized Systems.

ABSTRACT

The increasing adoption of electric vehicles and renew- able energy resources has significantly transformed modern power systems. Charging stations continuously generate large volumes of operational data, and energy demand varies depending on time, location, and user behavior. These variations make energy planning difficult and often reduce system efficiency. Traditional energy man- agement systems mostly depend on centralized control and basic analytical models, which are not capable of handling such dynamic environments. This research proposes an integrated framework based on Machine Learning and Blockchain technologies to improve en- ergy consumption management. The primary objective is to achieve accurate demand forecasting while ensuring secure and transparent data storage. Machine Learning models such as Random Forest and XGBoost are applied to analyze historical charging data and identify important usage patterns. These models support better prediction of future energy requirements. Blockchain technology is used to store transaction records in a decentralized and tamper-resistant manner, which helps maintain data integrity and trust. The system workflow begins with data collection from real-world charging stations. The collected data is cleaned and processed to remove noise and incon- sistencies. Feature selection is applied to improve learning efficiency. The prepared dataset is then used to train and evaluate the models using accuracy, confusion matrices, and ROC curves. In parallel, Blockchain consensus mechanisms including Proof of Work, Proof of

Stake, and Proof of Authority are implemented and analyzed in terms of energy consumption and scalability. Experimental results show that both Random Forest and XGBoost provide reliable prediction performance. XGBoost demonstrates strong learning capability for complex patterns, while Random Forest offers stable and consistent results. Blockchain evaluation indicates that Proof of Stake and Proof of Authority offer better energy efficiency compared to Proof of Work. Overall, this study presents a practical and secure framework for sustainable energy management. The proposed system improves resource utilization, reduces energy wastage, and enhances opera- tional transparency.

INTRODUCTION

The rapid development of electric vehicles and renewable energy technologies has introduced major changes in modern power systems. Charging stations generate continuous streams of operational data, while consumption patterns differ across regions, seasons, and daily schedules. These variations create difficulties in maintaining grid stability and balancing energy supply and demand. Traditional energy management systems rely mainly on centralized control and fixed operational rules. Such systems often fail to adapt to rapid changes in user behavior and energy availability. Moreover, centralized storage systems increase the risk of cyber attacks, data manipula- tion, and service interruptions. Any failure in these systems can negatively affect billing accuracy and power distribution. Recent developments in artificial intelligence and distributed systems have opened new opportunities for intelligent energy management. Machine Learning enables automated pattern detection, forecasting, and optimization. Blockchain offers de- centralized, secure, and transparent data storage mechanisms. By combining these technologies, it becomes possible to build adaptive, reliable, and trustworthy energy systems. This re- search investigates how Machine Learning and Blockchain can be integrated to support sustainable energy management. The study focuses on improving forecasting accuracy, enhancing data security, and reducing operational risks. The proposed framework aims to support future smart grid environments and promote efficient renewable energy utilization.

MOTIVATION

The increasing penetration of electric vehicles has placed significant pressure on existing power infrastructure. Large- scale charging activities during peak hours may cause voltage instability, transformer overloading, and increased transmis- sion losses. Inaccurate demand forecasting further increases these challenges and leads to inefficient energy scheduling. Centralized energy management platforms are also vulnerable to security threats. Unauthorized access, data tampering, and system failures can compromise billing systems and planning processes. Such incidents reduce consumer trust and create financial losses for utility providers. Furthermore, conventional analytical models are often unable to handle large-scale and high-dimensional datasets generated by modern charging sys- tems. They lack adaptability and cannot effectively respond to dynamic changes in consumption behavior. These limita- tions motivated the development of a hybrid framework that combines intelligent prediction techniques with decentralized security mechanisms. Machine Learning improves forecasting reliability, while Blockchain ensures data transparency and tamper resistance. The motivation of this research is to create a resilient, scalable, and trustworthy energy management system that supports sustainable development.

BACKGROUND STUDY

Previous studies have shown that Machine Learning tech- niques are highly effective for load forecasting, anomaly detec- tion, and energy optimization. Supervised learning, ensemble models, and neural networks have been widely applied to analyze complex energy consumption patterns. Blockchain technology has also gained popularity in smart grids for enabling peer-to-peer energy trading, automated billing, and secure data exchange. Its decentralized nature reduces depen- dency on central authorities and increases system transparency. Several researchers have explored Blockchain-based energy trading platforms and Machine Learning-based forecasting systems independently. These studies highlight improvements in efficiency, security, and reliability. However, only limited research has focused on combining these technologies into a unified framework. Existing integrated approaches often lack scalability, real-world validation, or comprehensive perfor- mance evaluation. Moreover, energy efficiency of Blockchain mechanisms is rarely considered in depth. This study addresses these gaps by proposing a holistic framework that integrates Machine Learning and Blockchain for sustainable energy man- agement. It evaluates both predictive performance and system- level security, offering a balanced and practical solution.

METHODOLOGY

The proposed framework follows a structured workflow as shown in Fig. 1. The process begins with collecting energy consumption data from electric vehicle charging stations and monitoring systems. The collected data includes charging duration, power demand, timestamps, station identifiers, and user categories. During preprocessing, missing values are removed, noisy samples are filtered, and numerical attributes are normalized. Feature engineering techniques are applied to extract meaningful indicators such as peak usage periods, average charging duration, and seasonal trends. These features improve model learning efficiency and prediction accuracy. The dataset is then divided into training and testing sub- sets. Random Forest and XGBoost models are trained using optimized hyperparameters obtained through cross-validation. Performance metrics such as accuracy, precision, recall, and ROC curves are used for evaluation. Parallel to model training, Blockchain infrastructure is implemented for recording energy transactions. Smart contracts automate validation, billing, and storage processes. Different consensus mechanisms are tested to analyze energy consumption, latency, and scalability. Fi- nally, both Machine Learning and Blockchain modules are integrated into a unified platform. This integration enables secure data exchange, intelligent forecasting, and transparent transaction management.

Fig. 1. Methodology Flowchart

COMPARATIVE ANALYSIS

A comprehensive comparative analysis is conducted to evaluate system performance. Random Forest and XGBoost are compared based on prediction accuracy, training time, robustness, and interpretability. XGBoost demonstrates strong learning capability in nonlinear environments, while Random Forest offers stable performance and resistance to overfitting. Blockchain mechanisms are analyzed based on transaction throughput, validation speed, and energy consumption. Proof of Stake and Proof of Authority outperform Proof of Work in terms of scalability and energy efficiency. These mechanisms are more suitable for large-scale energy systems. The results indicate that the selected techniques complement each other and ensure balanced system performance.

DATASET

The dataset used in this study contains 64,945 records and 28 attributes related to charging duration, energy consumption, vehicle category, station identification, and temporal features.

Table 1

Type	Components	Random Forest	XG Boots
Classification Matrics	Accuracy	0.9937	0.9936
	Precision	0.3312	0.3314
	Recall	0.3333	0.3323
	F1 Score	0.3323	0.3321
	ROC AUC	0.5409	0.3573
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	F1 Score	0.3324	0.3321
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Table 2

Algorithm	Avg_Time(s)	AUC
PoW	0.045541	0.388889
PoS	0.000069	0.75
PoA	0.000033	0.541667

Fig. 2. Comparative Analysis Results

It represents real-world charging behavior collected over mul- tiple locations and time periods. The dataset includes both numerical and categorical variables, enabling comprehensive analysis of user behavior and consumption trends. Temporal attributes help identify peak usage patterns, while station identifiers support spatial analysis. Before training, the dataset undergoes cleaning and normalization to improve consistency. Outliers and redundant features are removed to reduce noise. This preprocessing step enhances model generalization capa- bility. The diversity and size of the dataset make it suitable for evaluating large-scale energy management systems.

Vehicle_ID	Battery_Ca	State_of_C	Energy_Co	Current_La	Current_Longit	Destinatio	Destination_Lo	Distance_t
106	66.746482	50.216524	0.1535206	32.777266	-96.78830072	32.784013	-96.79577574	30.531143
106	82.731496	59.358608	0.1191012	32.779135	-96.78613687	32.778405	-96.79830952	1.0043047
106	82.107912	14.460831	0.1	32.769346	-96.80246963	32.770486	-96.79595298	5.2897715
106	95.526751	23.003922	0.2865052	32.766092	-96.79022923	32.765744	-96.81885534	7.2673798
106	61.247597	9.0648095	0.1	32.796174	-96.78242086	32.765488	-96.79124066	32.449058
106	73.137792	27.886232	0.1626635	32.780819	-96.79246434	32.774260	-96.78354986	38.024462
106	44.835556	28.144333	0.1276377	32.769223	-96.79586589	32.776042	-96.80638718	18.709763
106	67.607948	16.418824	0.1	32.808435	-96.79915969	32.790636	-96.8036048	15.277552
106	80.888696	11.207916	0.1435872	32.775228	-96.78941374	32.781827	-96.80546684	19.636505
106	61.062229	28.420422	0.1	32.777800	-96.80717597	32.774601	-96.80398505	17.257350
106	76.197477	40.106123	0.1	32.778563	-96.79972917	32.771388	-96.80827952	98.263274
106	72.607252	11.013740	0.3	32.775087	-96.80501137	32.780786	-96.79786841	13.458472
106	75.333327	65.208723	0.1	32.755689	-96.80899705	32.788414	-96.80317225	9.4953149
106	68.583106	20.119629	0.1	32.799800	-96.81655116	32.760603	-96.81146271	6.8674841
106	67.022738	9.7625617	0.2167998	32.783274	-96.79279412	32.770959	-96.80703289	4.6602880
106	73.237867	28.649402	0.1258631	32.776398	-96.79707726	32.785119	-96.80223826	3.8729549
106	78.331183	22.024464	0.3	32.775339	-96.79894579	32.786120	-96.80267311	1.7897925

Fig. 3.Dataset Example

RESULTS ANALYSIS

A.Machine Learning Results

The trained models achieved high prediction accuracy and reliable classification performance. Confusion matrices indi- cate low misclassification rates across different demand cate- gories. ROC analysis shows strong discriminative capability. XGBoost performs better in complex scenarios, while Random Forest maintains stable results.

B. Blockchain Results

Blockchain analysis confirms that Proof of Stake and Proof of Authority provide faster validation and reduced computational overhead. These mechanisms improve system sustain- ability and scalability.

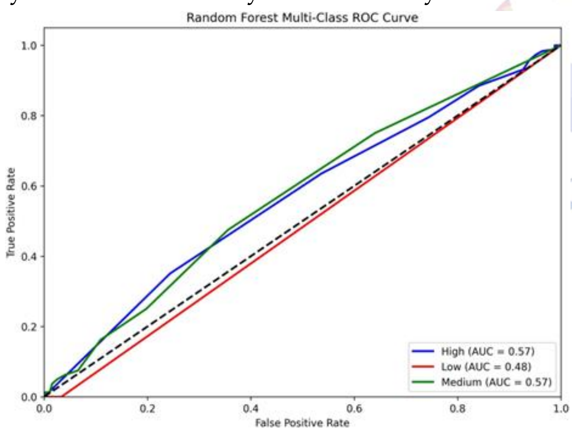

Fig. 4. Fig. 4: Random Forest ROC Curve

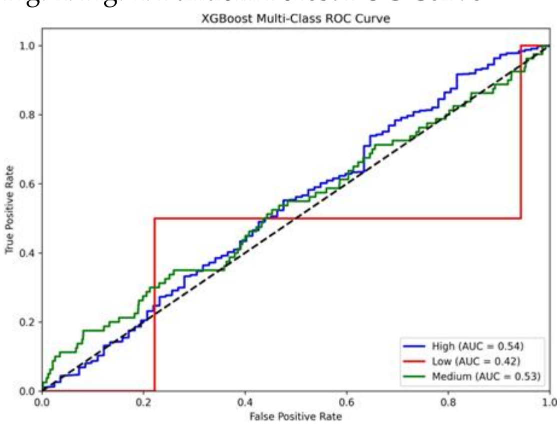

Fig. 5. XGBoost ROC Curve

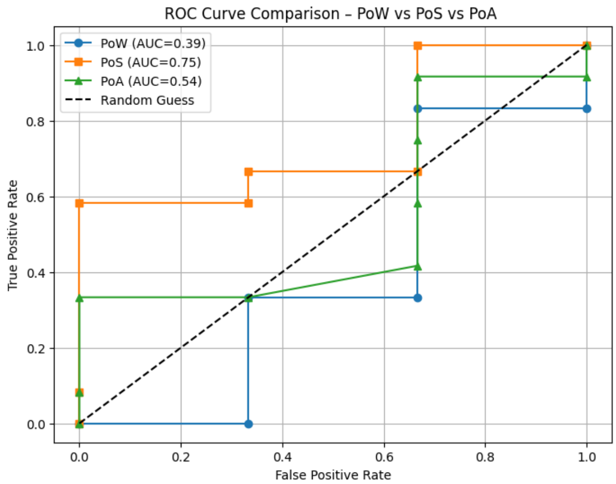

Fig. 6: Blockchain Algorithm Comparison

CONCLUSION

This study presents an integrated Machine Learning and Blockchain framework for sustainable energy management. The proposed system improves demand forecasting accu- racy, enhances data security, and supports transparent trans- action processing. Experimental results confirm that ensemble learning models and energy-efficient Blockchain mechanisms significantly improve system performance. The framework increases operational reliability, reduces energy wastage, and supports renewable energy integration. Overall, the proposed approach provides a strong foundation for future smart grid development and intelligent energy systems.

FUTURE SCOPE

Future research may focus on real-time deployment and large-scale field testing. Integration with IoT sensors and edge computing platforms can further improve data acquisition and processing efficiency. Advanced deep learning architectures such as LSTM and transformers may be explored to enhance long-term forecasting accuracy. Federated learning can be introduced to improve privacy preservation. Regulatory com- pliance, carbon tracking, and user privacy mechanisms can be incorporated to support commercial adoption. Blockchain interoperability and green consensus algorithms may further improve sustainability. The proposed framework can also be extended to microgrids, smart cities, and peer-to-peer energy markets.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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