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IMPROVING THE EFFICIENCY OF RICE HUSK FUEL USING MULTIPARAMETRIC ENHANCEMENTS & INCREMENTALLY CONTROLLED BIOINSPIRED TRIALS WITH TEA WASTE .

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Abstract: Innovative and sustainable energy sources are required to meet the rising global energy demand. Briquettes made from biomass, notably those made from rice husk and tea waste and bound with maize starch, offer a viable route towards producing cleaner energy. Even while earlier research was encouraging, it barely scraped the surface of this field's potential. These limitations included a lack of ideal composition, scant mechanical and chemical characterizations, insufficient energy efficiency evaluations, and insufficient emission analyses. Our work suggests a comprehensive approach for improving the effectiveness, cost-effectiveness, and storage capacities of rice husk fuel by using Tea Waste in order to counteract these difficulties. In order to improve calorific value and reduce ash content, we introduced multiparametric improvements, which are made up of an optimised mixture of rice husk, & tea waste briquettes. Deeper insights into the briquettes' physical characteristics and function as an energy source came from thorough mechanical and chemical characterizations. A thorough analysis of energy efficiency that took into account the energy needs at every step of the briquette-making process provided a detailed picture of the overall energy balance levels. To determine how these briquettes will affect the environment, we also performed a thorough emission analysis. Our comprehension of the features of the briquettes under various circumstances has been improved through investigations on long-term stability and storage process. To shed light on the environmental impact throughout the life cycle of the briquette, a comprehensive life cycle assessment (LCA) was conducted for different use cases. All of these improvements were carried out using an iterative Deep Q Network and a VARMAx approach, enabling the development of a highly accurate prediction model for the manufacture and use of biomass briquettes. The efficiency, price, storage capacity, and conversion efficiency of the briquettes were all significantly increased as a result of this iterative, bio-inspired method. Thus, our research establishes a new standard for biomass energy generation that is cleaner, more efficient, and more affordable, opening the door for future energy choices that are more environmentally friendly for real-time scenarios.

Keywords: Biomass Briquettes, Tea Waste, Rice Husk Fuel, Energy Efficiency, Emission Analysis, Deep Q Networks

1. Introduction

Alternative and greener energy sources are needed now more than ever because of the exponential growth in the world's energy consumption. Biomass, notably in the form of briquettes generated from agricultural waste materials like rice husk and tea waste, is one of the most promising sources of alternative energy. These biomass briquettes have two benefits: they offer a clean, sustainable source of energy and they enable the effective use of waste materials that would otherwise be thrown away thus causing wastage levels via Response Surface Methodology (RSM) and other methods [1, 2, 3].

Previous research has shown the potential of biomass briquettes made from waste tea leaves and rice husks. Corn starch is used as a binding agent for different scenarios, and can be estimated via Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) Process [4, 5, 6]. These briquettes have a good calorific value, a high carbon content, and a low ash level, which makes them a desirable energy source. However, there are still a number of undiscovered or underexplored facets to this energy producing techniques. To comprehend and improve the different aspects that affect the performance and efficacy of these briquettes, a more thorough analysis is required for different scenarios [7, 8, 9].

For instance, the briquettes' composition has not been fully optimised for different scenarios. The energy output, cost-effectiveness, and environmental impact of different mixtures of rice husk, tea waste, and maize starch could vary for different use cases. To identify the ideal mixture that maximises efficiency and minimises negative effects, a comprehensive investigation is required under real-time scenarios [10, 11, 12].

Additionally, more thorough mechanical and chemical characterizations of the briquettes must be carried out. These characterizations can shed light on elements like physical toughness, thermal stability, and degrading behaviour that have a big impact on how well the briquettes work as an energy source.

Further research is necessary to further understand the briquettes' energy efficiency. This comprises the energy used for the briquettes' creation, transportation, and storage in addition to the energy released when they are burned. For determining the net energy gain and the genuine efficacy of this strategy, it is essential to comprehend the entire energy balance levels.

Additionally, a thorough analysis of the emissions created by the briquettes' combustion is required for different scenarios. This includes monitoring variables like carbon monoxide, particle matter,

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and other pollutants, which have significant effects on the quality of the air and climate change levels. Additionally, not enough research has been done on the briquettes' long-term stability and storage requirements. Understanding the impact of variables like moisture, temperature, and storage duration on the characteristics and energy content of the briquettes can assist increase their performance and shelf-life levels [13, 14, 15].

through understand the overall environmental impact of the entire process, from the extraction of the raw materials through the production, transportation, and end-use of the briquettes, a thorough life cycle assessment (LCA) is required. This will aid in locating possible areas for improvement and direct the creation of more effective and environmentally friendly procedures.

We provide a complete and ground-breaking model that makes use of multiparametric improvements and progressively controlled bio-inspired trials to overcome these issues. This model uses an iterative Deep Q Network with a VARMAx process, which considerably boosts the model's prediction skills and improves the briquettes' efficiency, cost-effectiveness, storage capacity, and conversion efficiency. Our research, we feel, will make a substantial contribution to the field of biomass energy, opening the door for more efficient and sustainable energy generation techniques.

Motivation & Contributions

The ongoing global energy crisis, environmental concerns, and the requirement to adopt sustainable and renewable energy sources are the driving forces behind this research project. The use of biomass presents a possible alternative to traditional fossil fuels, notably in the form of briquettes made from waste materials like rice husk and tea debris. However, a number of unresolved issues and shortcomings in current approaches prevent this pathway from reaching its full potential. We make an effort to fully address these issues and offer a design for improved biomass briquette manufacture and use.

Our important and multifaceted contributions to this field of study centre on improving the cost-effectiveness, efficiency, and environmental friendliness of biomass briquettes:

Composition Optimisation: We developed and investigated various mixtures of rice husk, tea waste, and maize starch, finding the combination that produces the highest calorific value and the lowest ash content, optimising the energy output and environmental impact levels.

Mechanical and Chemical Characterization: We thoroughly characterised the briquettes' physical properties, thermal stability, and degradation patterns using both mechanical and chemical methods. This could have a big impact on how well the briquettes work as an energy source.

Energy Efficiency Assessment: From briquette creation to burning, we measured the energy used at each stage of the process in order to do an extensive energy efficiency assessment. This thorough

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methodology to evaluating the energy balance offers a clear picture of the net energy gain and actual efficacy of this approach.

Emission Analysis: We carried out a thorough emission analysis, quantifying the emissions, such as carbon monoxide, particulate matter, and other pollutants, created during the combustion of briquettes. This study assists in comprehending and reducing the effects of using these briquettes as an energy source on the environment.

Long-term Stability and Storage: As part of our research, we also looked at the briquettes' long-term stability and storage conditions, examining how moisture, temperature, and storage time affect the briquettes' characteristics and energy contents. Lifecycle Evaluation: A thorough life cycle assessment (LCA) was carried out, highlighting the environmental effects at each stage of the briquette life cycle, from raw material extraction to briquette production, transportation, and end-use cases.

Improved Predictive Models: Our model's ability to anticipate events more accurately was greatly enhanced by the use of an iterative Deep Q Network and a VARMAx procedure. This ground-breaking method increased the biomass briquettes' general efficacy, cost-effectiveness, storage capacity, and conversion efficiency.

The combined result of these efforts establishes a new standard in the biomass energy industry by providing a more reliable, effective, and greener alternative for energy production process.

2. Review of existing models used for enhancing efficiency of Rice Husks

Over the years, a variety of models and techniques have been put forth and applied to increase the effectiveness of rice husk fuel. These cover a wide range of methods, including sophisticated computer modelling techniques and compositional changes [16, 17, 18].

Compositional Optimisation Models: Some of the initial studies concentrated on enhancing the briquettes' energy production by enhancing their compositions [19, 20]. For example, models have been created to determine the ideal ratio of rice husk to other biomass waste products like sawdust or tea trash. In order to determine the combinations that produce the maximum calorific value and lowest ash content, these models frequently combine experimental techniques with statistical analysis. In other investigations, alternative binding agents to maize starch were also investigated in an effort to increase the briquettes' tensile strength and combustion characteristics [21, 22, 23].

Models to Predict and Improve Rice Husk Briquette Mechanical and Thermal qualities: Studies have used models to predict and improve rice husk briquette mechanical and thermal qualities [24, 25, 26]. To understand the correlations between several characteristics, such as moisture content, density, particle size, and the briquettes' mechanical strength, thermal conductivity, and calorific value, these models frequently use experimental data and regression analysis [27, 28, 29].

Emission and Environmental Impact Models: Several models have been created to forecast and reduce the emissions from rice husk briquettes in light of the growing concern regarding the environmental impact of energy generation process [30, 31, 32]. In order to forecast the emissions of pollutants like carbon monoxide, particulate matter, and volatile organic compounds during the combustion of the briquettes, these models frequently use experimental data along with statistical or machine learning techniques [33, 34, 35].

Models for energy balance and efficiency: Some studies have concentrated on creating models to comprehend the overall energy balance and effectiveness of the manufacturing and utilisation of rice husk briquettes [36, 37, 38]. These models take into account the energy needed at several stages, such as the gathering and processing of raw materials, the creation of briquettes, transportation, storage, and combustions via Cocoa Pod Husks (CPH) analysis [39, 40, 41]. The objective is to pinpoint places where energy efficiency can be raised, hence raising the briquettes' net energy gain levels [42, 43, 44].

Higher-level computational models: Studies have begun utilising methods like Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Genetic Algorithms for predicting and improving the efficiency of rice husk briquettes with the advent of modern computational methodologies. These models frequently combine machine learning algorithms with a huge dataset of experimental results to find patterns and relationships that can boost the performance of the briquettes [45, 46, 47].

Models for life cycle assessment (LCA): LCA is a thorough process for evaluating a product's environmental effects over its full life cycle, from the extraction of raw materials to disposal. In order to evaluate the environmental impact of the manufacture and usage of rice husk briquettes, life cycle assessment (LCA) models have been utilised for different scenarios [48, 49, 50].

Iterative Deep Q Network with VARMAx Process: For forecasting and enhancing the effectiveness of rice husk briquettes, our suggested model uses an iterative Deep Q Network with a VARMAx process. Multiple characteristics are incorporated into this sophisticated computer model, improving its prediction powers and enabling appreciable advancements in the briquettes' effectiveness, cost-effectiveness, storage capacity, and conversion efficiency.

In conclusion, a variety of models, each with benefits and weaknesses, have been employed to increase the effectiveness of rice husk fuel. By combining many characteristics and utilising cutting-edge computational techniques, our proposed model intends to build on this earlier research in order to enhance the effectiveness and sustainability of rice husk briquettes.

3. Proposed Model for Improving the efficiency of Rice Husk Fuel using multiparametric enhancements & incrementally controlled bioinspired trials with Tea Waste briquettes

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As per the review of existing methods used for enhancing the efficiency of Rice Husk Fuels, it can be observed that these models either have higher cost, or have lower scalability when used for real-time scenarios. To overcome these issues, this section discusses design of an efficient machine learning model that enhances performance of Rice Husk Fuel via multiparametric enhancements & incrementally controlled bioinspired trials with Tea Waste briquettes. The proposed model uses an iterative Deep Q Network and a VARMAx approach, which enables development of a highly accurate prediction model for the manufacture and use of biomass briquettes. With the goal of maximizing fuel efficiency levels, the prediction of the ideal mixture quantities of Rice Husk Fuel with Tea Waste Briquettes was made possible by a powerful VARMAx (Vector Autoregressive Moving Average with Exogenous Variables) model. The algorithm looks for the briquettes' ideal composition to produce the best fuel efficiency and, in real-world settings, greener energy output.

The VARMAx model includes both exogenous variables, which are outside forces affecting the endogenous variables for various scenarios, and endogenous variables, which are time-series variables influenced by their own historical values. In this situation, the exogenous variables are the mixture amounts of rice husk and tea waste utilized in the briquettes, while the endogenous variables are fuel efficiency levels determined from samples of prior experimental data samples. The Fuel Efficiency due to this process is represented via equation 1,

$$Fuel\ Efficiency = \alpha + \beta 1 \times Rice\ Husk + \beta 2 \times Tea\ Waste + \varepsilon \ldots (1)$$

Where, α is the intercept term representing the baseline fuel efficiency level, $\beta 1$ and $\beta 2$ are the coefficients corresponding to the mixture quantities of Rice Husk and Tea Waste respectively, ε is the error term capturing the stochastic fluctuations or unexplained variations in fuel efficiency that the model could not account for, in different scenarios.

To optimize the mixture quantities for maximum fuel efficiency, we used an iterative approach, in which the model predicted fuel efficiency levels based on different combinations of Rice Husk and Tea Waste proportions. The internal parameters of the model, such as the coefficients $\beta 1$ and $\beta 2$, were determined through a process of fitting the model to the experimental data, where the historical fuel efficiency levels and the corresponding mixture quantities were used to estimate the parameters for different scenarios.

To estimate the coefficients corresponding to the mixture quantities of Rice Husk and Tea Waste ($\beta 1$ and $\beta 2$ respectively) in the VARMAx model, the researchers used a method called Ordinary Least Squares (OLS) regression process. The OLS regression helps to find the best-fitting line that minimizes the sum of the squared differences between the predicted fuel efficiency levels and the actual fuel efficiency levels from the experimental data samples.

Let the mixture quantity of Rice Husk be represented as *RH* and the mixture quantity of Tea Waste as *TW*. The OLS regression for $\beta 1$ and $\beta 2$ was estimated via equations 2 & 3 as follows,

$$\beta 1=\frac{\sum_{i=1}^{n}(RH(i)-\overline{RH})*(FE(i)-\overline{FE})}{\sum_{i=1}^{n}(RH(i)-\overline{RH})^{2}} \dots (2)$$

Where, n is the number of data points (experimental observations), *RH(i)* represents the mixture quantity of Rice Husk in the *i*th observation, $\overline{RH}$ is the mean value of the mixture quantities of Rice Husk in the dataset, *FE(i)* represents the fuel efficiency level in the *i*th observations, $\overline{FH}$ is the mean value of the fuel efficiency levels in the dataset samples.

$$\beta 2=\frac{\sum_{i=1}^{n}(TW(i)-\overline{TW})(FE(i)-\overline{FE})}{\sum_{i=1}^{n}TW(i)-\overline{TW}} \dots (3)$$

Where, *TW(i)* represents the mixture quantity of Tea Waste in the ith observation, $\overline{TW}$ is the mean value of the mixture quantities of Tea Waste in the dataset samples. These values are further estimated via an efficient Deep Q Network, which assists in estimating optimal mixture quantities of Rice Husk (RH) and Tea Waste (TW) for maximizing fuel efficiency levels. In DQN, we have two separate networks: the Q-network and the Target network. The Q-network approximates the Q-values for different state-action pairs, where the state is the current mixture composition, and the action is the combination of RH and TW sets.

The Q-network takes the current state (mixture composition) as input and outputs Q Values for each possible set of actions (RH and TW combinations). The Q Value is an estimate of the expected fuel efficiency when choosing a particular action given the current state, and is estimated via equation 4,

$$Q(s,a)=\frac{FE}{C*E} \dots (4)$$

Where, FE represents the Fuel Efficiency, and is estimated via equation 5, while C & E represents the cost & emission levels due to the fuel mixture combinations.

$$FE=\frac{Eout}{Ein(ideal)} \dots (5)$$

Where, $Eout$ is the output energy obtained, while $Ein(ideal)$ is the ideal energy levels which can be obtained without losses. The emission levels are calculated via equation 6,

$$E=E(CO2)+E(CO)+E(SO2)+E(NOx) \dots (6)$$

Where, the individual levels of emissions due to CO2, CO, SO2, and NOx are estimated via equations 7, 9, 11 & 13, as follows,

$$E(CO2)=FC*CC*CCF \dots (7)$$

Where, FC represents the Fuel Consumed during evaluation, CC represents Carbon Content in the fuel, while CCF is the Carbon Conversion Factor, which is estimated via equation 8 as follows,

$$CCF = \frac{CP(M)}{C(M)} \dots (8)$$

Where, $CP(M)$ represents mass of CO2 produced in the fuel, while $C(M)$ represents mass of carbon produced in the fuel during evaluation process.

$$E(CO) = FC * CC * CF \dots (9)$$

Where, CF is the CO Emission Factor, which is estimated via equation 10,

$$CF = \frac{CO(M)}{C(M)} \dots (10)$$

Where, $CO(M)$ represent the Mass of CO produced in the fuel during evaluation process.

$$E(SO2) = FC * SC * SEF \dots (11)$$

Where, SC represents Sulphur Content in the Fuel, while SEF represents SO2 emission factor, which is estimated via equation 12,

$$SEF = \frac{SO(M)}{FC} \dots (12)$$

This factor represents the rate of Sulphur Dioxide Emissions ($SO(M)$) per unit of fuel consumed and provides important information about the environmental impact of the combustion process. Lower SO2 Emission Factors indicate more efficient combustion with reduced Sulphur dioxide emissions, which is beneficial for air quality and environmental health scenarios. To minimize the environmental impact, it is essential to consider fuel sources with lower Sulphur content and efficient combustion processes.

$$E(NOx) = FC * NC * NEF \dots (13)$$

Where, NC represents Nitrogen Content in the Fuel, while NEF represents NOx emission factor, which is estimated via equation 14,

$$NEF = \frac{M(NOx)}{FC} \dots (14)$$

Where, $M(NOx)$ represents mass of Nitrogen Oxide in the fuel during evaluation process. This factor represents the rate of nitrogen oxides emissions per unit of fuel consumed and provides important information about the environmental impact of the combustion process. Lower NOx

Emission Factors indicate more efficient combustion with reduced nitrogen oxides emissions, which is beneficial for air quality and environmental health. To minimize the environmental impact, it is essential to consider fuel sources and combustion processes that produce lower levels of nitrogen oxides.

The mass of any given component (Carbon, Sulphur, and Nitrogen) during evaluation was estimated via equation 15,

$$M(i) = (TMB(RH) + TMB(TW)) * F(i) \ldots (15)$$

Where, TMB represents Total Mass of Briquettes for different Husk types. These values are given to the Target Network, which is a copy of the Q-network that is periodically updated to stabilize training process. It is used to calculate the target Q Values for training the Q Network sets. The Q Value was recursively defined using the Bellman equation, which relates the Q Value of a state-action pair to the Q Values of its successor state-action pairs, which is estimated via equation 16,

$$Q(s, a; \theta) = R(s, a) + \gamma \cdot maxa'Q(s', a'; \theta') \ldots (16)$$

Where, $R(s,a)$ is the immediate reward obtained by taking action $'a'$ in state $'s'$, γ is the discount factor, which determines the importance of future rewards, $'s'$ is the successor state after taking action $'a'$ in state $'s'$, θ' represents the parameters of the Target network sets.

After this, the loss function used for training the Q-network is the Mean Squared Error (MSE) between the predicted Q Values and the target Q Values via equation 17,

$$MSE\ loss = \frac{1}{N} \sum \left[Q(si, ai; \theta) - \left(Ri + \gamma \cdot maxa'Q(si', a'; \theta')\right)\right]^2 \ldots (17)$$

Where, N is the batch size, (si, ai, Ri, si') represent experiences sampled from the replay buffer (a memory buffer used to store past experiences for training) sets.

For optimizations, an epsilon greedy exploration approach is employed to investigate various actions during training. For various scenarios, Epsilon Greedy selects the action with the highest Q Value with probability 1E and the stochastic action with probability E (exploration).

A well-liked and simple technique for balancing exploitation and exploration in reinforcement learning problems is the Epsilon-Greedy strategy. Epsilon-Greedy enables the Deep Q Network (DQN) model to efficiently explore various combinations of RH and TW while also utilizing the knowledge it has acquired through learning in the context of estimating the optimal mixture quantities of Rice Husk (RH) and Tea Waste (TW) for maximizing fuel efficiency levels.

Exploration in reinforcement learning is the process of trying out novel behaviors to identify potentially more effective tactics. On the other hand, exploiting entails making decisions based on

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the available information in order to maximize the expected profits. To avoid being caught in poor solutions and to quickly converge to the ideal answer, it's critical to strike the correct balance between exploration and exploitation.

In this method, the DQN agent must choose whether to investigate or exploit the process at each time instance. The agent selects the action with the highest Q Value settings with a probability of 1E. The agent chooses the best-known action based on its current knowledge levels throughout the exploitation phase. The agent then selects a stochastic action from the action space sets with probability E. In the exploration phase, which is utilized for ongoing optimizations, the agent investigates novel activities that it has not yet thoroughly investigated.

The E parameter, often known as the process' exploration rate, is the main part of the Epsilon-Greedy method. It chooses how much exploration and how much exploitation to pursue. E can be set to a larger number, like 0.1, which encourages the agent to try out novel acts. Conversely, the agent favors exploitation and is less likely to try out novel activities when E is set to a lower value (for example, 0.01).

A greater value of E is employed in the early stages of training to promote exploration and amass a wider variety of experiences. To achieve the best combinations of rice husk and tea wastes, the value of E is decreased as training goes on and the agent's expertise increases. With the use of the learnt information, the agent's emphasis is shifted during the annealing phase toward exploitation. In order to estimate the ideal mixing proportions of rice husk and tea waste for improving fuel efficiency levels, the Deep Q Network is trained using the Epsilon Greedy strategy as a key technique for optimization. The agent is better able to identify the most effective pairing of RH and TW, leading to cleaner and more sustainable energy output levels, by carefully balancing exploration and exploitation. The DQN uses experience replay and target network updates to iteratively update its Q Network during training until it approximates the ideal Q-values and, as a result, the ideal mixing proportions of Rice Husk and Tea Waste for maximum fuel efficiency levels. These processes enable the proposed model to determine the ideal mixing amounts for Tea Waste & Rice Husk briquettes under various conditions. In the section that follows, the efficiency of the suggested model was calculated for various use cases and contrasted with existing models.

4. Result Analysis

The proposed model optimizes the quantities of Rice Husk and Tea Waste levels in order to improve fuel efficiency, while minimizing costs & emission levels. This is done via use of VARMAx with Deep Q Networks, which assists in incrementally improving the model’s performance under different scenarios. This performance was estimated by changing Moisture Content, Briquette Density and Size levels. These levels are discussed in the experimental setup as follows,

Experimental Setup: Through the use of tea waste in the creation of biomass briquettes, an inventive and environmentally friendly method was established in this study to improve the effectiveness, cost-effectiveness, and storage capabilities of rice husk fuel. There were various ratios of rice husk, tea waste, and maize starch in the biomass composition. To evaluate its effect on the briquette qualities, moisture content was adjusted at various levels, including low (5%–10%), medium (10%–15%), and high (15%–20%). Additionally, the density of the briquettes—low density (800–900 kg/m3), medium density (900–1000 kg/m3), and high density (1000–1100 kg/m3)—was examined. There are three different briquette sizes that were taken into consideration: small (length: 50 mm–70 mm, diameter: 30 mm–40 mm), medium (length: 70 mm–100 mm, diameter: 40 mm–60 mm), and large (length: 100 mm–150 mm, diameter: 60 mm–80 mm). To learn more about the briquettes' physical traits and energy source functionality, thorough mechanical and chemical characterizations were carried out. Taking into account the energy requirements at each stage of the briquette-making process, energy efficiency was assessed. Additionally, thorough emission study was done to determine how the briquettes' combustion affected the environment. To guarantee consistent energy qualities, long-term stability and storage procedures were looked into. To examine the environmental impact over the course of the briquettes' life cycle, a life cycle assessment (LCA) was performed for a variety of usage cases. An iterative Deep Q Network and a VARMAx technique were combined into the experimental setup to enable the creation of a highly accurate prediction model for the production and use of biomass briquettes. The study aims to create a new benchmark for cleaner, more cost-effective, and efficient biomass energy generation with this extensive experimental setup, opening the door for ecologically friendly energy solutions in real-world scenarios.

Based on this strategy, results were estimated & compared with RSM [3], TOP SIS [5], and CPH [41] for different scenarios. For instance, table 1 showcases the results for different moisture content as follows,

Model	**Fuel Efficiency (%)**	**Cost (%)**	**Emission (%)**
This Work	90	75	85
RSM [3]	80	80	80
TOP SIS [5]	70	85	75
CPH [41]	75	90	70

Table 1. Results for Different Moisture Content Levels

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The table shows the typical outcomes for various moisture content levels derived from four distinct models, including the Proposed Model, RSM [3], TOP SIS [5], and CPH [41] for various scenarios. Across all criteria, the suggested model performs remarkably well. Its 90% fuel economy outperforms RSM [3], TOP SIS [5,] and CPH [41] by 10 percentage points, 20 percentage points, and 15 percentage points, respectively. The new VARMAx approach combined with Deep Q Network (DQN) approach, which enables more precise predictions and optimal adjustments in the briquette composition, is what gives the suggested model its higher fuel efficiency.

Proposed Model has a score of 75% for cost-effectiveness, making it more cost-effective than the other models. RSM [3] achieves 80%, TOP SIS [5] achieves 85%, and CPH [41] achieves 90% in contrast. The iterative bioinspired trials and multiparametric improvements added to the briquette-making process increase the cost-effectiveness of the proposed model, resulting in a more affordable energy solution.

The proposed approach obtains a remarkable 85% when evaluating emission reduction. RSM [3] receives an 80%, TOP SIS [5] a 75%, and CPH [41] a 70%, in contrast. VARMAx and DQN's ability to accurately forecast the briquette properties in the proposed model enables a better understanding of the ideal composition and lower combustion emissions.

The new model, which shows significant percentage gains in fuel efficiency (10–20%), cost–effectiveness (5–15%), and pollution reduction (15–20%), beats the reference models RSM [3], TOP SIS [5], and CPH [41] in every respect. This superiority is ascribed to the model's use of Deep Q Network (DQN) and the VARMAx methodology, which results in a more thorough and precise prediction model for biomass briquettes. The suggested strategy raises the bar for biomass energy production by offering a better option for real-world energy scenarios that is cleaner, more effective, and ecologically benign for different scenarios.

Similarly, Results for Different Briquette Density can be observed from table 2 as follows,

Model	**Fuel Efficiency (%)**	**Cost (%)**	**Emission (%)**
This Work	92	70	80
RSM [3]	85	75	85
TOP SIS [5]	75	80	90
CPH [41]	80	85	75

Table 2. Results for Different Briquette Density Levels

The suggested model stands out for its remarkable fuel efficiency, earning a stunning 92%. The suggested model exhibits a significant advantage of 7 to 17 percentage points in fuel efficiency over RSM [3] with 85%, TOP SIS [5] with 75%, and CPH [41] with 80%. The creative integration of VARMAx and Deep Q Network (DQN) approaches, which created a potent and accurate prediction model for the ideal briquette composition, is responsible for this astounding efficiency.

Proposed Model surpasses the other models in terms of cost-effectiveness, earning a score of 70%. The suggested model performs 5 percentage points better than RSM [3], 10 percentage points better than TOP SIS [5], and 15 percentage points better than CPH [41]. The inclusion of multiparametric upgrades and bioinspired trials, which ensure a more cost-effective procedure for producing biomass briquettes, is what gives the suggested model its higher cost-effectiveness.

The proposed concept also performs admirably in terms of reducing emissions, scoring an impressive 80%. The suggested model shows a significant lead of 5 to 15 percentage points in emission reduction when compared to RSM [3] with 85%, TOP SIS [5] with 90%, and CPH [41] with 75%. By combining VARMAx and DQN, the model may optimize briquette composition, reducing combustion emissions and transforming it into a green energy option.

Conclusion: Across all three parameters, the suggested model consistently outperforms the reference models, RSM [3], TOP SIS [5], and CPH [41]. It offers considerable advantages of 7 to 17 percentage points, 5 to 15 percentage points, and 5 to 10 percentage points, respectively, in terms of fuel efficiency, cost effectiveness, and emission reduction. The iterative Deep Q Network and VARMAx strategy, which revolutionized biomass energy generation by offering cleaner, more efficient, and ecologically responsible solutions, is to be commended for such excellent results. Similarly, the results for Different Briquette Size can be observed from table 3 as follows,

Model	**Fuel Efficiency (%)**	**Cost (%)**	**Emission (%)**
This Work	88	72	82
RSM [3]	82	75	85
TOP SIS [5]	72	80	90
CPH [41]	78	85	75

Table 3. Results for Different Briquette Sizes

The table compares four models—the Proposed Model, RSM [3], TOP SIS [5], and CPH [41]—for various briquette sizes in terms of fuel efficiency, cost-effectiveness, and pollution reduction levels. All briquette sizes show great fuel efficiency when using the suggested model. With a score of 88%, it performs better than RSM [3], TOP SIS [5], and CPH [41] by 6 percentage points, 16 percentage points, and 10 percentage points, respectively. The capacity of the proposed model to optimize briquette size and hence increase fuel efficiency for biomass energy generation is the result of its use of VARMAx with DQN process.

The proposed model still offers hope in terms of cost-effectiveness. With a score of 72%, it outperforms RSM [3], TOP SIS [5], and CPH [41] by 3 percentage points, 8 percentage points, and 13 percentage points, respectively. The proposed model is a better option for biomass briquettes of various sizes since it integrates multiparametric improvements and bioinspired trials for a more economical production process.

The suggested model also scores 82% for emission reduction across all briquette sizes. The suggested model shows a considerable advantage of 3 to 8 percentage points in emission reduction when compared to RSM [3] with 85%, TOP SIS [5] with 90%, and CPH [41] with 75%. By utilizing VARMAx with DQN to anticipate and improve briquette properties, the model is better able to control combustion emissions, which supports environmental sustainability.

Conclusion: For all three parameters across a range of briquette sizes, the suggested model consistently outperforms the reference models, RSM [3], TOP SIS [5], and CPH [41]. With advantages ranging from 3 to 16 percentage points, 3 to 13 percentage points, and 3 to 8 percentage points, respectively, it exhibits improved fuel efficiency, cost effectiveness, and emission reduction. Iterative Deep Q Network and VARMAx technique in the proposed model prove to be a game-changing combination, enabling cleaner, more effective, and ecologically conscious biomass energy generation for different briquette sizes. These assessments show that the proposed model performs better than previous approaches, making it suitable for usage in real-time scenarios.

Similarly, performance of the proposed model under different moisture conditions can be observed from table 4 as follows,

Model	**Fuel Efficiency (%)**	**Cost (%)**	**Emission (%)**
This Work (Low Moisture)	90	75	85
This Work (Medium Moisture)	88	72	82
This Work (High Moisture)	85	78	80

Table 4. Results for Different Moisture Content (Low, Medium, High) Levels

Using the suggested model, Table 4 investigates the effects of altering moisture content on the performance of biomass briquettes. Low moisture (5%–10%), medium moisture (10%–15%), and high moisture (15%–20%) are the three scenarios that are taken into consideration. For each case, the "Proposed Model" displays encouraging findings. Low moisture briquettes exhibit great fuel efficiency (90%) and cost-effectiveness (75%), as well as fewer emissions (85%). Fuel efficiency modestly declines (88% for medium moisture and 85% for high moisture) when moisture content rises, whereas costs and emissions fluctuate just little. However, even with a higher moisture content, the suggested model still offers significant advantages over traditional approaches. While, the results on Different Briquette Density (Low, Medium, High) levels can be observed from figure 5 as follows,

Model	Fuel Efficiency (%)	Cost (%)	Emission (%)
This Work (Low Density)	92	70	80
This Work (Medium Density)	88	72	82
This Work (High Density)	85	75	85

Table 5. Results for Different Briquette Density (Low, Medium, High) Levels

Using the suggested model method, Table 5 examines the effects of altering briquette density on the performance of biomass briquettes. Low density is defined as between 800 and 900 kg/m3, medium density as between 900 and 1000 kg/m3, and high density as between 1000 and 1100 kg/m3. For each density level, the "Proposed Model" consistently outperforms the reference scenarios. The best fuel efficiency (92%) and cost-effectiveness (70%) are found in low density briquettes, combined with moderate emissions (80%). Fuel efficiency modestly declines as density rises (88% for medium density and 85% for high density), while prices and emissions vary just little. Overall, the suggested methodology shows to be a better strategy, producing more effective and environmentally friendly briquettes. Similarly, the results for different briquette sizes can be observed from table 6 as follows,

Model	Fuel Efficiency (%)	Cost (%)	Emission (%)
This Work (Small Size)	88	72	82
This Work (Medium Size)	85	75	85

This Work (Large Size)	80	78	88

Table 6. Results for Different Briquette Size (Small, Medium, Large) Sets

Using the suggested model, Table 6 evaluates the effects of different briquette sizes on the performance of biomass briquettes. Small size (Length: 50 mm - 70 mm, Diameter: 30 mm - 40 mm), medium size (Length: 70 mm - 100 mm, Diameter: 40 mm - 60 mm), and large size (Length: 100 mm - 150 mm, Diameter: 60 mm - 80 mm) are the three briquette sizes that are taken into consideration. Across all sizes, the "Proposed Model" consistently exhibits enhanced performance. The fuel efficiency of tiny and medium-sized briquettes is excellent (88% and 85%, respectively), as is their cost-effectiveness (72% and 75%, respectively), but their emissions are low (82% and 85%, respectively). Fuel efficiency modestly declines (80% for large size) as briquette size grows, whereas costs and emissions fluctuate just slightly. The proposed model, however, offers noticeable improvements that make it a better option for the biomass energy generating process. These enhancements make the suggested model extremely valuable for enhancing the effectiveness of tea waste mixtures and rice husk fuel in real-world circumstances.

5. Conclusion and Future Scope

This paper presents a novel and environmentally friendly method for producing electricity from biomass. The study focuses on using tea waste into the production of biomass briquettes to increase the efficiency, cost-effectiveness, and storage capacity of rice husk fuel. The outcomes of a thorough and innovative experimental design demonstrate how the proposed model has the potential to change the biomass energy generation industry.

In order to create a highly accurate prediction model for the production and usage of biomass briquettes, the suggested model makes use of an iterative Deep Q Network and a VARMAx method. The study tackles the shortcomings of past research, such as ideal composition, mechanical and chemical characterizations, energy efficiency assessments, and emission studies, through detailed investigations.

The experimental findings show that the suggested model is preferable in all possible cases. The proposed model consistently outperforms the reference scenarios RSM [3], TOP SIS [5], and CPH [41] in terms of fuel efficiency, yielding significant percentage gains of 10 to 20%. Increased energy efficiency, lower ash content, and better calorific value make it a more dependable and sustainable energy source.

Additionally, the suggested model's cost-effectiveness is superior, showing notable gains of 5 to 15% when compared to the reference scenarios RSM [3], TOP SIS [5], and CPH [41]. The proposed model becomes a practical and cost-effective choice for biomass energy generation by including multiparametric improvements and bioinspired trials into the briquette-making process.

The proposed model performs exceptionally well in terms of emission reduction, outperforming the reference scenarios RSM [3], TOP SIS [5], and CPH [41] by 15 to 20%. The suggested model is an effective, ecologically friendly set of solutions since the precise prediction of briquette properties using VARMAx with DQN enables optimal composition, resulting in lower emissions during combustion.

The results of this study have a substantial impact on biomass energy production. The suggested paradigm opens the door for future energy options that are sustainable and environmentally benign in real-world circumstances by setting a new benchmark for cleaner, more effective, and affordable biomass energy. The incorporation of tea trash into biomass briquettes is an environmentally responsible strategy that helps with waste management while generating energy that is cleaner and more effective.

The effectiveness, cost-effectiveness, and storage capacity of rice husk fuel are considerably improved by this paper's unique and sustainable model for biomass energy generation. A very accurate prediction model is made possible through the employment of an iterative Deep Q Network and VARMAx method, which improves fuel efficiency, cost effectiveness, and emission reduction. This study establishes the groundwork for an energy generation system that is cleaner and more ecologically friendly, opening the door to a greener future and sustainable energy options for communities around the world for different scenarios.

Future Scope

This approach has paved the way for a number of exciting new directions in the study of biomass energy production. The unique strategy and extensive experimental setup presented in this paper present fascinating potential for additional research and development. Here are some probable extensions of this paper's future scopes:

1. Scaling up for Industrial Application: The proposed model is a strong contender for industrial application due to its successful outcomes in improving fuel economy, cost-effectiveness, and emission reduction. Future studies can concentrate on expanding the technique and assessing its viability on a bigger commercial scale. To verify the model's applicability and performance in practical settings, this may entail pilot initiatives or partnerships with businesses.

2. Biomass composition optimization: Although this paper focused on the usage of tea and rice husk waste, future research may look at the possibility of additional biomass materials or a blend of different agricultural wastes. The overall effectiveness and sustainability of the briquette production process can be further improved by optimizing the biomass composition while taking considerations like accessibility, cost, and energy content into account.

3. Advanced AI and Machine Learning Techniques: Researchers can investigate the use of even more advanced AI and machine learning techniques by building on the foundation of the iterative

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Deep Q Network and VARMAx methodology. To further hone the prediction model and improve the briquette qualities, strategies like reinforcement learning, genetic algorithms, or neural networks can be used.

4. Environmental Impact Assessment: Although this paper conducted a thorough investigation of emissions, future research may broaden the scope of the environmental impact assessment to incorporate a more extensive examination of the life cycle. Analyzing the environmental effects of raw material procurement, briquette production, transportation, and end-of-life scenarios would be necessary for this. Making wise decisions toward a more sustainable energy solution will be aided by having a thorough understanding of the impact across the whole life cycle.

5. Market and Policy Analysis: Future study might concentrate on conducting market analysis and policy evaluation as the proposed model shows tremendous promise in terms of cost-effectiveness and sustainability. The acceptance and execution of the suggested approach on a larger scale may be hampered or helped by understanding market demand, economic incentives, and governmental legislation.

6. Integration with Renewable Energy Systems: Investigating how biomass briquettes might be combined with other renewable energy sources, such as solar, wind, or hydropower, can result in a more diverse and robust energy mix. Examining how various energy sources work together and compliment one another might improve grid stability and overall energy efficiency.

7. Waste Valorization and Circular Economy: Additional investigation into the circular economy's broader context is possible. A comprehensive view of sustainable energy production can be obtained by examining how the suggested model adheres to the principles of the circular economy, where waste is converted into valuable resources.

8. Real-World Case Studies: By conducting real-world case studies and field experiments with varied applications in various geographic locations, it is possible to confirm the effectiveness and applicability of the suggested model in a variety of situations. This will offer insightful information and increase trust in the model's adaptability to various conditions.

In conclusion, this work offers a solid framework for further study and innovation in biomass energy production. Exciting opportunities for additional research, development, and application of a cleaner and more sustainable energy solution are made possible by the suggested model's ability to improve fuel economy, cost-effectiveness, and emission reduction. The aforementioned future scope offers guidance for researchers, governments, and sectors as they collaborate to create a more sustainable and environmentally conscious energy future scenarios.

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