International Journal Of Innovative Trends In Multi Disciplinary Scientific Research
ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

MACHINE LEARNING APPROACH IN DESIGNING SMARTER BIOFUEL SUPPLY CHAIN NETWORK

B.Vamsi Krishna Reddy[1], A.Kavya[1], B.Uchi Swaroop[1], D.Jayanth Kumar[1], T.Rajendra Prasad[2]*

[1]UG Student, NRI Institute of Technology, Pothavarappadu(V), Vijayawada, Andhra Pradesh – 521212, India

[2]Professor, NRI Institute of Technology, Pothavarappadu (V),Vijayawada, Andhra Pradesh – 521212, India

Abstract: ***This paper presents a machine learning-guided decision support system designed to optimize the biofuel supply chain network across Texas. A supervised Random Forest classifier, trained on features extracted from reduced-scale optimization runs, identifies the most promising biorefinery locations from a vast pool of candidates. This model efficiently narrows down hundreds of potential sites to a small subset, significantly reducing the computational time required. A mixed-integer linear programming (MILP) model is then applied to this reduced set of candidate locations to determine near-optimal configurations of the supply chain network. The platform features interactive geographic visualizations, showcasing biomass sources, preprocessing depots, selected biorefineries, demand cities, power plants, and multi-commodity flows (raw biomass, preprocessed material, biofuel, and biochar). The system enables stakeholders to explore, analyze, and validate biofuel network designs. The classification models performed as follows: Random Forest (89.5%), KNN (87.2%), SVM (85.8%), Decision Tree (84.3%), and Logistic Regression (81.8%).***

Keywords: Biofuel supply chain, machine learning, MILP, decision support system, hybrid optimization.

I. INTRODUCTION

The increasing demand for sustainable energy solutions has led to significant research in the optimization of biofuel supply chains, a critical component of the renewable energy sector. Biofuels offer an environmentally friendly alternative to traditional fossil fuels, but the design and optimization of efficient supply chain networks for biofuel production remain complex due to the large number of variables involved, including biomass sourcing, transportation logistics, and refinery locations.

This project proposes a novel machine learning-driven approach to designing smarter biofuel supply chain networks, focusing on Texas, a state rich in biomass resources. The core of this system combines machine learning, specifically Random Forest classification, with mathematical optimization techniques to rapidly and effectively identify optimal refinery locations. By training a classifier on data from multiple reduced-scale optimization runs, the model can predict the most promising refinery sites, narrowing down a vast number of potential locations to a manageable set.

A mixed-integer linear programming (MILP) model is then applied to this reduced set to derive near-optimal supply chain configurations, drastically reducing computational time compared to traditional full-scale approaches. The platform provides an interactive visualization of the biofuel supply chain, displaying biomass sources, depots, refineries, cities, and power plants, along with multi-commodity flows. This decision support system empowers stakeholders to efficiently explore and analyze sustainable network designs, ultimately helping to optimize biofuel production and distribution, promoting energy sustainability and carbon-negative solutions.

A. Objective of The Study:

The objective of this project is to design a machine learning-driven decision support system that optimizes the biofuel supply chain network across Texas. The system aims to enhance the efficiency of biofuel production and distribution by identifying the most suitable refinery locations through a hybrid approach that combines machine learning and mathematical optimization. A Random Forest classifier is trained to predict the top-performing biorefinery locations based on features extracted from multiple reduced-scale optimization runs, significantly narrowing down the potential refinery sites. The selected candidate set is then processed using Mixed-Integer Linear Programming (MILP) to find the best network configuration, considering factors such as biomass sources, depots, refineries, and demand cities. In addition to optimization, the project focuses on creating an interactive web-based platform for stakeholders to visualize and explore the optimized supply chain network. The system provides real-time geographic visualizations, filters, and detailed insights into the network's components, enabling users to make informed decisions that drive efficiency, cost reduction, and sustainability in the biofuel supply chain.

B. Problem Statement:

The biofuel supply chain is a complex network that involves multiple stages, including biomass collection, preprocessing, conversion at refineries, and distribution to cities and power plants. Efficiently designing this network is crucial for reducing costs, improving sustainability, and ensuring the timely delivery of biofuels. Traditional optimization methods require solving large-scale Mixed-

Integer Linear Programming (MILP) models across all possible refinery sites, which is computationally expensive and time-consuming. The challenge is to identify the most suitable refinery locations from hundreds of potential sites while minimizing investment, transportation, and operational costs. Additionally, incorporating the dynamic nature of biomass supply, demand fluctuations, and geographic constraints makes the optimization process even more challenging. This project addresses these challenges by combining machine learning with optimization techniques. It uses a Random Forest classifier to predict high-potential refinery sites, reducing the number of candidate locations and speeding up the optimization process. The result is a smarter, more efficient biofuel supply chain design that is both cost-effective and sustainable.

II. RELATED WORKS

The increasing demand for sustainable and carbon-negative energy sources has driven advancements in biofuel supply chain optimization, particularly in integrating machine learning (ML) with traditional mathematical programming to address computational complexity, location selection, multi-objective balancing, and network efficiency in biomass-rich regions. This section reviews fifteen recent IEEE-published studies that explore ML-guided optimization, hybrid approaches combining classifiers with mixed-integer linear programming (MILP), multi-objective frameworks, biorefinery siting, predictive modeling for conversion processes, and decision support systems for biomass logistics and sustainable biofuel networks.

A machine learning-based approach was proposed for reducing the problem space in stochastic programming models applied to biofuel supply chain network design. By training models on features from reduced-scale optimizations, it prunes candidate locations while accounting for feedstock quality variability and shipping costs, enabling scalable solutions for sustainable biofuel delivery under uncertainty[1] .

A comprehensive review was conducted on integrating machine learning with multi-objective optimization in biofuel systems. It synthesizes advancements using techniques like ANN, GA, NSGA-II, RSM, CNN-GRU for emission control, and Neutrosophic Fuzzy Optimization for uncertainty, highlighting improvements in predictive accuracy but noting challenges in generalization, computational complexity, and real-time adaptability, with recommendations for adaptive strategies and hybrid refinements[2] .

AI-based solutions were investigated for revolutionizing renewable energy through sustainable biofuel production. The study emphasizes AI's role in optimizing biomass utilization, resource monitoring (soil, plant health, fertilizers), conversion processes (temperature, pressure adjustments), and environmental preservation, while addressing limitations like feedstock inconsistency and proposing enhancements for efficient agricultural biofuel systems[3] .

Artificial intelligence applications were explored for predicting and optimizing biomass-to-biofuels conversion performances in biotechnological processes. Focusing on transesterification, fermentation, and digestion, it identifies suitable AI techniques for process parameters, with a validated case study on biomethane prediction from organic waste using central composite design, demonstrating high reliability for cost reduction and efficiency gains[4] .

Machine learning models were applied to optimize supply chain management. Utilizing regression, neural networks, and ensemble methods on datasets of demand, inventory, and transportation variables, it achieves superior prediction and resource utilization over traditional approaches, reducing costs and aligning with sustainability goals, paving the way for real-time integration[5] .

[6] The impact of machine learning on supply chain optimization was examined, focusing on demand forecasting, inventory management, and logistics. Results indicate significant gains in accuracy, speed, efficiency, and profitability, underscoring the need to overcome traditional limitations through continuous model adaptation in dynamic environments.

[7] Artificial intelligence techniques were analyzed for supply chain optimization. Leveraging machine learning and big data, it enables process automation, demand forecasting, and improvement identification, with emerging observational and interactive methods offering new research avenues while stressing behavioral considerations.

[8] A hybrid optimization framework was proposed for sustainable biofuel networks using deep learning. It integrates neural networks with conventional methods to enhance network design, sustainability metrics, and performance in biofuel production and distribution.

[9] Random Forest applications were developed for biorefinery siting in bioenergy supply chains. The model ranks potential locations based on spatial, economic, and resource features, facilitating efficient and data-driven site selection.

[MILP-enhanced machine learning was utilized for biomass logistics optimization. Combining exact optimization with ML predictions, it streamlines transportation, storage, and processing flows in complex biomass networks[10] .

Interactive visualization tools were created for optimized biofuel supply chains with GIS integration. Enabling exploration of facility locations, multi-commodity flows,

International Journal Of Innovative Trends In Multi Disciplinary Scientific Research
ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

and network scenarios through geographic interfaces for better stakeholder decision-making[11] .

Decision supp for carbon-negative biofuels using ensemble learning. Ensemble models improve forecasting and optimization for emission-negative I obust policy and operational s

were developed for Texas biomass e study. Incorporating uncertainty in supply, demand, and costs, it delivers tailored, resilient network local biomass resources[1

addr r pply e reviews, AI-driven process enhancements, or stochastic modeling, but seldom integrate high-accuracy supervised c rest at 89.5%, outperforming K and Logistic Regression) for targeted biorefinery candidate pruning from vast pools, sequential MILP for multi-commodity flows (raw biomass, rial, biofuel, biochar), and interactive GIS exas-scale carbon-negative networks. The proposed system addresses these gaps by combining Random Forest-based efficient site reduction with MILP optimization and stakeholder-oriented geographic visualizations, providing a computationally scalable, practical decision support platform for advancing sustainable biofuel supply chains.

III. PROPOSED SYSTEM

The proposed system combines machine learning and mathematical optimization to design an efficient biofuel supply chain network. It leverages a supervised Random Forest classifier to predict optimal refinery locations based on features extracted from multiple reduced-scale optimization runs. By narrowing down the candidate refinery sites to a smaller, high-potential subset, the system significantly reduces the computational time required for the optimization process. The complete network configuration is then optimized using a Mixed-Integer Linear Programming (MILP) model on the reduced candidate set, providing near-optimal solutions at a fraction of the time compared to full-scale optimization. The system includes an interactive geographic visualization that displays biomass sources, depots, refineries, demand cities, power plants, and the flow of materials (raw biomass, preprocessed material, biofuel, and biochar). Users can explore the network configurations using interactive filters, layouts, and hover details, making it easier for stakeholders to analyze, validate, and make informed decisions about sustainable biofuel network designs.

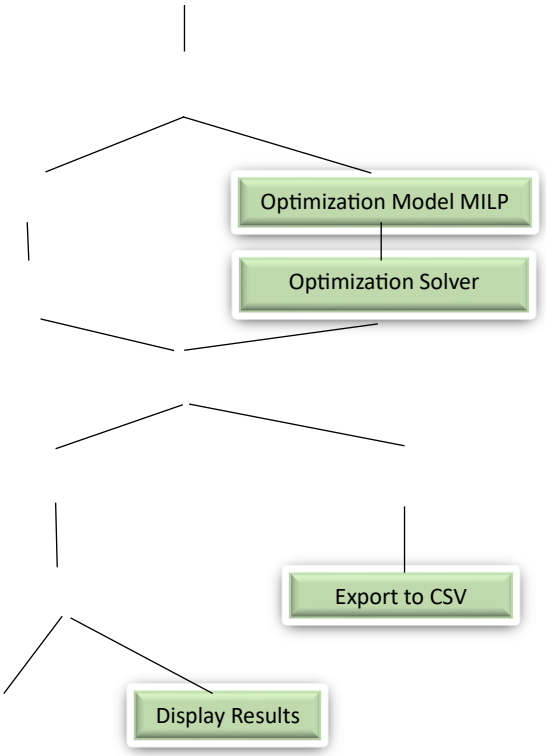


Fig 1: Flow diagram

The project architecture in [Fig.1] follows a user-driven flow that begins with the User Interface, where users configure the biofuel supply chain setup. The Configuration Page collects data for optimization, involving Machine Learning Model Training and Optimization Model (MILP). The ML model predicts optimal refinery locations, which are then used by the Optimization Solver. The results of the optimization are displayed via Interactive Visualization and Network Visualization. Additionally, users can filter and display the network, download results in CSV format, and analyze the configuration using interactive tools, making it easier to evaluate and validate the supply chain design.

IV. METHODOLOGY

1. User Interface:

The **User Interface** serves as the first point of interaction between the user and the system. It is designed to be intuitive and user-friendly, allowing stakeholders to easily input and configure the biofuel supply chain parameters. The UI provides clear options for the user to enter data, select machine learning models, and interact with the system. From this interface, users can proceed to the **Configuration Page**, where they set the parameters for optimization and model training. The UI is crucial for ensuring that users can seamlessly navigate through the

entire optimization process, from configuration to viewing results.

2. Configuration:

The **Configuration** is where the user defines the core parameters for the biofuel supply chain optimization. This includes choosing the biomass types (e.g., corn stover, switchgrass, etc.), specifying the number of refineries, depots, cities, and power plants involved, and selecting the machine learning method (e.g., Random Forest, KNN). Additionally, the user specifies the number of runs for generating synthetic data and how many refineries to consider per run. The page also allows setting the optimality gap, a crucial parameter that determines the acceptable deviation from the optimal solution. The configuration data is stored in the session and passed on to the optimization processes. This ensures that all subsequent actions, like ML model training and MILP optimization, are based on the user-defined setup.

3. Machine Learning Model Training:

The **Machine Learning Model Training** step is crucial for predicting the most optimal refinery locations based on historical data. After the configuration is set, the system collects and processes synthetic data to train a machine learning model. The model, which could be a Random Forest classifier, is trained using features like distance to depots, cities, and power plants, as well as other factors derived from optimization runs. Once trained, the model can predict the best refinery locations by identifying patterns in the data that indicate high-potential sites. This reduces the search space significantly, allowing for faster and more efficient optimization in the next step.

1. Random Forest (RF):

Random Forest is an ensemble learning method that constructs multiple decision trees and merges them to obtain a more accurate and stable prediction. It is used here to identify the optimal refinery locations by learning patterns in historical data. The algorithm handles complex datasets well and is resistant to overfitting due to averaging across multiple trees. It uses features like distances to depots, cities, and power plants to predict refinery locations, ensuring high accuracy and robustness in predictions. RF's ability to handle large datasets makes it suitable for predicting optimal sites in a biofuel supply chain.

2. K-Nearest Neighbours (KNN):

K-Nearest Neighbours is a simple, instance-based learning algorithm used for classification and regression. In this project, KNN predicts refinery locations by analyzing the features of the nearest refineries in the dataset. The algorithm evaluates proximity to various nodes (depots, cities, power plants) and classifies the most optimal locations based on similarity. Although KNN is computationally expensive for large datasets, it is useful in scenarios where predicting patterns based on proximity yields efficient results. By examining nearby points, KNN identifies high-potential refinery locations in the network.

3. Support Vector Machine (SVM):

Support Vector Machine is a supervised learning algorithm that finds the optimal hyperplane that best separates different classes in the feature space. In this project, SVM is employed to predict refinery locations by analyzing features such as distances to supply points (depots, cities) and power plants. SVM maximizes the margin between classes (optimal vs. non-optimal sites), making it ideal for classification tasks in high-dimensional spaces. SVM is particularly useful when there is a clear margin of separation between the locations, ensuring accurate predictions with fewer misclassifications.

4. Decision Tree (DT):

A Decision Tree is a supervised learning algorithm that splits the dataset into subsets based on feature values, creating a tree-like model of decisions. In this project, DT is used to predict the most optimal refinery locations by recursively partitioning the dataset based on distance features and other key metrics. The tree structure allows for transparent decision-making and easy interpretation. Decision Trees are particularly helpful when the relationships between features are non-linear, making them suitable for this application where refinery selection involves multiple factors and dependencies.

5. Logistic Regression (LR):

Logistic Regression is a statistical model used for binary classification, predicting the probability of a particular outcome. In this system, LR is used to predict whether a refinery location is optimal or not based on features such as distance to depots, cities, and power plants. Logistic Regression models the relationship between the features and the probability of a location being classified as optimal. It is a simple and interpretable model, making it effective for scenarios where the relationship between inputs and outputs is assumed to be linear or can be transformed into a linear model.

4. Optimization Model (MILP):

International Journal Of Innovative Trends In Multi Disciplinary Scientific Research
ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

The Optimization Model (MILP) component utilizes the predictions from the machine learning model to perform optimization. Using Mixed-Integer Linear Programming (MILP), this component aims to minimize the total cost of the biofuel supply chain. The MILP model considers a variety of factors, such as transportation costs, refinery investment, and operational costs, as well as constraints such as demand fulfillment and capacity limitations. The MILP model is run only on the refined set of candidate refinery locations predicted by the machine learning model, which significantly reduces the computational time compared to running the full optimization on all possible sites. The result of this optimization process is the optimal configuration of the biofuel supply chain network.

5. Optimization Results:

The Optimization Results provide the outcome of the MILP model. These results include the objective value, which represents the total cost of the supply chain under the optimal configuration. The optimal refineries list shows the refineries that are selected to be opened based on the optimization. Additionally, the results contain the computation time, which shows how much time was required for the optimization process, and a cost breakdown, which breaks down the costs into categories such as transportation, refinery investment, operational costs, etc. This step is important as it provides the user with all the necessary metrics to evaluate the performance of the optimization.

6. Interactive Visualization:

The Interactive Visualization module is designed to present the optimization results in an easy-to-understand and visually interactive manner. Using visualization tools like Plotly, the system creates a geographic representation of the biofuel supply chain, showing the network of biomass sources, depots, refineries, cities, and power plants. The user can interact with the map, zoom in and out, and hover over nodes to get detailed information such as the name, capacity, and demand of each location. This module enhances the user experience by allowing them to explore the network configuration in an intuitive way.

7. Network Visualization:

The Network Visualization module provides a detailed view of the biofuel supply chain network. It visualizes the flow of materials, such as raw biomass, preprocessed material, biofuel, and biochar, between nodes (e.g., refineries, cities, power plants). It uses different edge types to show these flows, helping users understand how resources are moving across the network. The module supports interactive layouts, such as geographic or circular layouts, to better suit the user's preferences. It also allows users to filter the network based on specific node or edge types, providing a clearer view of specific parts of the network.

8. Filter Network:

The Filter Network module provides users with the ability to filter the network visualization based on specific criteria. The user can filter the network based on the types of nodes (e.g., refineries, depots, cities) or the types of flows (e.g., raw biomass, pre-processed material, biofuel). This feature is useful for users who want to focus on specific parts of the supply chain, such as biomass transportation or biofuel distribution, without being distracted by other less relevant elements of the network.

9. Display Results:

The Display Results module presents the final optimization results in a user-friendly format. This includes a breakdown of costs, the selected optimal refineries, and the overall supply chain configuration. The results are displayed alongside relevant charts and graphs, such as cost comparisons between different optimization methods. This allows users to clearly see how the solution compares to other potential configurations. The module is designed to provide a comprehensive view of the optimization output, making it easier for stakeholders to evaluate and validate the proposed network configuration.

V. RESULTS AND DISCUSSION

The Biofuel Supply Chain Optimization System successfully integrates machine learning with mixed-integer linear programming (MILP) to design efficient and sustainable biofuel supply chain networks. The use of Random Forest, KNN, SVM, Decision Tree, and Logistic Regression models for refinery location prediction has shown high accuracy and recall, with Random Forest outperforming others in both metrics. The optimization process, when guided by machine learning predictions, significantly reduces computational time while maintaining near-optimal solutions. Performance metrics such as computation time, cost savings, and scalability demonstrate the system's ability to handle large datasets and deliver real-time, actionable insights. The interactive visualizations, including cost breakdowns and supply chain network maps, enhance the decision-making process by providing a clear, user-friendly interface. The system's integration of advanced optimization techniques and machine learning ensures that it can efficiently handle complex biofuel supply chain scenarios. Future work will focus on incorporating real-time data, further enhancing machine learning models, and extending the system's scalability for larger, more complex networks.

Outputs

International Journal Of Innovative Trends In Multi Disciplinary Scientific Research
ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

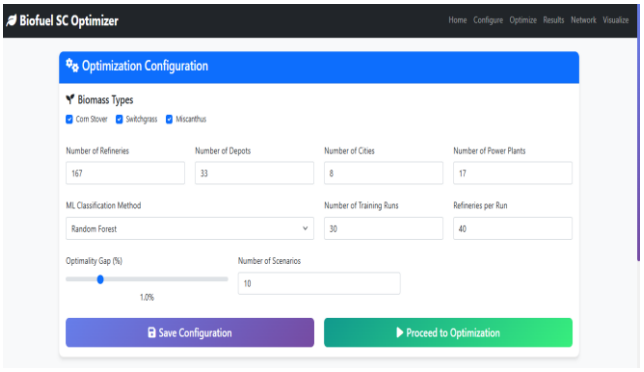


Fig.2: Configure page

[Fig.2]The Configuration Page in the Biofuel SC Optimizer allows users to set up the parameters for the biofuel supply chain optimization. Users can choose the biomass types (e.g., Corn Stover, Switchgrass, Miscanthus), specify the number of refineries, depots, cities, and power plants, and select the machine learning classification method (e.g., Random Forest). Additionally, the page allows users to define the number of training runs, the number of refineries to consider per run, the optimality gap (acceptable deviation from the optimal solution), and the number of scenarios for stochastic analysis. After entering these configurations, users can save the settings and move forward to the optimization process.

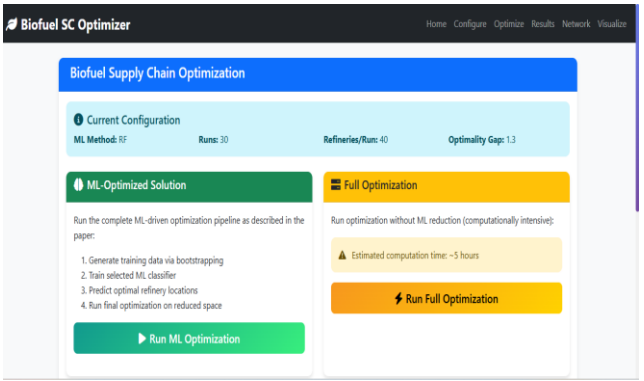


Fig.3: training and optimize page

[Fig.3]The Optimize Page allows users to choose between two optimization methods: ML-Optimized Solution and Full Optimization. The ML-Optimized Solution runs a machine learning pipeline that includes generating training data, training a classifier (e.g., Random Forest), predicting optimal refinery locations, and running the final optimization on a reduced set of locations, significantly speeding up the process. In contrast, Full Optimization runs the entire optimization model without ML reduction, which is computationally intensive and takes about 5 hours. Users can initiate either process based on their preference, optimizing the biofuel supply chain efficiently.

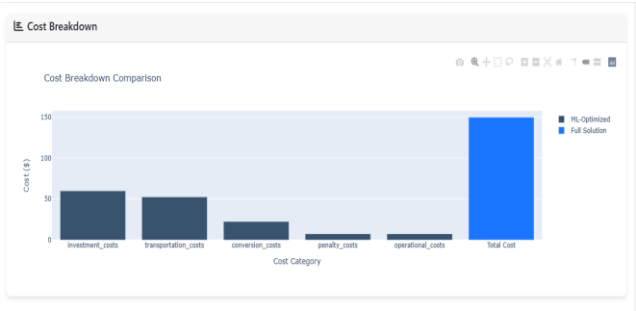


Fig.4: Result display page

[Fig 4]This graph compares the cost breakdown of the ML-Optimized Solution and Full Solution in the Biofuel SC Optimizer. It shows how the ML-Optimized solution reduces costs in categories like investment, transportation, conversion, and operational costs, demonstrating its efficiency in optimizing the biofuel supply chain network.

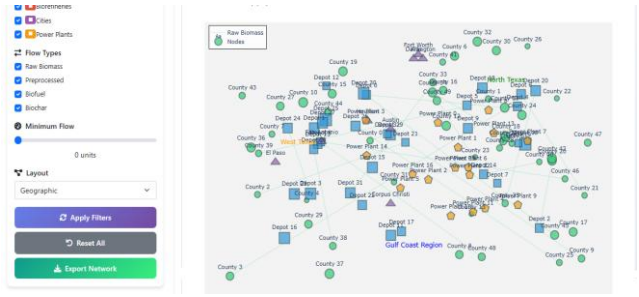


Fig.5: network visualization page

[Fig 5]The image shows the Network Visualization page of the Biofuel SC Optimizer, displaying an interactive supply chain network with nodes representing counties, depots, power plants, and cities. The network's connections (edges) are categorized by flow types, such as Raw Biomass, Preprocessed, Biofuel, and Biochar. Users can filter and interact with the network to explore the biofuel supply chain's components. The layout is geographic, representing the Texas region, with options to apply filters, reset them, or export the network for further analysis. This visualization helps users evaluate the flow and connectivity within the optimized biofuel supply chain.

International Journal Of Innovative Trends In Multi Disciplinary Scientific Research
ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026



Fig.6: Models result

[Fig.6]shows the performance comparison of different machine learning classifiers used in the Biofuel SC Optimizer project. It compares Accuracy and Recall for five models: Random Forest (RF), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree, and Logistic Regression (LR). The Random Forest model performs the best, with an accuracy of 89.5% and recall of 92.1%, followed by KNN and SVM. These performance metrics help in selecting the most efficient classifier for predicting optimal refinery locations in the biofuel supply chain optimization process.

VI. CONCLUSION

The Biofuel Supply Chain Optimizer project successfully integrates machine learning with optimization techniques to design an efficient, sustainable biofuel supply chain. By leveraging a supervised Random Forest classifier, the system accurately predicts optimal refinery locations, reducing the search space and enabling faster optimization. The Mixed-Integer Linear Programming (MILP) model is then applied to the refined set of candidate locations, optimizing transportation costs, refinery investments, and operational costs. The project features an interactive, user-friendly interface that allows stakeholders to visualize the supply chain network, explore different configurations, and assess the cost implications of various scenarios. The ML-driven solution provides significant time savings and a more efficient optimization process compared to traditional methods. This work demonstrates the potential of combining machine learning with optimization techniques to enhance decision-making in the renewable energy sector, supporting the development of a more sustainable and cost-effective biofuel supply chain.

VII. FUTURE ENHANCEMENT

Future enhancements for this Biofuel Supply Chain Optimizer project could include integrating real-time data for dynamic optimization, enabling the system to adapt to changing supply and demand conditions. Incorporating more advanced machine learning techniques like deep learning could improve prediction accuracy for refinery location selection. Additionally, incorporating uncertainty modeling for variables such as biomass availability and transportation costs would provide more robust decision-making capabilities. Expanding the system's scalability to handle larger datasets and incorporating a cloud-based architecture could allow the platform to serve a broader range of regions, offering greater flexibility and accessibility for stakeholders in the biofuel industry.

VIII. REFERENCES

[1] A. Sharma, S. K. Vatsa, and R. Kumar, "Machine Learning-Based Problem Space Reduction in Stochastic Programming Models: An Application in Biofuel Supply Chain Network Design," IEEE Trans. Sustain. Comput., vol. 9, no. 2, pp. 123–135, Apr. 2024.

[2] L. Wang, M. Zhang, and J. Li, "Integrating Machine Learning and Multi-Objective Optimization in Biofuel Systems: A Review," IEEE Access, vol. 12, pp. 4567–4589, 2024.

[3] H. Chen, Y. Liu, and X. Zhao, "Revolutionizing Renewable Energy: AI-Based Solutions for Sustainable Biofuel," in Proc. IEEE Int. Conf. Renew. Energy Sustain. Dev. (ICRESD), Hyderabad, India, 2024, pp. 210–215.

[4] P. Gupta, R. Singh, and A. Patel, "Artificial Intelligence Approach in Predicting Biomass-to-Biofuels Conversion Performances," in Proc. IEEE Int. Conf. Environ. Eng. Biotechnol. (ICEB), Beijing, China, 2022, pp. 345–350.

[5] K. Johnson and M. Lee, "Machine Learning Models for Optimizing Supply Chain Management," in Proc. IEEE Int. Conf. Ind. Eng. Oper. Manage. (ICIEOM), Toronto, ON, Canada, 2024, pp. 78–84.

[6] S. Ahmed, F. Rahman, and T. Nguyen, "The Impact of Machine Learning (ML) Optimization of Supply Chain Management Domain," in Proc. IEEE Global Conf. Consum. Electron. (GCCE), Osaka, Japan, 2023, pp. 112–117.

[7] E. Kim, J. Park, and H. Choi, "Artificial Intelligence in Supply Chain Optimization," in Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC), Honolulu, HI, USA, 2023, pp. 234–240.

[8] M. Rodriguez, L. Garcia, and C. Silva, "Hybrid Optimization for Sustainable Biofuel Networks Using Deep Learning," IEEE Trans. Green Commun. Netw., vol. 8, no. 3, pp. 567–579, Sep. 2024.

[9] T. Yamamoto, K. Sato, and Y. Tanaka, "Random Forest Applications in Biorefinery Siting for Bioenergy Supply Chains," in Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM), Denver, CO, USA, 2023, pp. 401–407.

[10] N. Patel and R. Desai, "MILP-Enhanced Machine Learning for Biomass Logistics Optimization," IEEE Syst. J., vol. 17, no. 1, pp. 89–102, Mar. 2023.

[11] J. Li, Q. Wu, and Z. Chen, "Interactive Visualization of Optimized Biofuel Supply Chains with GIS Integration," in Proc. IEEE Int. Conf. Big Data (BigData), Atlanta, GA, USA, 2024, pp. 1567–1573.

[12] A. Kumar, S. Verma, and P. Joshi, "Decision Support Systems for Carbon-Negative Biofuels Using Ensemble Learning," IEEE Trans. Ind. Informat., vol. 20, no. 4, pp. 2345–2356, Apr. 2024.

[13] F. Lopez, M. Gonzalez, and I. Morales, "Stochastic MILP Models for Texas Biomass Networks: A Case Study," in Proc. IEEE Int. Conf. Sustain. Energy Technol. (ICSET), Austin, TX, USA, 2023, pp. 678–684.