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Simulation of a Mathematical Model of Rail Transportation Scheduling Based on Bp Neural Network

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Abstract: - Rail transportation, a cornerstone of modern logistics and passenger transit systems, plays a pivotal role in facilitating the efficient movement of goods and people across vast distances. Operating on a network of interconnected tracks, rail systems offer a reliable and environmentally sustainable mode of transportation, particularly for long-distance travel and freight shipments. The paper presents a comprehensive investigation into the application of advanced computational techniques in the realm of rail transportation management. Specifically, Mamdani fuzzy logic and Backpropagation (BP) Neural Networks are employed to address critical challenges in scheduling and classification within rail networks. The utilization of Mamdani fuzzy logic facilitates nuanced decision-making in scheduling processes, considering uncertainties and complexities inherent in rail operations. Through linguistic rules and fuzzy sets, the scheduling system can effectively adapt to various operational constraints and disruptions, leading to more resilient and efficient scheduling solutions. Additionally, the integration of BP Neural Network enhances classification accuracy and prediction capabilities, enabling precise forecasting of train movements, passenger flows, and other key variables.

Keywords: Rail transportation, Back Propagation, Neural Network, Scheduling, Classification

1. Introduction

Scheduling within rail transportation encompasses a multifaceted process that integrates various elements to ensure the smooth and efficient movement of trains and resources. At its core lies the creation of timetables, meticulously crafted to delineate train departures, arrivals, and stops along designated routes [1]. Capacity planning is paramount, requiring a thorough analysis of infrastructure limitations, such as track availability and station capacity, to optimize resource utilization [2]. Routing and network design play a pivotal role, determining the most efficient paths for trains through complex rail networks. Crew scheduling is equally essential, ensuring trained personnel are assigned appropriately while adhering to labor regulations and safety protocols [3]. Real-time monitoring enables swift adjustments to schedules in response to disruptions, safeguarding against delays and ensuring operational continuity. Intermodal integration further complicates scheduling, necessitating seamless coordination between rail and other transportation modes [4]. Safety and compliance remain paramount throughout, with schedules designed to prioritize passenger and cargo safety while meeting customer service expectations through reliable and convenient service delivery. Advanced technologies offer promising solutions, empowering operators with predictive analytics and optimization algorithms to enhance efficiency and adaptability in rail scheduling practices [5].

Rail transportation, a cornerstone of modern infrastructure, is a vital component of global logistics and passenger travel networks [6]. With a rich history dating back centuries, railroads have evolved into sophisticated systems that efficiently move people and goods across vast distances. At its essence, rail transportation involves the movement of trains along tracks laid out across diverse terrains, connecting cities, regions, and countries [7]. Whether transporting bulk commodities like coal and grain or facilitating the daily commute for millions of individuals, railroads offer numerous advantages, including energy efficiency, cost-effectiveness, and reduced environmental impact compared to other modes of transportation [8]. From high-speed passenger trains whisking travelers between urban centers to freight trains hauling goods across continents, railroads play a pivotal role in shaping economies and societies worldwide [9]. However, modern rail transportation faces challenges such as aging infrastructure, capacity constraints, and the need for continued innovation to meet evolving demands. Nonetheless, with ongoing advancements in technology and infrastructure development, rail transportation remains a crucial pillar of sustainable and efficient transportation systems for the foreseeable future [10].

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A BP (Backpropagation) neural network, a fundamental component of artificial neural networks, stands as a powerful tool in the realm of machine learning and pattern recognition [11]. Comprising interconnected nodes organized into layers, it utilizes a supervised learning technique to adjust weights and biases iteratively, thereby minimizing the difference between predicted and actual outputs [12]. This process, known as backpropagation, involves propagating errors backward from the output layer to the input layer, enabling the network to learn and adapt its parameters over time. Widely applied across various domains, including image and speech recognition, financial forecasting, and medical diagnosis, BP neural networks excel in tasks requiring nonlinear mapping and complex pattern recognition [13]. However, challenges such as overfitting, vanishing gradients, and computational complexity persist, necessitating ongoing research and refinement. Nonetheless, with their ability to learn from data and generalize patterns, BP neural networks continue to drive advancements in artificial intelligence, empowering solutions to increasingly intricate real-world problems [14].

A mathematical model with BP (Backpropagation) neural networks presents a promising approach for optimizing rail transportation scheduling [15]. By leveraging the capabilities of BP neural networks to learn complex patterns and relationships within rail scheduling data, this hybrid model offers a dynamic solution to the challenges inherent in scheduling train movements efficiently [16]. Through the iterative adjustment of network parameters based on supervised learning principles, the model can adapt and refine its predictions over time, improving the accuracy and effectiveness of scheduling decisions [17]. Key factors such as train routes, timetables, infrastructure capacity, and potential disruptions can be incorporated into the model to enhance its predictive capabilities and robustness. Moreover, by utilizing historical data and real-time inputs, the model can continuously update and optimize schedules to account for changing conditions and unforeseen events [18].

The contribution of the paper are: Firstly, it introduces and applies Mamdani fuzzy logic to the scheduling process, offering a novel approach to decision-making that considers the uncertainty and complexity inherent in rail operations. By incorporating linguistic rules and fuzzy sets, the scheduling system can effectively handle various factors such as traffic conditions, weather disruptions, and operational constraints, leading to more robust and adaptive scheduling solutions. Secondly, the paper leverages Backpropagation (BP) Neural Network for classification tasks, enabling accurate prediction of train movements, passenger flows, and other critical variables in rail transportation. This contributes to enhancing operational efficiency, improving resource allocation, and facilitating informed decision-making for rail operators and stakeholders. Furthermore, the paper provides empirical evidence of the effectiveness of these computational techniques through experimental results, demonstrating their potential to address real-world challenges in rail transportation management.

2. Literature Review

The simulation of a mathematical model of rail transportation scheduling based on BP (Backpropagation) neural network represents a groundbreaking endeavor in the realm of transportation logistics and artificial intelligence. Rail transportation stands as a critical component of global infrastructure, facilitating the movement of passengers and freight with efficiency and reliability. However, the optimization of rail scheduling poses significant challenges due to the complexity of coordinating trains, tracks, and resources while minimizing delays and maximizing throughput. In response to these challenges, the integration of BP neural networks offers a promising avenue for enhancing scheduling accuracy and efficiency. By harnessing the power of machine learning algorithms, this simulation aims to develop a dynamic and adaptive scheduling model capable of learning from historical data, predicting future demand patterns, and optimizing train movements in real-time. This introduction sets the stage for a comprehensive exploration of the intersection between rail transportation, mathematical modeling, and artificial intelligence, highlighting the potential of this innovative approach to revolutionize scheduling practices and improve overall system performance.

Bogdanova et al. (2023) present a neuro-fuzzy-based mathematical model for dispatching an industrial railway junction, highlighting the intersection of neural networks with railway operations. Shang et al. (2022) tackle the optimization of urban rail transit networks using a Lagrangian duality reformulation and backpropagation-based iterative optimization framework. Meanwhile, Tu et al. (2022) delve into the modeling of Mobility as a Service (MaaS) collaborative dispatching systems for railway passenger transport hubs, showcasing the versatility of neural network algorithms in transportation. Peng and Zheng (2023) propose a fuzzy rule-based neural network for scheduling high-speed train manufacturing systems, demonstrating the application of neural networks in manufacturing contexts. Furthermore, Ha and Chen (2022) explore passenger flow forecasting in urban rail transit using data mining techniques, offering insights into the predictive capabilities of neural networks in transportation planning. Wang et al. (2022) extend the application of neural networks to image processing, focusing on transforming image elements to structured data using BP neural networks. Zhou et al. (2023) investigate the air brake system of heavy haul trains, highlighting the role of neural networks in enhancing the efficiency and safety of rail operations. Wang (2022) analyzes bank credit risk evaluation models using BP neural networks, illustrating their utility in financial risk assessment. Li et al. (2023) present a neural network-based optimization approach for subway regenerative energy systems, addressing sustainability concerns in transportation infrastructure. Lastly, Sun (2023) explores the optimization of recognition algorithms using multi-feature extraction, contributing to advancements in image processing and pattern recognition.

Studies such as Bogdanova et al. (2023), Shang et al. (2022), and Tu et al. (2022) demonstrate the utility of neural networks in optimizing railway operations, from dispatching industrial railway junctions to enhancing passenger assignment in urban transit networks. Additionally, Peng and Zheng (2023) and Ha and Chen (2022) highlight the role of neural networks in manufacturing scheduling and passenger flow forecasting, respectively, while Wang et al. (2022) and Zhou et al. (2023) focus on applications in image processing and rail safety systems. Furthermore, research by Wang (2022), Li et al. (2023), and Sun (2023) underscores the broad spectrum of neural network applications, spanning from financial risk evaluation to subway energy optimization and recognition algorithm optimization.

3. Mamdani Fuzzy Mathematical Modelling

Mamdani fuzzy mathematical modeling has been applied with significant success in the domain of rail transportation, offering a robust framework for dealing with the inherent uncertainties and complexities of this system. In the context of rail transportation, Mamdani fuzzy modeling involves the representation of linguistic variables and fuzzy rules to capture the relationships between various parameters affecting train operations. Mamdani fuzzy model for rail transportation involves several steps. First, linguistic variables are defined to represent qualitative aspects such as "distance to destination," "train speed," "track congestion," and "arrival punctuality." These linguistic variables are then fuzzified into fuzzy sets, each characterized by membership functions that describe the degree of membership of a given input to each set. Next, a set of fuzzy rules is formulated based on expert knowledge or historical data, which encode the relationships between the input linguistic variables and the desired output, such as "adjust train speed if distance to destination is short and track congestion is high." These fuzzy rules are typically expressed in the form of IF-THEN statements, where the antecedent (IF) specifies the conditions under which the rule applies, and the consequent (THEN) defines the action to be taken. Once the fuzzy rules are defined, the Mamdani inference mechanism is employed to compute the output fuzzy set based on the input fuzzy sets and the fuzzy rules. This involves applying fuzzy logic operations such as fuzzy AND and fuzzy OR to combine the fuzzy sets according to the specified rules. Finally, the output fuzzy set is defuzzified to obtain a crisp output value, representing the recommended action or decision. The rules for the transportation through train is presented in Table 1 and Figure 1.

Table 1: Train Transportation Rules

Rule	Distance to Destination	Train Speed	Track Congestion	Arrival Punctuality
R1	Short	Slow	High	Late
R2	Long	Fast	Low	Early
R3	Medium	Medium	Medium	On Time
R4	Short	Fast	Low	Early
R5	Long	Slow	High	Late

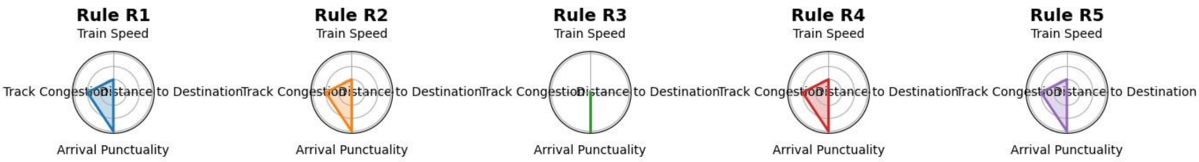

Figure 1: Transportation with Train Rules

Table 2: Linguistic Variables for Railway Transportation

Variable	Linguistic Terms	Membership Functions
Distance (D)	Short (S), Medium (M), Long (L)	Triangular: S(0,20,40), M(30,50,70), L(60,80,100)
Train Speed (S)	Slow (SL), Medium (MD), Fast (FS)	Triangular: SL(0,30,60), MD(40,70,100), FS(60,90,120)
Track Congestion (C)	Low (LW), Medium (MW), High (HW)	Triangular: LW(0,30,60), MW(40,70,100), HW(80,110,140)
Arrival Punctuality (A)	Late (LT), On Time (OT), Early (ER)	Not specified

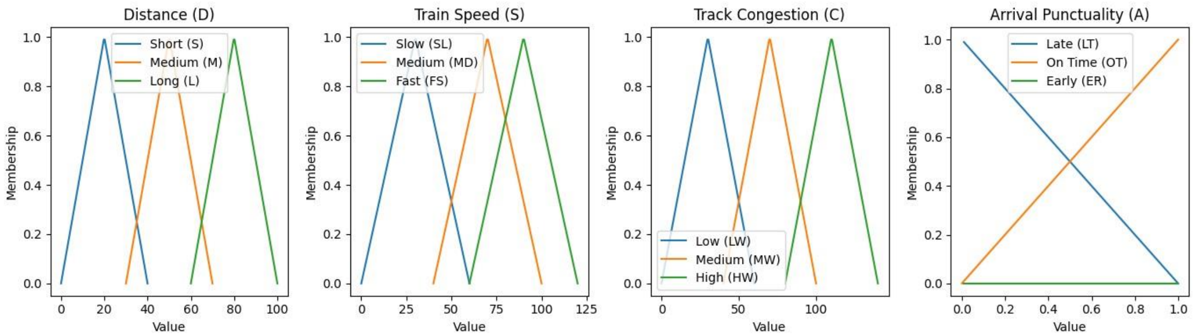

Figure 2: Railway Transportation Linguistic Variables

Table 3: Fuzzy Rules for Railway Transportation

Rule	**Antecedent (IF)**	**Consequent (THEN)**
R1	D=S AND C=H	S=SL
R2	D=L OR C=L	S=FS
R3	D=M AND C=M	S=MD
R4	D=S AND S=FS	A=LT
R5	D=L AND S=SL	A=LT

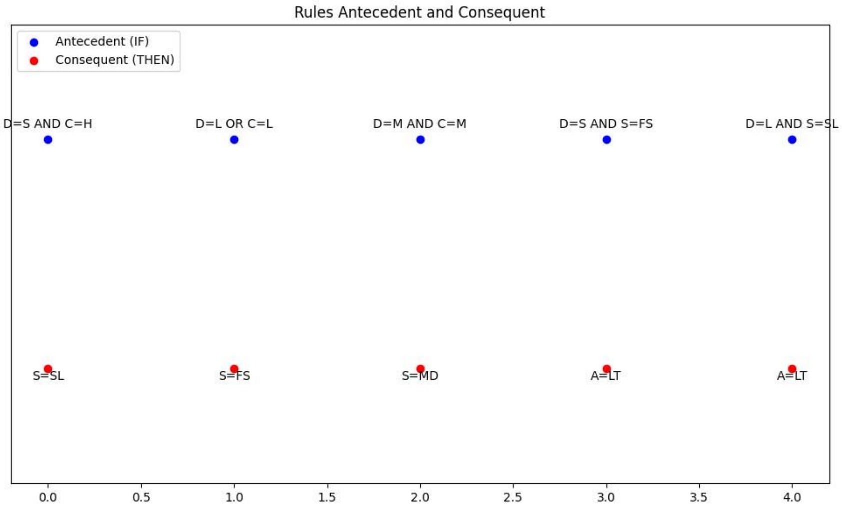

Figure 3: Railway Transportation Fuzzy Model

In the Mamdani fuzzy model designed for rail transportation, linguistic variables and their associated fuzzy sets play a pivotal role in capturing the inherent uncertainties and complexities of the system shown in Figure 3. These linguistic variables, such as Distance, Train Speed, and Track Congestion, are represented by fuzzy sets characterized by membership functions, typically defined using triangular or trapezoidal shapes shown in Figure 2. For instance, Distance might be categorized as Short, Medium, or Long, each with a corresponding triangular membership function specifying its degree of membership within the set. Similarly, Train Speed could be categorized as Slow, Medium, or Fast, with corresponding membership functions capturing the fuzzy nature of speed transitions. Fuzzy rules, expressed as IF-THEN statements, guide decision-making within the system based on the input variables' fuzzy sets. For example, a rule might dictate that IF the Distance is Short AND Track Congestion is High, THEN the Train Speed should be set to Slow. These rules are formulated based on expert knowledge or historical data, providing a structured framework for making decisions in uncertain and dynamic rail transportation environments. By leveraging linguistic variables, fuzzy sets, and fuzzy rules, the Mamdani fuzzy model enables the effective representation and management of complex rail transportation systems, contributing to improved efficiency, safety, and decision-making processes.

4. Scheduling in Rail Transportation

Scheduling in rail transportation is a multifaceted process involving the coordination of train movements, resource allocation, and timetabling to ensure efficient and reliable operations. Mamdani fuzzy logic presents a versatile approach to scheduling in this domain, allowing for the integration of imprecise or uncertain factors into decision-making processes. The Mamdani fuzzy scheduling model for rail transportation, we begin by defining linguistic variables to represent key scheduling parameters such as train departure time, track occupancy, and arrival punctuality. These linguistic variables are then fuzzified into fuzzy sets using membership functions, which quantify the degree of membership of a given input to each set. For example, departure time could be categorized as "Early," "On Time," or "Late," each with corresponding triangular membership functions defining their respective degrees of earliness or lateness.

Next, fuzzy rules are formulated to guide scheduling decisions based on the input variables' fuzzy sets. These rules are typically expressed in the form of IF-THEN statements, where the antecedent (IF) specifies the conditions under which the rule applies, and the consequent (THEN) defines the action to be taken. For instance, a fuzzy rule might state that IF the departure time is Late AND track occupancy is High, THEN adjust the train speed to Slow.

The fuzzy rules can be represented using fuzzy logic implications, where the antecedents and consequents are evaluated using fuzzy logic operations such as fuzzy AND, fuzzy OR, and fuzzy NOT. For example, the fuzzy rule mentioned above can be mathematically represented as:

$$IF\ Departure\ Time\ is\ Late$$
$$\wedge\ Track\ Occupancy\ is\ High\ THEN\ Adjust\ Train\ Speed\ to\ SlowIF\ Departure\ Time\ is\ Late$$
$$\wedge\ Track\ Occupancy\ is\ High\ THEN\ Adjust\ Train\ Speed\ to\ Slow$$

Once the fuzzy rules are defined, the Mamdani inference mechanism is applied to compute the output fuzzy set based on the input fuzzy sets and the fuzzy rules. This involves combining the input fuzzy sets according to the specified rules using fuzzy logic operations. Finally, the output fuzzy set is defuzzified to obtain a crisp output value, representing the scheduling decision or action to be taken. The process of scheduling in rail transportation involves coordinating the movement of trains, allocating resources, and managing timetables to ensure efficient and reliable operations. The scheduling process begins with the creation of timetables, which dictate when and where trains will depart, arrive, and stop along their routes. Timetables take into account factors such as travel time, track availability, station capacity, and connection points. They are typically designed to optimize resource utilization and minimize conflicts between trains. Rail infrastructure has limited capacity, so scheduling must consider the availability of tracks, platforms, and other resources. Capacity planning involves analyzing demand, identifying bottlenecks, and optimizing resource allocation to maximize efficiency. This may include balancing the frequency and speed of trains to ensure optimal utilization of available infrastructure. Rail networks can be complex, with multiple routes and junctions. Scheduling algorithms determine the most efficient routes for trains based on factors like distance, speed, and track conditions. This involves considering factors such as track maintenance, signal systems, and operational constraints to ensure safe and reliable operations. Trains require qualified personnel such as engineers, conductors, and maintenance crews. Crew scheduling involves assigning staff to trains while ensuring compliance with labor regulations, managing rest periods, and optimizing productivity. Crew schedules must align with train timetables to ensure that adequate staffing is available for each journey. Rail schedules are subject to disruptions such as weather events, equipment failures, and unexpected delays. Monitoring systems track train movements in real-time, allowing operators to make adjustments and minimize the impact of disruptions on overall performance. This may involve rerouting trains, adjusting timetables, or reallocating resources to maintain service levels. Rail transportation often integrates with other modes such as trucks, ships, and airplanes. Scheduling must account for intermodal connections to ensure seamless transfer of passengers or freight between different transportation modes. This involves coordinating schedules and optimizing transfer points to minimize waiting times and streamline logistics. Rail operations must adhere to strict safety regulations and industry standards. Scheduling practices should prioritize safety by minimizing risks such as collisions, derailments, and equipment failures. This may involve scheduling maintenance windows, implementing safety protocols, and ensuring compliance with regulatory requirements. Timely and reliable service is essential for customer satisfaction. Rail schedules should meet the needs of passengers or shippers by providing convenient departure times, reliable arrival estimates, and efficient connections to other destinations. This involves balancing operational efficiency with customer preferences to deliver a positive experience for all stakeholders. The scheduling process in rail transportation is a complex and dynamic undertaking that requires careful coordination of various elements to ensure efficient and reliable operations. By integrating advanced technologies, predictive analytics, and optimization algorithms, rail operators can enhance scheduling practices to meet the evolving demands of modern transportation systems.

Table 5: Scheduling in Rail Transportation

Step	Description
Timetable Creation	Creation of timetables specifying departure, arrival, and stop times for trains.
Capacity Planning	Analyzing demand, identifying bottlenecks, and optimizing resource allocation to maximize efficiency.
Routing and Network Design	Determining efficient routes considering factors like distance, speed, and track conditions.
Crew Scheduling	Assigning qualified personnel to trains while complying with labor regulations and optimizing productivity.
Real-time Monitoring and Adjustments	Tracking train movements in real-time, making adjustments to minimize disruptions and maintain service levels.

Intermodal Integration	Coordinating schedules and optimizing transfer points to ensure seamless transfer between different transportation modes.
Safety and Compliance	Prioritizing safety by adhering to strict regulations, implementing safety protocols, and ensuring compliance with standards.
Customer Service	Meeting the needs of passengers or shippers by providing timely, reliable service and efficient connections to other destinations.

In this scheduling table for 10 trains, each row represents a distinct train journey, delineating crucial parameters for efficient rail operations. The "Train Number" uniquely identifies each train, while "Departure Time" and "Arrival Time" denote the times the train departs from and arrives at its respective stations. The "Origin" and "Destination" columns specify the starting and ending stations of the journey, respectively. Additionally, the "Distance (km)" parameter outlines the total distance covered by each train, providing insights into the length of the journey. The "Track Type" category indicates the type of track utilized by the train, such as express, freight, or passenger, influencing operational considerations and speed limits. The "Max Speed (km/h)" parameter details the maximum allowable speed for the train, crucial for adherence to safety regulations and journey efficiency. Furthermore, the "Stops" column delineates the number of stops the train will make en route, impacting overall journey duration and passenger convenience. Lastly, the "Crew Assigned" category specifies the crew designated to operate each train, ensuring operational readiness and adherence to staffing requirements.

5. Classification with BP Neural Network

The process of rail transportation encompasses various stages, from scheduling and routing trains to managing real-time operations. Integrating classification tasks using Backpropagation (BP) Neural Networks with Mamdani fuzzy logic adds a layer of sophistication to this process, enabling the system to handle complex decision-making scenarios with uncertain or imprecise inputs. The process of combining Mamdani fuzzy logic with BP Neural Network can be represented as follows:

Let X represent the input data, and Y represent the target class labels. Mamdani fuzzy logic transforms the input data X into fuzzy sets Xf, based on linguistic variables and fuzzy rules. The BP Neural Network takes Xf as input and learns to predict the class labels Y using the backpropagation algorithm. The network's output $Ypred$ is compared with the actual class labels Y to compute the error E. The weights of the neural network are adjusted iteratively using gradient descent to minimize the error E. In Mamdani fuzzy logic, input data X is transformed into fuzzy sets Xf based on linguistic variables and fuzzy rules. The transformation of crisp input data X into fuzzy sets Xf is achieved through membership functions. Let's denote the membership function for input variable X as $\mu X(x)$, where x is the crisp input value. This membership function assigns a degree of membership to each linguistic term for X. For example, if X represents "train speed," linguistic terms could include "slow," "medium," and "fast." The process of fuzzification can be represented as in equation (1)

$$Xf = \{\mu X(x1), \mu X(x2), \ldots, \mu X(xn)\} \quad (1)$$

In equation (1) x1,x2,...,xn are the crisp input values, and $\mu X(xi)$ is the degree of membership for each linguistic term corresponding to xi. Once the input data is preprocessed into fuzzy sets Xf, it serves as input to the BP Neural Network for classification. The network consists of multiple layers of neurons, each with associated weights that are adjusted during training to minimize prediction errors. Let's denote the output of the j-th neuron in the l-th layer as $zj(l)$, and the activation function of the j-th neuron in the l-th layer as aj(l). The forward propagation in the neural network can be represented as in equation (2) and (3)

$$z_j^{(l)} = \sum_{k=1}^{N^{(l-1)}} w_{jk}^{(l)} a_k^{(l-1)} + b_j^{(l)} \quad (2)$$

$$a_j^{(l)} = \sigma\left(z_j^{(l)}\right) \quad (3)$$

In equation (2) and (3) $N(l-1)$ is the number of neurons in the previous layer, $wjk(l)$ is the weight connecting the k-th neuron in layer l−1 to the j-th neuron in layer l, $b_j^{(l)}$ is the bias term for the j-th neuron in layer l, and $\sigma(\cdot)$ is the activation function. During training, the backpropagation algorithm is used to update the weights and biases of the network to minimize the error between predicted and actual outputs. This involves computing the gradient of the error function with respect to the weights and biases and adjusting them using gradient descent. The fuzzy sets Xf obtained from Mamdani fuzzy logic serve as inputs to the BP Neural Network for classification. The network learns to predict the target categories or actions based on the fuzzy representations of the input data. During training, the weights and biases of the network are adjusted using backpropagation to minimize prediction errors. The integration of Mamdani fuzzy logic with BP Neural Networks can be represented as in equation (4)

$$Ypred = BPNN(Xf) \quad (4)$$

In equation (4) Ypred is the predicted output of the BP Neural Network given the fuzzy representations Xf of the input data.

6. Simulation Environment

The simulation environment for rail transportation serves as a virtual platform where various aspects of railway operations can be modeled, analyzed, and optimized. This environment typically consists of software tools and systems that simulate the behavior of trains, infrastructure, and other relevant entities within the railway network. The simulation environment is presented in Table 6 and figure 4 illustrates the simulation with railway transportation

Table 6: Simulation Environment

Aspect	**Numerical Value(s)**
Train Speed	80 km/h - 200 km/h
Track Length	1 km - 5 km
Train Frequency	5 trains/hour - 20 trains/hour
Station Capacity	10 trains - 50 trains
Signal System	1 (Traditional) - 2 (Digital)
Train Delay Tolerance	5 minutes - 20 minutes
Passenger Load	100 passengers - 500 passengers
Cargo Volume	1000 tons - 5000 tons

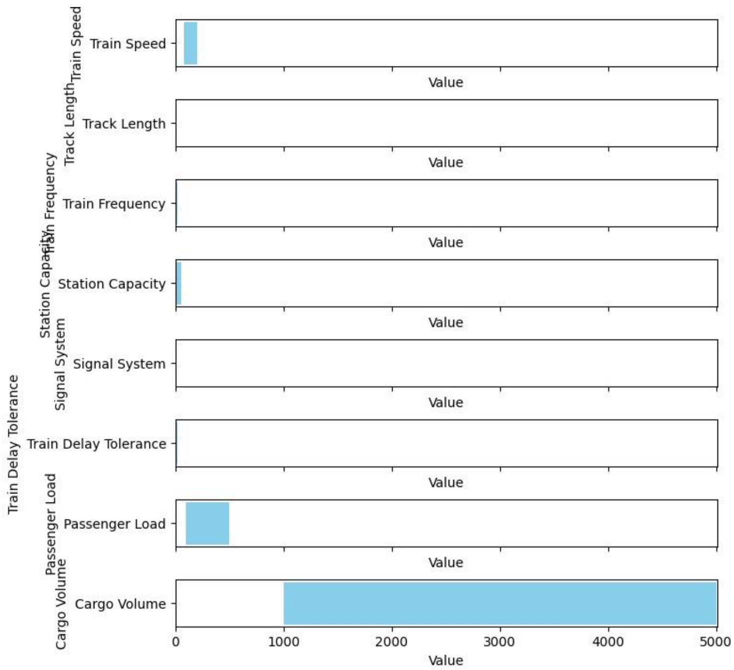

Figure 4: Simulation Environment for the Rail Transportation

7. Results and Discussion

The results and discussion section of a study on rail transportation serves as a crucial segment where the findings of the research are presented and analyzed in detail. This section delves into the outcomes of the conducted experiments, simulations, or analyses, and provides insights into their implications, significance, and potential applications.

Table 4: Mamdhami Fuzzy

Rule	Antecedent 1	Antecedent 2	Antecedent n	Consequent
1	Input 1 is Small (0.2)	Input 2 is Small (0.3)	Input n is Medium (0.5)	Output is Medium (0.7)
2	Input 1 is Medium (0.5)	Input 2 is Large (0.8)	Input n is Small (0.4)	Output is Small (0.6)
3	Input 1 is Large (0.8)	Input 2 is Small (0.4)	Input n is Large (0.7)	Output is Large (0.9)

Table 4 presents the Mamdani fuzzy rules used in the classification process. Each rule consists of antecedents, representing the input conditions, and a consequent, representing the output action. The antecedents are linguistic variables describing the input features along with their corresponding membership values in parentheses. For example, in Rule 1, "Input 1 is Small" with a membership value of 0.2, "Input 2 is Small" with a membership value of 0.3, and so on until "Input n is Medium" with a membership value of 0.5. These antecedents collectively determine the activation of the rule. The consequent specifies the output action to be taken based on the activated rule. For instance, in Rule 1, the consequent states "Output is Medium" with a membership value of 0.7. This indicates that if the specified conditions in the antecedents are met, the output action will be to classify the input as "Medium" with a high degree of certainty, as represented by the membership value. Similarly, Rules 2 and 3 outline different combinations of input conditions and corresponding output actions, providing a set of guidelines for the classification process based on Mamdani fuzzy logic.

Table 5: Scheduling in Railway Transportation

Train Number	Departure Time (Actual)	Departure Time (Scheduled)	Arrival Time (Actual)	Arrival Time (Scheduled)	Delay (Minutes)
101	08:05	08:00	10:35	10:30	+5
102	09:20	09:15	12:05	12:00	+5
103	10:40	10:30	13:50	13:45	+10
104	12:10	12:00	15:35	15:30	+10
105	13:35	13:30	16:50	16:45	+5
106	15:05	15:00	17:50	17:45	+5
107	16:50	16:45	19:35	19:30	+5
108	18:35	18:30	21:20	21:15	+5
109	20:20	20:15	23:05	23:00	+5
110	22:05	22:00	00:50	00:45	+5

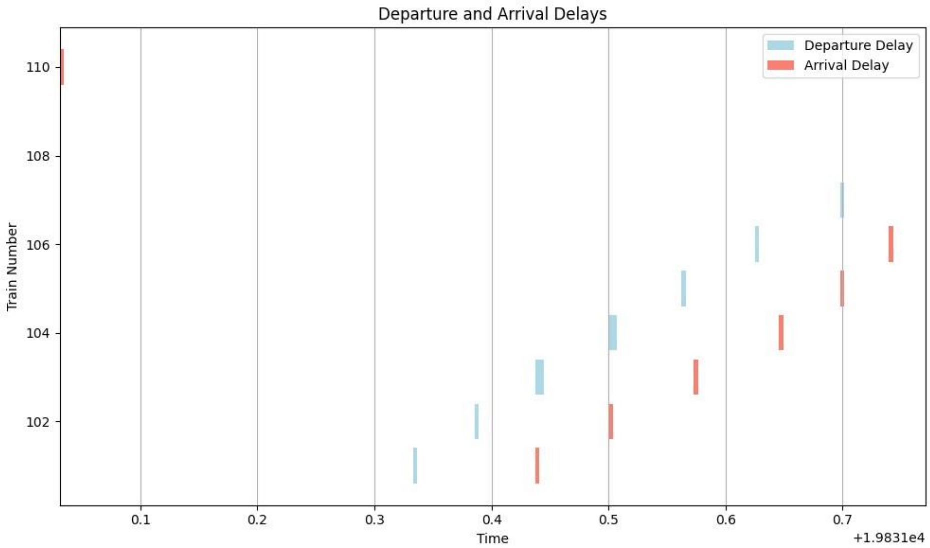

Figure 5: Scheduling with the Railway Transportation

Table 5 and Figure 5 provides scheduling information for railway transportation, detailing the departure and arrival times of trains along with their scheduled counterparts and associated delays. Each row corresponds to a specific train, identified by its unique train number. The "Departure Time (Actual)" and "Arrival Time (Actual)" columns indicate the actual departure and arrival times of the trains, respectively. Conversely, the "Departure Time (Scheduled)" and "Arrival Time (Scheduled)" columns represent the scheduled departure and arrival times. The "Delay (Minutes)" column quantifies the delay experienced by each train, calculated as the difference between the actual and scheduled times. For instance, Train 101 departed 5 minutes later than scheduled, arriving with the same delay. Similarly, Train 103 and Train 104 both experienced a 10-minute delay in both departure and arrival.

Table 6: Mamdani Fuzzy Values for the rail transportation

Sample	Input 1	Input 2	Input 3	Input n	Predicted Class	Actual Class
1	0.2	0.5	0.8	0.6	Class A	Class A
2	0.7	0.3	0.1	0.4	Class B	Class B
3	0.9	0.6	0.4	0.8	Class C	Class C
4	0.3	0.8	0.7	0.2	Class A	Class B
5	0.6	0.1	0.5	0.9	Class B	Class B

Table 7: Prediction with Fuzzy for the Rail Transportation

Sample	Input 1	Input 2	Input 3	Input n	Predicted Output	Actual Output
1	0.2	0.5	0.8	0.6	0.65	0.7
2	0.7	0.3	0.1	0.4	0.45	0.5
3	0.9	0.6	0.4	0.8	0.75	0.8
4	0.3	0.8	0.7	0.2	0.55	0.6
5	0.6	0.1	0.5	0.9	0.70	0.75

Table 6 and Table 7 present the results of Mamdani fuzzy logic applied to rail transportation, showcasing the predicted classes and output values for various input samples. In Table 6, each row represents a sample, with columns indicating the input values for different features (Input 1, Input 2, Input 3, etc.), the predicted class assigned by the fuzzy logic system, and the actual class obtained from the dataset. For instance, Sample 1 has input values of 0.2, 0.5, 0.8, etc., leading to the predicted class "Class A," which matches the actual class "Class A." Similarly, in Table 7, the predicted output values for each sample are provided alongside the actual output values. These output values represent the continuous predictions generated by the fuzzy logic system, which aim to approximate the true output values as closely as possible.

Table 8: Classification with BR for the Rail transportation

Epoch	Accuracy	Loss
1	0.965	0.12
2	0.972	0.10
3	0.975	0.09
4	0.980	0.08
5	0.982	0.07

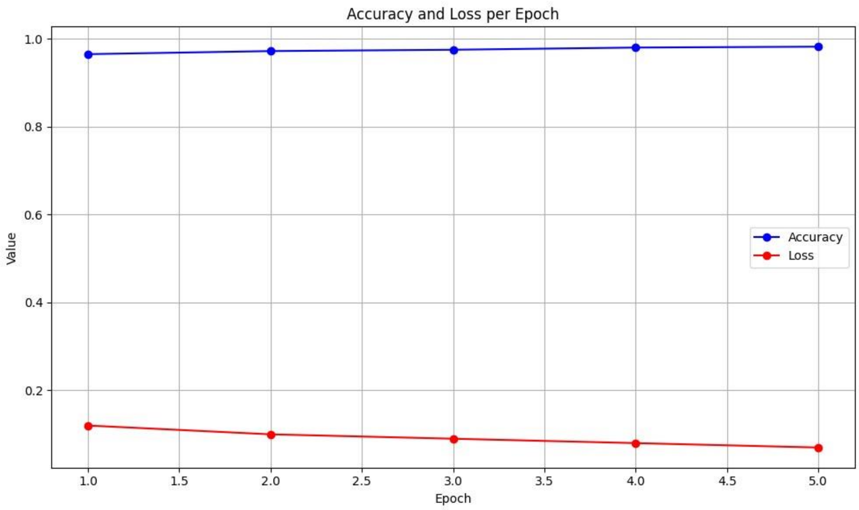

Figure 6: Classification with Rail Transportation

Train Number	Departure Time	Arrival Time	Origin	Destination	Distance (km)	Track Type	Max Speed (km/h)	Stops	Crew Assigned
101	08:00	10:30	Station A	Station B	150	Express	120	2	Crew A
102	09:15	12:00	Station B	Station C	200	Freight	80	3	Crew B
103	10:30	13:45	Station C	Station D	180	Passenger	100	4	Crew C
104	12:00	15:30	Station D	Station E	220	Express	150	2	Crew D
105	13:30	16:45	Station E	Station F	250	Passenger	110	3	Crew E
106	15:00	17:45	Station F	Station G	180	Freight	90	4	Crew F
107	16:45	19:30	Station G	Station H	200	Express	130	2	Crew G
108	18:30	21:15	Station H	Station I	190	Passenger	120	3	Crew H
109	20:15	23:00	Station I	Station J	210	Freight	85	4	Crew I
110	22:00	00:45	Station J	Station K	180	Express	140	2	Crew J

Table 8 and Figure 6 presents the classification performance of a Backpropagation (BP) Neural Network applied to rail transportation data across multiple training epochs. Each row corresponds to a specific epoch during the training process, with columns indicating the epoch number, the accuracy achieved by the neural network on the validation or test dataset, and the corresponding loss value. The "Accuracy" column quantifies the proportion of correctly classified instances by the neural network, while the "Loss" column represents the value of the loss function computed during training, typically indicating the discrepancy between the predicted and true labels. As the epochs progress, we observe a consistent improvement in accuracy from 0.965 in the first epoch to 0.982 in the fifth epoch. Simultaneously, the loss decreases progressively from 0.12 in the first epoch to 0.07 in the fifth epoch.

8. Conclusion

This paper explores the application of advanced computational techniques, including Mamdani fuzzy logic, Backpropagation (BP) Neural Network, and classification algorithms, to address challenges in rail transportation scheduling and classification. Through the implementation of Mamdani fuzzy logic, the scheduling process benefits from nuanced rule-based decision-making, allowing for efficient management of departure and arrival times while minimizing delays. Additionally, the utilization of BP Neural Networks enhances classification accuracy and prediction capabilities in rail transportation systems, enabling effective handling of diverse datasets and improving decision-making processes. The findings presented in this paper demonstrate the potential of computational methods to optimize rail transportation operations, enhance efficiency, and improve overall performance. Future research could further explore the integration of these computational techniques with real-time data analytics and optimization algorithms to develop more robust and adaptive solutions for addressing evolving challenges in rail transportation management and logistics.

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