Research Article

Application of Artificial Intelligence Algorithm in Relay Protection of Distribution Network

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1. Introduction

Relay applications and places perform a process that controls the workflow of goods and products. Relay applications provide the necessary set of data for various fields and applications. Relay application is widely used in supply chain networks (SCNs) to improve the transportation services of goods [1]. Relay application controls the central part of the transportation system in SCN. SCN location and transportation provide an appropriate data set for the analysis and detection process. Relay application first tracks the goods ID number using an operating model [2]. Delivering products and goods to customers is a complicated task to perform in SCN. Relay applications reduce the latency rate in delivering services and the costs of services. Relay application maximizes the performance rate in the goods transportation system [3]. Relay application delivers the products to the customers with a high-security level. Relay application reduces the threats and problem rate due to third-party members. The automatic relay application takes control over distribution and the SCN system. Automatic relay controls the heavy workload of the transportation system [4, 5].

Relay protection is a process that identifies the faults that occurred during certain services. Relay protection detects faults and eliminates them before leading to severe damage. The relay protection process reduces the system’s damage rate, which improves the application’s performance and feasibility [6]. The supply chain network (SCN) mostly uses relay protection for transportation. In SCN, relay protection is used to discover the drawbacks and problems while delivering goods to the customers [7]. Numerical relay protection is commonly used in SCN that detects problems based on digital signals. Digital signals are enclosed with every product and truck that sends real-time information to the SCN management system [8]. Numerical relays use certain devices to track and locate the faults available during transportation. Relay protection provides various sets of schemes for SCN that reduce the error rate and damage rate of delivering process. Relay protection controls the whole...
goods delivery process, enhancing the supply chain network system's efficiency and reliability. The automatic relay protection process recloses the delivery process when damage is detected in SCN. First, an operation is performed to detect the faults and damages that cause customer and organization problems [9, 10].

Artificial intelligence (AI) is a stimulation process that utilizes human intelligence to perform particular tasks via machines and computers. AI is a superset of machine learning (ML) techniques that improve the efficiency and feasibility of the system [11]. AI is commonly used in various fields that reduce the workload of an organization and its application. AI technique is mostly used in relay protection schemes that improve the accuracy rate in the fault identification process [12]. AI-based relay protection is used for SCN, which requires an accurate data set for the goods transportation system. An adaptive fuzzy logic algorithm is used for relay protection in SCN. The fuzzy logic algorithm performs an optimization process to find out the faults that are occurred in SCN [13]. The classification method is used here to classify the optimized data by the optimization process. Features such as location, goods, types, positions, and problems are classified in the classification process. A fuzzy logic algorithm improves the overall accuracy rate in the classification process, improving the system's efficiency. The artificial neural network (ANN) approach is commonly used for the relay protection process in SCN. ANN implements a classification and identification process to determine the actual problems presented in a transportation system [14, 15]. Based on the above discussion, the major contribution of the work is listed as follows:

(i) The fuzzy algorithm can measure the density of different vehicles and goods in the design and development of protective relays

(ii) They are developing a populous relay management scheme (PRMS) for multi-access delivery networks to improve relay utilization without congestion

(iii) These features are analyzed for the stagnancy and dispatch priority in maximizing the goods delivery

2. Related Works

Livesay et al. [16] introduced a theoretical approach for reliability within the information supply chain. The proposed approach analyzes the terms of functionality presented within the supply chain. The proposed approach solves the non-uniqueness of information within the supply chain. The proposed model is used to extend the cycles that are available in storage space. The proposed approach maximizes the flexibility and reliability of the system.

Zhang et al. [17] introduced a cooperative coevolutionary bare bones particle swarm optimization (CCBBPSO) method for large-scale supply chain networks using function independent decomposition (FID). The binary encoding method is used here to decode the problems available in the optimization process. The step translation method is implemented in CCBBPSO to evaluate the variables that are occurred due to bounds. The proposed CCBBPSO-FID improves the efficiency and reliability of the supply chain network.

Zhou et al. [18] proposed a robust optimization for the distribution network. The proposed method is used to identify the location-routing problems presented in the distribution network. The robust optimization process finds out the variables and problems that provide the necessary data set for the data analysis process. The proposed method increases the accuracy rate in the decision-making process, enhancing the system's performance.

Khanduzi and Sangaiah [19] introduced a genetic algorithm for a biomedical supply chain network. The decomposition method (DM) is used here to investigate the problems available in the optimization process. The fast branch and cut method (FBC) is also used in the proposed method, providing feasible solutions to solve the problems. The proposed method is mainly used to find out the problems that are occurred due to the lack of protection schemes. The proposed method maximizes the accuracy rate in the detection process and reduces the latency rate in the identification process.

Saen et al. [20] proposed a network data envelopment analysis (NDEA) model for sustainable supply chain management (SSCM) systems. NDEA model analyzes the data set that is necessary for further process. NDEA model maximizes the accuracy rate in the decision-making process using decision-making units (DMUs). Data envelopment analysis is mainly used here to enhance the sustainability rate of the system. The proposed NDEA model improves the sustainability and reliability of the SSCM system.

Rezaei and Behnamian [21] introduced a competitive model to improve the sustainability rate of the supply chain network. The particle swarm optimization (PSO) algorithm is used here to find the structural features presented in the supply chain network. The PSO algorithm identifies multilevel competition-oriented problems. The proposed model maximizes the interaction process's efficiency rate, improving the relationship among networks. The proposed method achieves a high sustainability rate that enhances the performance and feasibility of the system.

El Amrani et al. [22] proposed a supply chain sustainability index (SCSI) using a Bayesian network. Bayesian is used here to identify the relationship between variables of SCSI. SCSI is mainly used for the prediction process that provides the necessary data set for data analysis and development. The proposed SCSI method achieves a high sustainability rate and reduces the time consumption rate in the identification process.

Alikhani et al. [23] introduced a stochastic optimization framework using resilience capabilities for supply chain networks. The optimization framework identifies the relationship between variables and data patterns available in the supply chain network. The proposed framework reduces the network's computation cost and maximizes the system's feasibility and reliability. The proposed framework improves the sustainability and efficiency of the supply chain network.

Yang et al. [24] proposed an evaluation method for supply chain networks. The proposed method is used to identify the robustness of the supply chain system. A
recovery strategy is used here to retrieve the data necessary for the evaluation process. Supply chain networks require more robustness to manage huge amounts of data. The proposed method improves the supply chain network’s robustness rate, which enhances the system’s efficiency.

Moslehi et al. [25] introduced a multi-objective stochastic model for supply chain networks. The proposed model is mainly used to reverse the logistic strategies of the supply chain network. Scenario-based stochastic programming (SSP) approach is used here to identify the available features in the supply chain network. The proposed method improves the system’s feasibility and effectiveness, reducing the computation cost.

Haoues et al. [26] proposed an optimization method for a two-echelon supply chain network. A genetic algorithm is used here to find out the outsourcing features of the supply chain network. The optimization method identifies both multi-subcontractors and multi-outcomes of the supply chain. The proposed method reduces the computation cost and time in the optimization process. The proposed method enhances the reliability and efficiency of the supply chain network.

Ignaciuk [27] introduced an inventory control model for supply systems. Arbitrary multi-echelon topology is used here to find out the structures and features of the supply chain network. State-space model is also used here to analyze the data presented in a supply network. The proposed method achieves a high sustainability rate and efficiency rate in the system. The proposed model improves the feasibility and effectiveness of the supply chain network.

Tamym et al. [28] proposed a big data (BD) analysis-based architecture for supply chain networks (SCNs). The proposed method is used for collaboration networks that require high robustness in SCN. The proposed method is mainly used to improve the relationship among shareholders. The proposed BD-based method increases the performance rate and stability rate of SCN.

3. Proposed Scheme

The distribution network in the supply chain management connects the warehouse and delivery of goods to the customers via transportation. In supply chain management, handling goods to the customers is very important in delivery. It should be managed by considering priority-based delivery and zero-delay delivery, maintaining the relationship between the customers and the warehouses. The relays between the warehouses and the customers are considered the most prominent in delivering goods and maintaining a balance between production and demand. Figure 1 presents the proposed scheme in an SCN scenario.

The relay process between warehouses at the point of delivery is being monitored. Multiple relays are used for delivering between the warehouse and the customer, the producer, and the warehouse. Each relay in the supply chain management manages the demand, i.e., crowded with priority-based delivery. If the relays cannot meet the populous, producers must be able to satisfy the customers’ requirements. The delivery cost is calculated based on the consumer goods to control the congestion. A populous relay management scheme is being proposed to address the priority-based delivery with congestion reduction. A flow model is defined based on the factors satisfying the customers’ demands, i.e., delivery of goods between the relay and the populous. The distribution flow between warehouse, relay, and customers is designed as a network node, which is represented by the following equation:

$$\sum a = \{a_{th}^{th}, \beta_{a}^{th} \in E(th, T)\} \leq \chi_{th}, \quad h = 1, 2, \ldots 0, \quad (1)$$

$$\sum h \sum a = \{a_{th}^{th}, \beta_{a}^{th} \in E(th, T)\} \leq \min(\sum h_{f}, f). \quad (2)$$

In Eqn (1) and (2), the relay regulates the flow to meet the demands from the customer that are defined by $a_{th}$ and $\beta_{a}$. The total flow denoting the delivery of goods from the relay to a customer is given by $\sum a = \{a_{th}^{th}, \beta_{a}^{th} \in E(th, T)\}$. The flow of goods from the producer to the relay and the delivery of goods from the relay to the customer is identified by $\sum h \sum a = \{a_{th}^{th}, \beta_{a}^{th} \in E(th, T)\}$. From the above equation, $h_{f}$ is the quantity of goods in the relay. $E$ is the path between the warehouse, relay, and customer. $f$ is the demand populous that exists in the network. Eqn (1) and (2) denote the goods and flow along with the relays, warehouses, and product distribution network. Based on the crowded demand from the customer, the availability of goods is also calculated. The flow of goods and availability of goods in relays, warehouses, and the producer are monitored for the factors of increasing populous demand. Figure 2 illustrates the migration possibility and transport assignment process.

The migration possibility and delivery assignment rely on the priority feature. If a priority is assigned, then first-in-first-out-based delivery is performed with the available vehicles. Contrarily, the priority unassigned relay goods are identified for their delivery time. This is performed for partial goods based on the capacity for preventing stagnancy (refer to Figure 2). The transfer of goods from relays to the populous demands from the customer is identified and should be controlled so that delivery of goods from relays must not exceed the availability of goods in the relay network as depicted in Eqn (1).

Along with the distribution flow, the goods to be delivered from the relays should be equal to the available goods present in the relays. The transfer of goods should also be maintained equal to the populous demand from the customers as defined in Eqn (2). Some conditions are being monitored to direct the flow of goods without congestion and a priority-based delivery of goods.

Condition 1: the goods available in relays must satisfy the populous demands of the customers ($\sum h_{f} \geq f$), such that the producers in the network need not deliver the goods to the warehouse to maintain the distribution flow of goods that is expressed by the following equations:

$$\sum h \sum a = \{a_{th}^{th}, \beta_{a}^{th} \in E(th, T)\} = f, \quad (3)$$

$$\sum d \sum a = \{a_{td}^{to}, \beta_{a}^{to} \in E(td, T)\} = 0. \quad (4)$$
The flow of goods from the warehouse to the relays is denoted as \( \sum d \sum a \{ a^{td}_a, \beta^{td}_a \in E(td, T) \} \); the transfer of goods from the producer to the warehouse is \( td \). The total flow of goods from the relays to the customers is considered to equalize the demand \( f \).

Condition 2: the availability of the goods in the relay is maintained. If the crowded demand cannot be satisfied by the goods present in the relay (\( \sum h \chi_h < f \)), then the distribution flow of goods addressing the demands can be represented as follows:

\[
\sum h \sum a \{ a^{th}_a, \beta^{th}_a \in E(th, T) \} = \sum h \chi_h, \quad (5)
\]

\[
\sum d \sum a \{ a^{td}_a, \beta^{td}_a \in E(td, T) \} = f - \sum h \chi_h. \quad (6)
\]

3.1. Distribution Flow and Its Capacity. The distribution flow of goods with their available capacity is calculated to identify the possible delivery of goods in the available network. The delivery capacity is denoted as \( Y = (y_1, y_2, \ldots y_n) \), where \( y_i \) is the current delivery capacity, the maximum delivery capacity is denoted as \( Y = (c_1, c_2, \ldots c_n) \), \( \psi \) is the consumed delivery capacity of goods in the distribution flow, and \( \lambda \) is
the distribution flow pattern through route \( r \). The delivery of goods to the customers from relays and the goods from producers to the relays is shown in the following equation:

\[
|\rho| \left[ \sum d \sum a_{ai} \in \beta_{ar} \right] + \sum h a_{ai} \in \beta \left[ \rho \sum a_{ai} \in \beta \right] \leq c_i \] (7)

The total flow of available goods from the producers to warehouses is denoted as \( |\rho| \sum d \sum a_{ai} \in \beta_{ar} \). The flow of goods from the warehouses to the customers is denoted as \( \sum h a_{ai} \in \beta \). Thus, the overall flow of goods in the distribution network with its capacity in the flow is denoted as \( |\rho| \sum d \sum a_{ai} \in \beta_{ar} + \sum h a_{ai} \in \beta \). Which are considered to be maintained under the distribution flow pattern \( \lambda \) through the route \( r \). This \( \lambda \) is feasible on those conditions that fulfill the delivery capacity \( Y \), which is satisfied by the following:

\[
|\rho| \left[ \sum d \sum a_{ai} \in \beta_{ar} + \sum h \sum a_{ai} \in \beta \right] \leq y_i. \] (8)

3.2. Delivery Assessment. The delivery of goods along the flow depends on factors, i.e., consumed delivery of goods and capacity. The overall delivery of goods along the flow pattern is given by the delivery of goods along with the distribution flow between the relay and the customer and the relay and the producer as shown in Eqn (10):

\[
\left[ \sum h a_{ai} \in \beta \left( \rho \sum a_{ai} \in \beta \right) \right] + \sum d \sum a_{ai} \in \beta \left( \rho \sum a_{ai} \in \beta \right) \geq f, \] (9)

\[
\omega \left[ \rho \sum d \sum a_{ai} \in \beta + \sum h \sum a_{ai} \in \beta \right] \leq \tau. \] (10)

The delivery cost, along with the distribution flow through \( r \), is denoted by \( \omega \left[ \rho \sum d \sum a_{ai} \in \beta + \sum h \sum a_{ai} \in \beta \right] \). Eqn (9) denotes the flow pattern that must satisfy demand \( f \). Therefore, the delivery capacity \( Y \) must satisfy both the demand \( f \) and budget \( \tau \). Based on the delivery of goods, the distribution flow and its capacities are identified. The populous demand that exceeds the availability of goods in the relay factors is to be calculated. It includes a priority-based delivery, and a congestion-reducing mechanism will be designed. The delivery assessment based on populous and stagnancy factors is illustrated in Figure 3.

The delivery delay is analyzed based on consumer feedback to prevent further errors. In this process, the learning model classifies stagnancy and congestion. Based on these factors, the goods (priority) reassignment and transport schedules are provided. This swiftly enhances the delivery without increasing delay (refer to Figure 3). The proposed populous relay management addresses the customers’ demands by identifying the priorities from the demands and calculating the congestion that happens in the distribution flow of the network, which delays the delivery of goods to the customers. From Eqn (9), the flow pattern is considered whether it meets the demand in the network. Demands are not met by the availability of goods for the relays and warehouses, a priority in the following equation:

\[
\sum h a_{ai} \in \beta \left( \rho \sum a_{ai} \in \beta \right) + \sum d \sum a_{ai} \in \beta \left( \rho \sum a_{ai} \in \beta \right) \leq \tau. \] (11)

To reduce the congestion in handling the delivery to the populous demand from the customers, the budget \( \tau \) with its cost \( \omega \) is calculated if condition (11) is not satisfied, and then, congestion of delivery along the distribution flow path occurs, which is represented by follows:

\[
\omega \left[ \rho \sum d \sum a_{ai} \in \beta + \sum h \sum a_{ai} \in \beta \right] \leq \tau. \] (12)

3.3. Back Propagation Network Process. The back propagation neural network is a neural network where the network tuning is based on the error rate obtained through iterations. The fine-tuning of the network thus reduces the error rates and increases the network’s output. It allows the calculation of gradient loss function considering the weights in the network. A gradient steepest descent algorithm is used to interconnect the neurons with the input, hidden, and output layers. The randomization of weights initiates the optimal search in the network. It computes each layer at a time. It computes the gradients based on the delta rule. The sum of squared errors \( \varsigma \) between the target values \( u_p \) and the output \( s_p \) is defined as follows:

\[
\text{Min} \varsigma = \frac{1}{2} \sum_p (u_p - s_p). \] (13)

Using the gradient steepest descent, the minimization of the errors is done by taking the partial derivative of the errors, as shown in the following equation:

\[
\frac{\partial \varsigma}{\partial w_{mn}} = \frac{\partial \varsigma}{\partial s_m} \frac{\partial s_m}{\partial x_m} \frac{\partial x_m}{\partial w_{mn}}. \] (14)

From the above equation, \( w_{mn} \) is the corresponding weights that are associated between the neurons \( m \) and \( n \). \( s_m \) is the output, and the sum of the weighted input neuron is \( \xi_m \). The partial derivative of each weighted function is known, and then, the simple gradient descent function is updated by the following equation

\[
w_{mn} (i + 1) = w_{mn} (i) - \mu \frac{\partial \varsigma}{\partial w_{mn}} (i). \] (15)

From the above Eqn (15), \( \mu \) is the learning rate that determines the network’s performance. If \( \mu \) is small, then the convergence time to obtain the output is too long. If \( \mu \) is large, then the convergence makes the minimization at an infeasible point. The activation function in each hidden and output layer makes the values \( \xi_m = \sum w_{nm} x_m \) by sending it to the neurons in the network. The activation function uses a
sigmoid function to deal with the continuous variable of weights that is as shown in the following equation:

\[ f_n(x_m) = \frac{1}{1 + \exp(-x_m)} \]  

(16)

Based on the training sets obtained from the populous demand, the transfer of goods between the relays and customers, warehouse, and relays is calculated. The initial value of weights is set. The BP neural network process for stagnancy and congestion estimation is presented in Figure 4.

The inputs are the flows observed in the previous deliveries that are validated for \( \alpha_a \) and \( \beta_a \) throughout its availability. This feature is verified that “r” distributions are handled. The distribution handling is pursued to achieve \( s_p \in u_p \) by reducing errors. This error refers to the delay and stagnancy observed within the delivery time (refer to Figure 4). The training values \( x_m \) are given as the input to the input layers neurons to obtain the output \( s_p \). The vector \( (x_p, s_p) \) is used for training. Based on the training, the activation function from Eqn (16) is calculated. However, the activation function is considered to be 1. The error function is calculated based on the activation function, as shown in Eqn (13). From this, the weights are adjusted based on the error function. For iteration, the initial steps are being followed with the training pair \( (x_p, s_p) \). The new weights are calculated until the network learns all the training pairs \( (x_p, s_p) \). From this back propagation network, the priority-based management of goods in the distribution network is achieved, thus reducing the congestion in the distribution flow of goods in the network.

### 3.4. Proposed Scheme Assessment

In this section, the proposed scheme’s performance is validated using the data set from [29]. This data set provides information on various shipped product parcels and logistics. The delivery and stocks from 2017 September to 2017 December for 469978 products with delivery time, category, and date are provided in the data set. With this information, the model presented in Figure 1 is replicated with the relay hub design presented in Figure 5.

The required details for the consumers, producers, transport, and relay are in Figure 5. This is required for mutual supply chain product tracking and delivery in the transportation process. The aim of delivery maximization and congestion control requires independent features and information mapping. The two processes are illustrated in Figure 6.

The information for relays, transport, and consumers is mapped as a single entity to prevent congestion (vehicles) and stagnancy (goods). This is pursued to prevent delayed delivery regardless of the priorities assigned. The infrastructure and stagnancy for various points are analyzed in a correlation with the data set provided.

The above Figure 7 representation provides the congestion observed in the four months for the varying vehicle densities similarly, and the stagnancy based on stored goods is also analyzed for the different months. In the “After” (priority) and BP process, the expected (estimation) is also presented for the same input. This is the expected output that may slightly vary from the actual observation. Depending on the joint crowded and stagnancy factors analyzed by the BP neural network, the prioritization for the products (actual and estimation) is analyzed using Figure 8.

The prioritization is required for maximizing the delivery without stagnancy and congestion features. The learning is performed depending on the BP outputs to identify maximum relay utilization. As the utilization is maximized, stagnancy is reduced through precise priority assignment. In particular, the priority assignment relies on the actual delivery of products from different relay points. The priorities are reassigned based on available vehicles (increased/decreased). This assignment is performed using delivery details and congestion-to-stagnancy factors.

### 3.4.1. Comparative Assessments

For the comparative assessments, the metrics of delivery improvement, migration...
factor, task prioritization, delivery delay difference, and congestion factor are considered. The methods used for the above comparisons are TESCN [26], CCBBPSO [17], and SCN-UCF [24]. The relay points and populous factors are varied for analyzing the above metrics.

### 3.4.2. Delivery Improvement

The proposed method identifies the demand from the populous, availability of goods in relays, and demand-based transfer of goods from warehouse to the relays. In the distribution flow of the network, goods delivery capacity along route between relay and the customers, warehouse, and relays are identified based on improving the delivery of goods concerning the customer demand. The proposed scheme relies on the congestion and stagnancy factors analyzed using the neural network with back propagation for mitigating its impact. This process is recurrent until the goods are assigned with time and delivery-based priorities. The streamlining is performed based on the neural network and activation function modifications for the varying relay points and populous factors. Besides, the possible derivatives for improving the delivery swiftly are performed using different recommendations and analyses. The analysis is performed recurrently until the maximum delivery with less stagnancy is achieved. The back-dropping stagnancy is further analyzed without requiring distinct priorities. Based on the capacity and flows, further distribution maximizes the expected output (refer to Figure 9).

### 3.4.3. Migration Factor

Based on the availability of goods at the relays, goods from the producer are being fetched, ensuring a fair delivery of goods to the customer’s demands. By monitoring the demands and availability of goods, a migration of goods from the producer to the relays is being performed. Goods based on availability and demand for the goods from producer to relays are ensured by maintaining communication between the relays, warehouse, and the producer. With the proposed populous demand management system, the migration factor increases with the distribution flow of goods. The migration factor is improved with the relay point analysis for stagnancy and congestion. These two factors are analyzed to reduce the delivery delay at the initial stage. Depending on the consumer feedback and vehicle density, further allocations are performed. The flows and distribution are reassigned in this process to reduce the...
stagnancy. Therefore, the migration features are further differentiated to improve the delivery flow. In the proposed scheme, the cumulative flows are streamlined using the partial derivatives formulated using $f$. The target values are initially achieved to improve the migration factor by reducing the delay (refer to Figure 10).

3.4.4. Task Prioritization. The proposed populous demand management system uses a back propagation algorithm in which a priority-based demand is identified along with the flow of distribution networks, which improves the delivery of goods to the demands of the customers based on the priority. The priority of demand is being provided with the goods based on the availability in relays. If the goods are unavailable in the relay, the goods are being migrated from the producer. Thus, priority-based task management is being increased by the proposed technique. In the proposed scheme, two different priorities are assigned. The initial priority relies on goods’ stagnancy without disturbing the delivery flow. In the distinct analysis, the total delivery flow is aligned using the $f$ factor. The proposed scheme is
analyzed using the distribution using $r$ such that a warehouse to different dispatches is performed. Therefore, further priority allocation is performed using the congestion factor and learning rate. The neural network emphasizes the improved learning rate for maximizing prioritization. This enhances the delivery and flow rate without confining the prioritization (refer to Figure 11).

### 3.4.5. Delivery Delay Difference

The proposed populous demand management system minimizes the delivery delay by maintaining the availability of goods in relays and the availability of goods in the warehouse of producers. The transfer of goods to the relays from warehouses to address the customer demand makes a cyclic chain manner in providing the goods to the customers’ demands in time. This makes the proposed populous-based management system a very efficient and zero-delay system. The distinct priority assignment process and learning rate improvements reduce the delivery delay regardless of the vehicle and goods availability. The assignments are relaxed to the stagnancy and congestion rates independently as determined using the delay factor. Based on the learning rate, further delivery assignments are performed without maximizing stagnancy. In the stagnancy-preventing process, the learning rate differentiates the flows and demands. If the demands are estimated to prevent errors, then the deliveries are planned based on priority. The proposed scheme identifies target outputs and extractions based on the learning recommendation to prevent delivery delays. Therefore, the deliveries are planned and augmented with the previous stagnancy knowledge and learning rates, diminishing delivery delays (Figure 12).

### 3.4.6. Congestion Factor

The delivery capacity with its distribution flow of goods along the route is calculated based on which congestion in the network is reduced using a back propagation algorithm. With the sufficient availability of goods in relays and to address the increasing number of populous demands, the congestion in the network along the distribution flow of goods is decreased by increasing the improvement of delivery with task prioritization. Thus, engaging a congestion-free delivery of goods to the customer demands is achieved. The congestion factor is unanimously rectified for the varying populous factor and relay points by identifying the errors. The errors are identified based on delays and stagnancy factors for preventing further congestion. In the learning process, the distribution flows are
modelled using the demand factor and outputs using back propagation. Depending on the capacity and activation function, the learning model is rescheduled to prevent further stagnancy. The proposed scheme performs improved migration possibility by preventing congestion due to vehicles. The neural network synchronizes the populous and stagnancy factors reducing the congestion (Figure 13). The comparative analysis results are summarized with the
findings in Tables 1 and 2 for the varying relay points and populations.

4. Concluding Remarks

This article introduced a populous relay management scheme for improving the goods delivery in a supply chain distribution network. The problem of delayed deliveries and congestion due to limited relay points are jointly addressed using this scheme. This scheme estimates the relay congestion due to vehicle migration and goods stagnancy due to non-prioritized assignments. Based on the estimation, the conventional back propagation neural networks are employed for distinguishing the influencing factors. The influencing factors are identified using the populous to delay and stagnancy to congestion validations with a recurrent learning iteration. The feature analysis is performed without reducing the prioritization and reshuffling the priorities based on stagnancy. This reshuffling and priority reassignment is recommended by BP neural learning for improving the migration factor. The performance assessment shows that for the varying relay points, this scheme achieves 6.71% high delivery improvements, 8.79% high migration factor, 6.87% high prioritization, 7.93% less delivery delay, and 8.26% less congestion factor.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there are no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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| Table 1: Comparative analysis results (relay points). |
|-----------------------------------------|----------------|----------------|----------------|----------------|
| Metrics                                | TESCN | CCBBPSO | SCN-UCF | PRMS | Findings       |
| Delivery improvement                   | 0.222 | 0.273   | 0.315   | 0.3371 | 6.71% high     |
| Migration factor                       | 0.365 | 0.439   | 0.493   | 0.5202 | 8.79% high     |
| Prioritization (tasks/migration)       | 15    | 21      | 31      | 38     | 6.87% high     |
| Delivery delay difference (min)         | 55.95 | 45.83   | 31.58   | 23.292 | 7.93% less     |
| Congestion factor (tasks/vehicle)      | 0.274 | 0.226   | 0.156   | 0.0534 | 8.26% less     |

| Table 2: Comparative analysis results (population). |
|-----------------------------------------|----------------|----------------|----------------|----------------|
| Metrics                                | TESCN | CCBBPSO | SCN-UCF | PRMS | Findings       |
| Delivery improvement                   | 0.229 | 0.271   | 0.303   | 0.3369 | 6.92% high     |
| Migration factor                       | 0.366 | 0.449   | 0.493   | 0.5232 | 8.72% high     |
| Prioritization (tasks/migration)       | 15    | 21      | 29      | 39     | 7.41% high     |
| Delivery delay difference (min)         | 56.39 | 42.5    | 32.45   | 21.481 | 8.94% less     |
| Congestion factor (tasks/vehicle)      | 0.271 | 0.229   | 0.155   | 0.0924 | 12.59% less    |
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