ECONOMIC GROWTH FORECAST MODEL URBAN SUPPLY CHAIN LOGISTICS DISTRIBUTION PATH DECISION USING AN IMPROVED GENETIC ALGORITHM

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ABSTRACT

The proposed way of estimating the associated macroeconomic index based on a supply chain network is a novel strategy that might give useful insights for firms and organizations trying to enhance their supply chain logistics operations. To aid in this process, the suggested technique utilizes multiple regression analysis and adaptive extreme learning machine models to determine the relative importance of each indicator in the supply chain logistics decision-making process. Firms may be able to save expenses and boost economic value by employing enhanced genetic algorithms and mathematical modeling to develop a logistics distribution model for urban supply chains based on reconstructive genetic algorithms. It is possible that the paper's study of the issues plaguing the current distribution of logistics in metropolitan areas would prove valuable to organizations that are seeking to improve their own supply chain logistics procedures. This paper appears to take a thorough strategy that might assist assure the accuracy of the forecasting method by preprocessing macroeconomic indicators using imputation, classification, and other approaches to generate a time series consistency model. Some novel ways that may shed light on logistics in the supply chain include using a two-dimensional discrete mesh structure built on wireless sensors to depict the national economic development scenario and using a coding matrix to convey the extent of economic growth. A thorough and all-encompassing way that might aid organizations in making better judgments about their supply chain logistics strategies is to employ multiple regression analysis, an adaptive extreme learning machine model, and other approaches to examine the effect degree of each key indicator. Experiments demonstrating excellent and steady prediction accuracy of the algorithm model are encouraging and point to the possible usefulness of the suggested forecasting approach. The paper's contributions, including its analysis of supply chain logistics cost accounting, determination of the basic path optimization, improvement of the genetic algorithm, and design of the mathematical model of supply chain logistics distribution path decision, all look promising in terms of their potential to help businesses cut costs and boost economic value. The positive outcome of the successful design of the mathematical model demonstrates the possible efficacy of the suggested technique.

Keywords: Supply chain; logistics distribution; mathematical model; genetic algorithm; time window.

1.0 INTRODUCTION

Manuscripts GDP is a key indicator of macroeconomic progress. Among the many areas that have begun to include AI is macroeconomics, which has seen a rise in popularity with the development of AI technology. In order to make educated national macroeconomic decisions, it will be necessary to use AI algorithms that can forecast and apply macroeconomic growth. ML is an essential subfield in AI that works effectively with nonlinear and unpredictable information. This has made the study of machine learning algorithms for forecasting GDP a hot issue of academic inquiry. In order to better inform policymakers and decision-makers about the current economic climate and possible future trends, experts are increasingly turning to machine learning algorithms [1]. Growth rate projections have been made using a wide range of techniques, including ML algorithms, ARIMA models, and international factor models like DFM [2], BVAR [3], and DSGE [4]. The high predictive accuracy and the simplicity of data collection for machine learning algorithms make them the algorithm of choice. ARIMA models are widely used because of its flexibility in coping with uncertain time series data and producing reliable long-term projections. Factor models with a global scope, such as DFM, BVAR, and DSGE, are commonly employed because of their high level of forecast accuracy. In this regard, DFM [6] is an adaptable and potent instrument, capable of dealing with enormous datasets and including time-varying elements. Moreover, BVAR is widely used since it can deal with both endogenous and exogenous factors and capture nonlinear interactions between variables.

Instead, DSGE is a robust method for modelling the dynamics of macroeconomic variables and capturing the complexities of economic interactions. In spite of their usefulness for making predictions, several of these models have restrictions that can't be overcome [7]. In order to forecast the values of a variable measuring economic development, like GDP [8,9], a neural network is trained with the specified indices as input. This strategy may successfully decrease the data dimensions and boost the reliability of predictions. The technique also incorporates real-time updates to the forecasting model, making it responsive to market shifts. When applied to GDP forecasting, neural network machine learning algorithms show promise as a way to increase confidence in economic growth projections [10].

Thus, it is important to research alternative, more effective methods for optimising the supply chain's logistical distribution routes. Genetic algorithms have been shown to be useful in Supply chain logistics for optimising the flow of goods. The logistics business may become more efficient and competitive if genetic algorithms are used to optimise the distribution channel and lower the cost of the Supply chain. Supply chain logistics can also benefit from the usage of wireless sensor network technology, which helps to increase productivity. Using real-time data from wireless sensors, we can determine the most efficient route for transporting items based on their current position, temperature, and humidity [11]. Because of this, Supply chain logistics distribution channel optimization using a combination of evolutionary algorithms and wireless sensor networks has much promise. I have made some really valid arguments here. Government policy assistance may go a long way towards guaranteeing the success of logistics businesses by providing the necessary financing for the growth of Supply chain logistics. New pledge modalities, such as warehouse receipt pledge, can offer much-needed finance for logistics firms, and the People's Bank of China has established special funds and provided lending support to help lower the upfront costs of building supply chain logistics. Because of their high demand and unique logistical requirements, agricultural and ancillary goods typically benefit from favorable regulations that encourage the growth of Supply chain logistics services for them. These regulatory reforms have the potential to boost China's Supply chain logistics' growth [11,12] and position the country's logistics businesses to meet the needs of the contemporary economy.

Because, there is a growing need in the industry for reliable logistics providers. Supply chain logistics service providers need to raise their game in several key areas, including logistics management, logistics service quality, logistics network setup and optimization, and logistics technology innovation and development. Logistics firms, especially small and medium-sized logistics firms, can benefit from government policy and financial support to help them overcome funding issues and increase market competitiveness. To further assure the security and quality of perishable commodities during travel, it is important to boost the development of refrigerated transportation and the creation of cold chain logistics infrastructure. Overall, Supply chain logistics growth is a difficult and time-consuming process that calls for cooperation between logistics businesses, governments, and the public [13].

2.0 RELATED WORK

Scholars began to examine the logistics distribution combinatorial optimization issue after Dantizig academics outlined the challenges and laid the groundwork for further study. Balinski researchers proposed the set splitting approach, which formed the basis of the practical solution and the mathematical model [14,15]. Scientists then started doing research using this mathematical paradigm and introducing new kinds of algorithms. Other researchers, including those working on Alain Hertz's work, combined the greedy technique with the insertion method to find the first answer. In [16], we see the results of the many researchers who laboured to perfect the mathematical model and algorithm. In the 1990s, a time component was added to the mathematical model used to determine the most efficient distribution routes for goods. Both an exact method and a heuristic approach are provided for solving the distribution path problem in domestic logistics. Particle swarm, annealing, and hill-climbing algorithms were recently shown [17]. It was Toshihide academics who first employed the evolutionary algorithm to study the path optimization problem using time frames. The usual genetic algorithm has been upgraded by Braysy academics. An important step forward was made in solving the local convergence problem [18]. In this study, an enhanced version of the genetic algorithm, based on adaptive crossover mutation and the hill climbing algorithm, is provided. It enhances the first two phases of genetic operation—the selection of a population and the mutation of that population. Next, we investigate the world's top options. In order to maintain genetic variety within a population, the crossover operator is incorporated into the problem-solving process. The model is built on this premise, and the algorithm flow is planned accordingly.

3.0 METHODOLOGY

3.1 Logistics distribution path common model

Everything from clients to vehicles to transportation routes to objectives and limits must be considered throughout the logistics distribution system's journey [19]. Time of service, location of service, kind of packaging, and quantity purchased are all critical characteristics to consider while purchasing items. Considerations such vehicle kind, number, parking spot, carrying capacity, and similar factors should be considered while arranging transportation. Both individual consumers and commercial enterprises need to know exactly what they may expect in terms of demand and turnaround time. Distinct distribution models include their own unique limitations. It is common for time and distance to be two of the limiting factors in the everyday operations of businesses.

In practice, there are many more considerations in logistics distribution networks than just the lowest mileage. As an illustration, some clients may need expedited shipping while others can wait. Time becomes a crucial issue under these conditions. Not only should the time and money costs and quality of service be factored into the optimization model, but also the distance. The purpose of the optimization model used to study the distribution routing problem in logistics might change. The objective may be to increase the number of clients serviced in a certain amount of time, or it may be to decrease the overall cost of transportation.

Improve customer happiness and save transportation costs with the more all-encompassing and realistic logistics distribution model based on the degree of customer satisfaction. Several heuristic techniques may be used to determine the best possible model optimization.

3.2 Model Analysis of Coverage of supply chain Growth

Suppose all the nodes in the economic development alarm-aware network are the same nodes shown in (1) above. In that case, this induction network is a homogeneous economic-growth alarm-aware network with the same scale.

$$H(x_i) = \{Q(x,y) | L \leq l, \mu_i - \frac{\alpha}{2} \leq \delta \leq \mu_i + \frac{\alpha}{2}$$
$$\mu_i - \frac{\alpha}{2} \leq arcsin\left(\frac{L_y}{L}\right) \leq \mu_i + \frac{\alpha}{2} \tag{1}$$

Because there is a tendency for economic growth in early warning area E, from the perspective of describing matrix represents the economic growth near this grid. If the economic development trend of a certain region is taken as

$$A = \{Q(x,y) | \langle x,y \rangle \in \{\langle i,j \rangle | N(i,j) = 1\}\} \tag{2}$$

If there is an economic growth momentum within the scope is said to have a growth point. Development areas are denoted by $A(x_i)$. If the adequate coverage of all economic development warning nodes in the early warning area is represented by $H''(x_i), H''(x_i) = H(x_i) - A(x_i) - H'(x_i)$, the following formula is established

$$E' = \cup_{i=1}^{n} (H''(x_i) \cup H'(x_i)) \tag{3}$$

In an economic growth, in addition to ensuring the adequate coverage of the network, it is also necessary to consider the network's transmission capacity. According to equation (2), the area has communication [20] with its surrounding nodes is denoted as $Y(x_i)$,

$$Y(x_i) = \{Q(x,y) | \sqrt{(x - x_i)^2 + (y - y_i)^2} \leq r\} \tag{4}$$

The coverage of the economic development warning perception network in early warning area (4) is denoted by ,

$$r(E) = \frac{\iint_{x,y} E\prime}{\iint_{x,y}(E-A)} \times 100\% \tag{5}$$

This paper must calculate its weight of it. The weight is (6) is the maximum weight. The higher the weight, the more attention is paid to the early warning area. If the primary danger zone of (6) is set to , then

$$L = \{Q(x,y)|\langle x,y\rangle \in \{\langle i,j\rangle|N(i,j) = 2\}\} \tag{6}$$

$$r'(E) = \frac{\iint_{x,y}(E\prime-(E\prime\cap L))+\oint_L z(E\prime\cap L)}{\iint_{x,y}(E-A+(z-1)L)} \tag{7}$$

The ideal limit increases the coverage rate of the early warning perception network for economic growth. Due to the enormous computational complexity of this problem, the general mathematical statistics method is challenging to solve, so the quantum genetic algorithm is used to carry out a similar heuristic search of the understanding space [21,22].

3.3 Mathematical model of Supply chain logistics distribution decision making

There are a number of considerations that go into determining the best route for a supply chain, not just price and time. It is important that the ideal route not only minimizes total cost and time, but also ensures that the delivery is made within the allotted window and that the vehicle's capacity is completely used [23,24]. The urban Supply chain logistics vehicle is depicted in Fig. 2. The transportation cost in this model is determined by several variables, including the distance between the distribution centre and the clients, the fuel consumption rate, and the vehicle's travel speed. Time is also considered because it has an effect on both product quality and customer satisfaction, depending on how long it takes to transport and deliver the goods. There is a cap on vehicle capacity that has to be maximized so that as few cars as possible are needed for transport. Lastly, route optimization is essential for cutting down on transportation costs and times while also increasing delivery productivity. The following is a description of a challenge encountered during the development of a model for making decisions on logistics and distribution. Since a customer's location, product needs, and expected arrival time are all known, it's possible to more efficiently send cars to their locations to deliver goods and perform services [23,24]. Among them, demand from customers serves as a reliable indication, and the fixed sum accounts for both cargo and travel distance [25].

The parameter variables are briefly described in light of the mathematical model and the assumption of the time frame limitation. The node I stands for a client node. If i=0, that would be the warehouse, and any other integer would be a consumer. The m denotes motorised means of transportation. According to the summary of the related literature at home and abroad, related costs should cover the fixed cost, damage costs, transportation costs and penalties in the Supply chain logistics path model. Fixed cost is a series of costs generated in each distribution, covering vehicle losses, employee wages, and equipment costs. It is independent of distance and is represented by *C1*. The calculation formula can be expressed as follows.

$$C1 = F\sum_{k=1}^{m} sign(k) \tag{8}$$

In the formula, F represents the fixed cost, and sign (k) means the cost of the vehicle participating in the delivery. If you don't participate, it's 0. Transport cost refers to the variable costs in distribution services, including fuel consumption, maintenance and other costs, which is represented by using laser *C2*. The calculation formula can be expressed as follows.

$$C2 = A\sum_{i=0}^{n}\sum_{j=1}^{n}\sum_{k=1}^{m} d_{ij}\cdot x_{ij}^{k} \tag{9}$$

In the formula, A represents transportation cost, and dij represents distance. Cost of damage refers to changes in the cost of vehicle distribution, such as the damage of goods and product freshness decline. The influencing factors include temperature, consumption and time. It is represented by C3 and the calculation formula is as follows.

$$C3 = P\sum_{j=1}^{n}\sum_{k=1}^{m} y_j^k\ [\varepsilon_1\sum_{i=0}^{n} t_{ij}\cdot x_{ij}^{k} + \varepsilon_2 L_j] \tag{10}$$

In the formula, P represents price and L represents product demand, and t indicates time. The penalty cost of Supply chain distribution refers to the failure to reach the destination according to the time requirement, including arrival in advance and delayed arrival. C4 is used to express penalty cost and the calculation formula can be expressed as follows.

$$C4=\sum_{i=0}^{n} \delta_{ik} \tag{11}$$

In the formula, δ_{ik} represents the penalty cost function. In a certain time, window, the customer can allow the vehicle to arrive without on time, but there is still a certain penalty cost.

After establishing the cost factors of Supply chain, the optimization model is established with the aim of minimizing the cost. The objective function is expressed as follows.

$$min\, C = min[\, F \sum_{k=1}^{m} sign(k) + A \sum_{i=0}^{n} \sum_{j=1}^{n} \sum_{k=1}^{m} d_{ij} \cdot x_{ij}^{k} + P \sum_{j=1}^{n} \sum_{k=1}^{m} y_j^k \,[\varepsilon_1 \sum_{i=0}^{n} t_{ij} \cdot x_{ij}^{k} + \varepsilon_2 L_j] + \sum_{i=0}^{n} \delta_{ik}] \tag{12}$$

In the formula, the first term is the fixed cost, followed by cloud function cost, damage costs and penalty cost. The vehicle load constraint function can be expressed as follows.

$$M \geq \sum_i r_i \cdot x_{ij}^{k} \tag{13}$$

It is required that the delivery volume of the vehicle is less than this index. The vehicle mileage transportation condition is expressed as follows.

$$N \geq \sum_i \sum_j d_{ij} \cdot x_{ij}^{k} \tag{14}$$

The number of vehicles to be transported should be determined in the model and this indicator needs to be changed according to the customer's needs. The calculation formula is as follows.

$$m = INT[\frac{\sum_{i=1}^{n} r_i}{M}] + 1 \tag{15}$$

In the formula, m represents the number of vehicles and M represents the maximum capacity of vehicles, and *R* represents the customer's demand.

3.4 Improved genetic algorithm analysis

Basic genetic algorithms are a way of addressing problems that takes their cues from the process of evolution in living things. For the technique to work, the issue domain must be encoded before it can be used to seed a population. Each member of the population is scored using the fitness function, and the result is utilised to calculate the operator. Crossover techniques, such as multi-point and single-point crossover, are used during algorithm execution to facilitate the transfer of genetic information across people in order to generate new individuals. Initialization, fitness assessment, selection, crossover, mutation, and termination are the fundamental phases of the algorithm. Fig 1. Shows the baseic steps used in Genetic Algorithms.

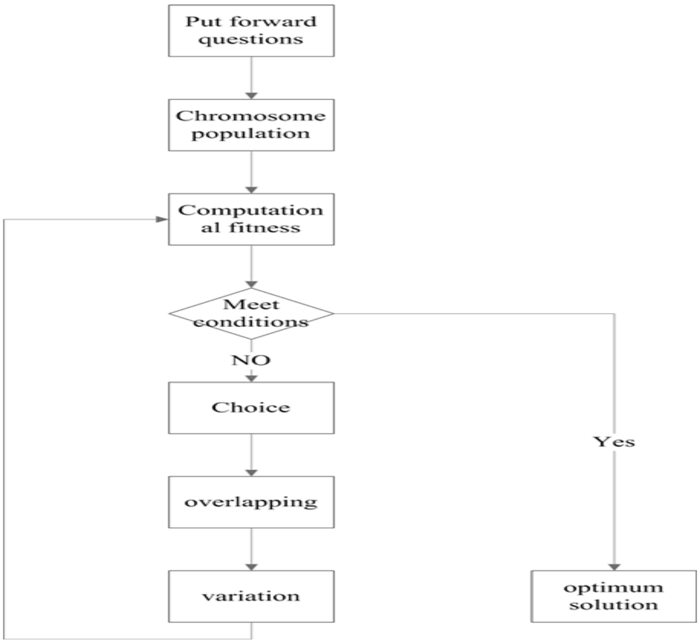

Fig. 1 Basic steps of genetic algorithm

For better results, the hybrid genetic algorithm combines the genetic algorithm with various optimization techniques. For instance, the pheromone trail of the ant colony algorithm and the genetic operators of the genetic algorithm can be merged to create a hybrid algorithm. Using elements of both the genetic algorithm and the virus algorithm, the viral evolutionary genetic algorithm (VEGA) is a hybrid approach to problem solving. The virus algorithm introduces random mutations into the population, increasing variety and decreasing the likelihood of a population reaching a local optimum. This new hybrid system, called the tabu-parallel genetic algorithm (TPGA), combines the genetic algorithm with the tabu search technique. The genetic algorithm's genetic operators are utilised to keep the population diverse, while the tabu search algorithm directs the search towards promising areas of the search space.

The genetic algorithm is made more effective with the use of heuristic algorithms. They can be used to boost the efficiency of the genetic operators or to direct the search towards more fruitful areas of the search space. Certain local search techniques, such hill climbing and simulated annealing, can be employed to enhance the quality of the solutions found by the genetic algorithm. The formula is expressed as follows.

$$Pc = \begin{cases} P_{c1} - \frac{(P_{c1}-P_{c2})(f^{/}-f_{avg})}{favg_{max}} \\ P_{c1} \end{cases} \tag{16}$$

Crossover probability (Pc) and mutation probability (Pm) are defined in the formula. Over time, the ideal solution is reached without factoring in individual damage using a deformed formula that includes the golden section rate. The golden section algorithm is introduced, which is based on the contraction interval, and the hill-climbing operator is defined as the implementation of the hill-climbing algorithm before the execution of the algorithm. An explanation of the enhanced genetic algorithm's workings is as follows. Size of the original population, the chance of crossover, and other characteristics are all determined at this stage. Targets for the future are established, and the level of utility is quantified. After that, we sort the fitness function to get its maximum and average values. The method is implemented by assigning a probability to the process of climbing a hill. It is proposed to use the golden section to improve search efficiency. The fitness of an individual is computed after the crossover algorithm and the mutation algorithm have been run. An adequate number of iterations are performed until an optimal solution is found, and then the process is complete.
These are the stages that make up the enhanced genetic algorithm workflow:

1. Create the starting population by setting its size and other specifications.
2. Learn how to evaluate people by figuring out their objective function and fitness function.
3. Apply the fitness function to the population data to get an ordering and then average and maximum values.
4. Improve search performance by using the hill climbing algorithm with a predetermined hill climbing probability.
5. Add the golden ratio search algorithm to further improve the search process.
6. Create new individuals by using the crossover and mutation operators, then determine their relative fitness.
7. Determine when the ideal number of iterations has been reached and stop the process.
   The modified genetic algorithm improves search efficiency and accuracy by integrating diverse strategies, such as hill climbing, the golden section, and crossover/mutation operators, to find optimum solutions to difficult problems.

3.5 Methods of forecasting macroeconomic indices

The authors of this paper present a new correlation-based approach to index forecasting, which includes index preprocessing, index correlation analysis, and index forecasting. Time series data for several economic indices may be made more reliable and manageable by index preparation. The purpose of this index correlation study is to select the most reliable index of correlation. The exponential forecasting model is a natural synthesis of several quantitative analysis and forecasting approaches. As such, the article presents the prediction computation for the macroeconomic index based on the above (Figure 2) [26].

3.5.1 Preliminary preparation of the index

Economic index preprocessing refers to preprocessing, such as interpolating and classifying many economic index sequences. This can achieve smoothness and dimensionality reduction [27]. This process lays the foundation for the subsequent index correlation analysis. Exponential interpolation is to interpolate the missing index in some years to make up for the deficiency of the missing year. In this paper, a Lagrangian interpolation method is proposed. If the index in year $t_0, t_1, \cdots, t_n$, then the index in year is calculated as:

$$x(t) = \sum_{i=0}^{n} \sum_{\substack{j=0 \\ j \neq i}}^{n} \frac{(t-t_j)(t+t_j)}{t^2{}_i + t^2{}_j} x_i \tag{17}$$

In this paper, type interpolation polynomial is used to prevent the occurrence of Runge oscillation. Classification is to unify the indices with similar meaning and a high degree of correlation into one category. This paper chooses the critical point of the correlation factor of 0.995. When the absolute correlation between the two indices exceeds 0.995, the two indices are classified into the same category [28].

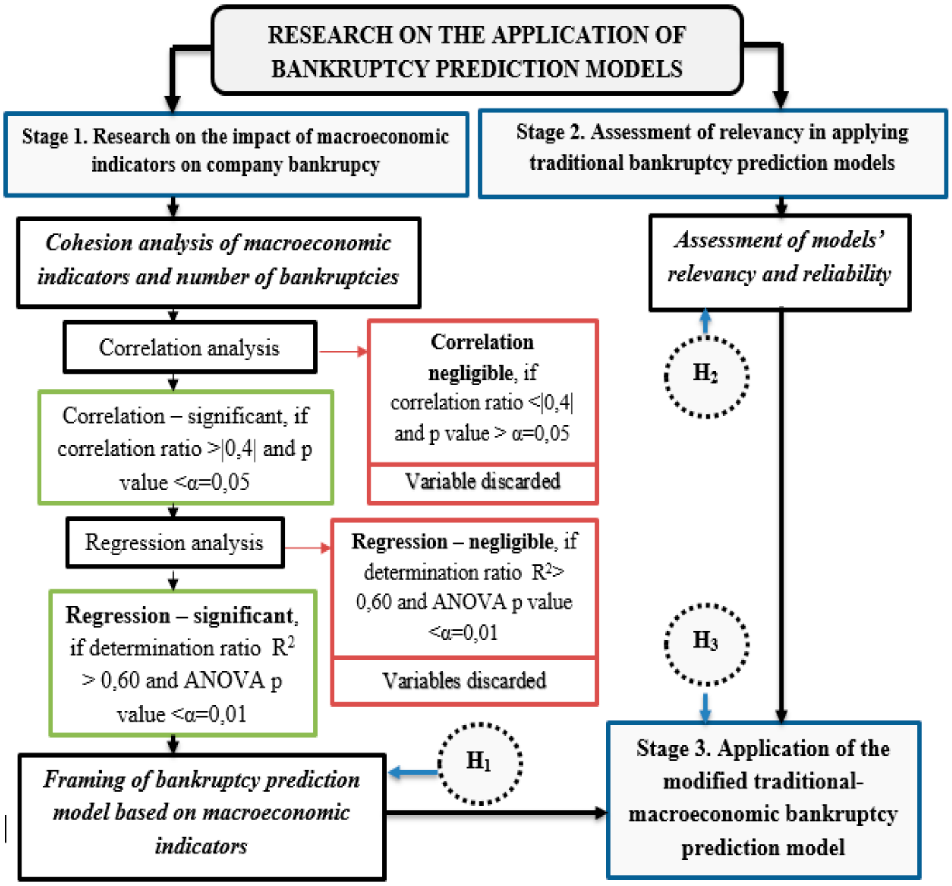

Fig. 2: Correlation analysis method of macroeconomic indices.

3.5.2 Correlation between indices

The index correlation ranking mainly quantifies the mutual relationship between each index. This paper selects the correlation degree with high correlation to provide the basis for the next choice. This paper uses the Pearson correlation coefficient to express the correlation between the indices. In this paper[29], the two economic indices are regarded as two random variables. Then the relational formula of the relation is as follows:

$$r(x,y) = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2 \sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{18}$$

It is the value of indicator in year which is the average of each year. The value of the correlation factor is [-1,1], a trend of 1 indicates a linear positive correlation, a trend of -1 indicates a linear negative relationship, and a trend of 0 indicates no linear relationship between the two. The relationship between each indicator and other indicators can be classified using the calculation method of correlation factor. This paper uses the first N indices with relatively large mutual relations as the preliminary correlation degree [30].

3.5.3 Method of choosing an index

The index selection mechanism obtains the original correlation degree by sorting the relation sequence relative to each other. Factor assumptions and stepwise regression analysis further screened the uncorrelated indices. This way, the correlation degree with each index's most significant comprehensive influence is obtained.

3.5.4 Multivariate regression

Multiple regression takes the target index as the dependent variable and the index of the relevant index set as the independent variable. This paper analyzes the linear or nonlinear numerical calculation formulas between variables and uses sampling data for analysis. The calculation formula of the multiple linear regression model is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_m X_m + \varepsilon \tag{19}$$

it is a target metric. $X_0, X_1, \cdots, X_m$ is the correlation index. $\beta_0, \beta_1, \cdots, \beta_k$ is the marginal to-be-fit factor representing the correlation index relative to the target index? Which is the error. In this paper, the fitting coefficient vector $\beta = (X^T X)^{-1} X^T Y$ can be obtained by the least square method. The basic patterns of multiple linear regression are:

$$Y = \beta_0 + \beta_1 f_1(X_1, X_2, \cdots, X_m) + \cdots + \beta_m f_m(X_1, X_2, \cdots, X_m) + \varepsilon \tag{20}$$

$f_j(X_1, X_2, \cdots, X_m)(j = 1,2, \cdots, m)$ is a known function. Variable substitution can transform this equation into a multidimensional linear regression equation.

4.0 RESULT ANALYSIS AND DISCUSSION

4.1 Algorithm implementation

In the operation of genetic algorithm, gene coding is the basic link. In this paper, simple natural numbers are selected for editing. Gene chooses customer points ikl, and chromosome is formed in vehicle order. The vehicle starts from the center and goes through the customer point, and finally returns to the distribution center to form a loop. In combinatorial optimization problems, chromosome coding can be expressed as (o, i_{11}, i_{12}, i_{13},…, i_{1t}, 0, $i_{m,}$ …, i_{mv}, 0). The total length of chromosomes is equal to t+m+1. In the distribution logistics, three sub paths are formed. In the genetic algorithm, according to the change of the environment, the independent individuals in the population will also change. Therefore, it is necessary to assess the goodness of the individual population and select the most suitable chromosome. In this paper, the minimum cost was considered as the objective function. Due to the complex constraints of mathematical model, the constraint condition chooses the penalty cost method to ensure the diversity of chromosomes in the solution.

In solving the optimization problem of Supply chain logistics distribution path, there are too many influencing factors. If the crossover algorithm is used in the calculation, the local optimal solution can be obtained in the search, and then a large number of infeasible solutions appear. This method can get the optimal solution quickly. The crossover operator in the paternal coding chromosome may lose a good individual, or a mutation occurs. Fig. 4 represents crossover operator. In order to reduce this possibility, the maximum preserving crossover operator is adopted to reduce the risk and improve the system running speed. Suppose the encoded chromosome is labeled as t1 and t2 with a total of 9 clients. When preserving the crossover operator, two adjacent intersections are randomly formed. The crossover operation is performed according to the genetic algorithm, and two sub generations are obtained, which are denoted as son. The progeny gene is adjusted and the cross-section gene is put in the first place. Then, two new offspring sons are obtained, which are arranged in sequence until the coding is 0. In a parent chromosome, the chromosome length is randomly generated to identify the gene and a new chromosome is formed. Finally, according to the fitness function, the largest chromosome is selected to continue the subsequent operation.

4.2 Expectations of economic development

This study uses the statistical data of China from 1988 to 2022. The above analysis results are tested in this paper. This paper uses fixed assets investment, fiscal revenue, fiscal input, national income, total import and export, consumer price, added value of primary industry, added value of secondary industry, added value index of tertiary industry, and real estate value-added index, financial industry Value added index [31,32], wholesale and retail value-added index, retail price index and retail price index. It is found that the above various economic factors are not always good, and the mathematical model established after using more economic indices will become more complicated. The conclusions drawn at this time are not so accurate. Although most existing studies use artificial methods to select specific indices as forecasting tools for economic development, the inability to select a better measurement standard in this method leads to a decrease in forecasting accuracy. This paper adopts the self-evaluation method when selecting the economic index with a higher level of China's economic development. This paper selects an economic index with a higher level of China's economic development. Under the guidance of this model, the neural network is used to forecast economic development.

Table. 1: Various economic indicators related to economic development

Investment in fixed assets	-0.0027	Total import and export	-0.0059	Real estate index	0.0213
Revenue	0.0365	Consumer price index	0.1433	Industrial Value-Added Index	-0.1361
Financial input	0.0551	Primary Industry Index	0.0730	Financial Sector Index	-0.0159
National Income Index	0.2913	Secondary Industry Index	0.4658	Wholesale and Retail Trade Index	-0.0173
National Consumption Index	-0.0198	Tertiary Industry Index	0.2964	Commodity price index	-0.1245

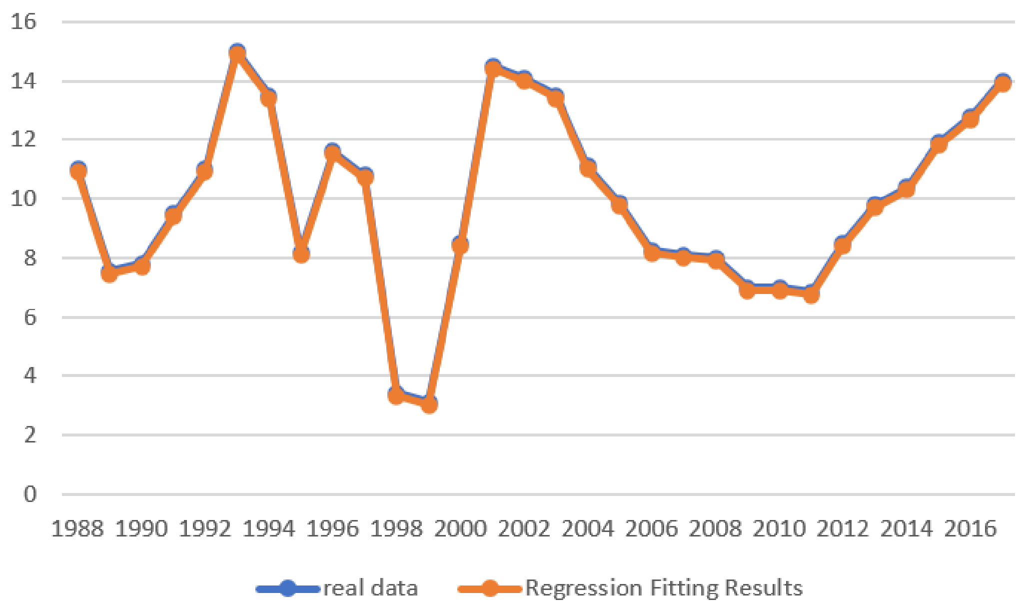

Fig. 3: Regression models fit the correlations between various economic indices and economic growth.

This article uses the data from 1988 to 2017 as a sample and the data from 2018 to 2022 as empirical data to test the correctness of the analysis. The research results show that the autoregressive model can better reflect the correlation between various economic indices and economic growth (Figure 2) [33]. Table 1 shows the national income index, consumer price index, the primary industry added value index, the secondary industry added value index, tertiary industry added value index, industrial added value index, and consumer price index. The economic criteria used in many documents are not the same. For example, many scholars once believed that fixed asset investment is closely related to the economy, but the results of this study show that there are certain discrepancies. This is because the government's investment in fixed assets accounts for the vast majority, and the government mainly invests in maintaining economic development. Much of the investment was made during a downturn. Therefore, a robust negative relationship exists between fixed asset investment and economic development.

This paper uses an adaptive learning machine to analyze China's economic development and obtains the basis of national income, the consumer price index. The secondary industry added value index and the tertiary industry added value index. AR, BP neural network, self-organizing model, etc., are the main forecasting models of current economic development. This paper compares AR, BP neural network, self-organization mode, and single extreme learning machine mode [33]. Figure 3 shows the forecast results of different models for China's economic growth expectations. From Figure 4, we can see that the method described in this paper can predict China's economic growth rate very well. The comparison results between the different modes are shown in Table 2. It can be seen from Table 2 that the two errors of this model are better than the other three algorithms. The NMSE value was 0.0359, and the MAPE value was 1.10%. The ELM algorithm overcomes the shortcomings of the BP neural network, such as many iterations and falling into local optimization. It is better than the conventional BP neural network. At the same time, the prediction accuracy of the wireless sensor network model is also higher than that of the ELM. The model can effectively use past data to improve forecast accuracy [34].

Table. 2: Comparative forecast accuracy between different models.

	Autoregressive model	**Self-organizing model**	**BP**	**ELM**	**Supply Chain Based Model**
NMSE	0.8706	0.7301	0.6100	0.5100	0.0401
MAPE	15.61%	7.42%	6.71%	4.70%	1.21%

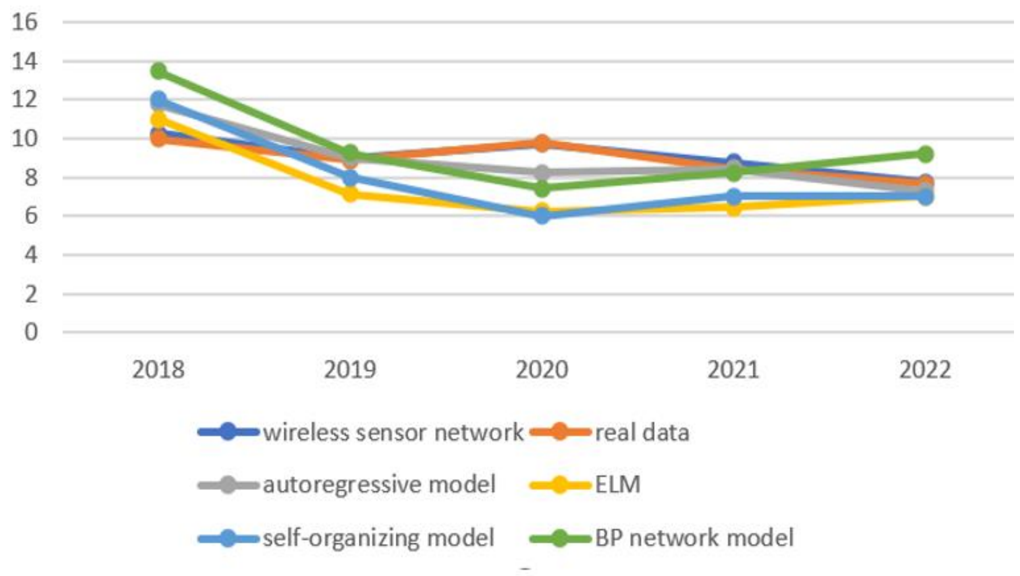

Fig. 4: Simulation results of economic growth forecasts by different models.

4.3 Model application

According to the actual situation, the parameters of urban Supply chain logistics distribution are determined. The initial population size is 80 with 400 iterations. Fig.3 shows the number of iterations. It can be seen from Fig.5 that the fitness of the genetic algorithm has been basically stable after 100 iterations, and the best state has been reached. The fitness of improved genetic algorithm has reached a steady state after 40 iterations. It shows that the convergence speed of the improved genetic algorithm is improved obviously.

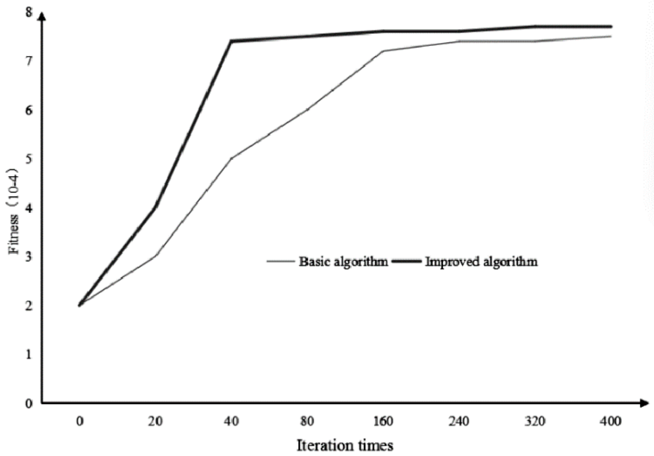

Fig. 5: Evolutionary graph of genetic algorithm

The results of software analysis show that the objective function converges to 1289 in the path decision of the basic genetic algorithm. Three routes of transportation are obtained. After the departure of the vehicle M1, products are distributed to customer 8, 7, 1, 5, and then it goes back to the center with the demand of 3.2 tons. After the departure of the vehicle M2, it is successively through customer 6, 2, 3. After the departure of the vehicle, it has passed customers 4, 9, 10. The allocation of distribution vehicles is shown in Table 3. Cost calculation shows the fixed cost of vehicle M1 is 150, and transportation cost is 179 and the cost of the damage is 122. The penalty cost is 42 and the total cost is 493. Fixed cost of vehicleM2 is 150, and transportation cost is 193 and the cost of the damage is 146. The penalty cost is 39 and the total cost is 528. The fixed cost of vehicle M3 is 150, and the transportation cost is 196. Damage cost is 84 and penalty cost is 0. Total cost is 430 and the total cost of the three routes is 1451.

Table. 3: Based genetic algorithm transportation path

Distribution vehicle	order	load	Full load rate	Distance (km)	Time (minutes)
M1	P0 - 8 - 7 - 1 - 5 - 0	3.2	92.3%	11.2	36.7
M2	P0 - 6 - 2 - 3 - 0	3.6	100.0%	11.8	40.0
M3	P0 - 4 - 9 - 10 - 0	1.7	51.6%	12.9	40.0

The objective function of the improved genetic algorithm converges to 1326 and three transportation routes are formed. The Fig. 6 shows the comparison of varied cost metrics.

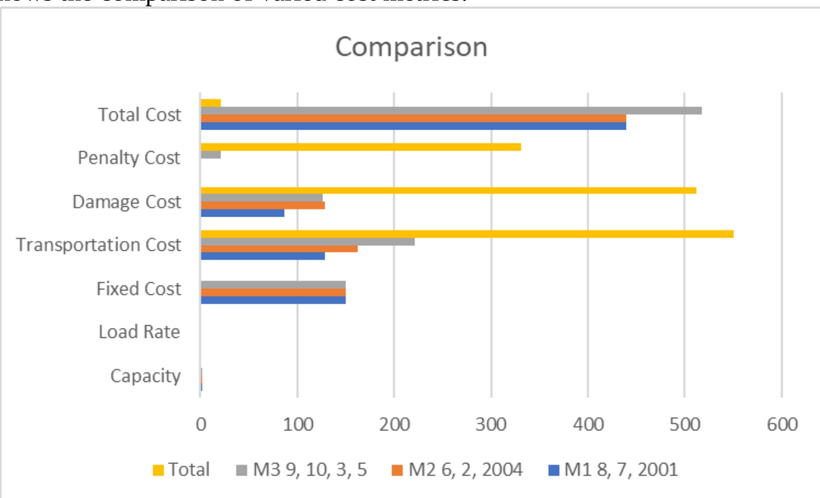

Fig. 6: Comparison on varied cost metrics

After the departure of the vehicle M1, customers 8, 7, 1 have been carried out with a capacity of 2.1 tons and a load rate of 60%. Vehicle M2 has gone through customers 6, 2, 4. Vehicle M3 has passed through customers 9, 10, 3, 5. Details of vehicle transportation and distribution are shown in Table 4. The fixed cost vehicle M1 is 150 and transportation cost is 129, and damage cost is 87 and penalty cost is 0 as well as total cost is 440. The fixed cost vehicle M2 is150 and transportation cost is 162, and damage cost is 128 and penalty cost is 0 as well as total cost is 440. The fixed cost of vehicle M3 is 150 and transportation cost is 221, and damage cost is 126 and penalty cost is 21 as well as total cost is 518. The total cost of the three routes is 1392. It can be seen from the cost that the average daily distribution cost has decreased significantly, and the improved model has more uniform vehicle arrangement. Vehicle travel time and path have declined.

Table .4**:** Improved genetic algorithm Supply chain distribution

Distribution vehicle	**Order**	**load**	**Full load rate**	**Distance (km)**	**Time (minutes)**
M1	P0 - 8 - 7 - 1 - 0	2.0	61.2%	8.6	29.3
M2	P0 - 6 - 2 - 4 - 0	3.2	88.5%	10.8	36.1
M3	P0 - 9 - 10 - 3 - 5 - 0	3.4	92.3%	13.9	47.2

Thus, it could be worth pointing out that using our proposed technique has helped in several aspects and has also translated into quantifiable benefits.

- A quantifiable reduction in travel time which can reduce fuel consumption and improve schedule delivery as well [35]. This has made good reduction in distribution costs and thus, can increase profits.
- Also, there is observed reduction in shipping costs which can save businesses good profit [36].
- A nominal increase in fleet utilization can reduce total fleet costs.
- A better supply speed can help businesses recover from a crisis in 50% less time. Considerable reduction in the chances of supply chain failures can proved improved supply chain flexibility [37].
- Reduction in fuel consumption can reduce greenhouse gas emissions by 2%.
- A considerable increase in the use of eco-friendly vehicles can lead to a 5% decrease in environmental impact.

5.0 CONCLUSIONS

Data study of the modified genetic algorithm's application to logistics distribution path selection reveals the algorithm's benefits. Transport distance, vehicle count, and delivery window limits were among the variables studied to determine their impact on logistics distribution costs. To achieve this goal of reducing logistical expenditures, the VRPTW mathematical model was developed. The logistics distribution channel was optimised using a genetic algorithm upgrade that featured hill climbing and self-executing crossover. The data analysis findings demonstrated that the enhanced genetic algorithm may successfully lessen distribution costs and boost logistics distribution efficiency. Nonetheless, optimising the Supply chain logistics distribution route remains a challenging topic with many open questions, such as how to handle the simultaneous distribution of many product kinds and whether or not to account for temperature in the model. Distribution decision problems in supply chain logistics can be helped by the study's enhanced genetic algorithm. The method generates a cost-effective distribution path by considering the many elements that affect distribution costs and applying soft time window limitations into the VRPTW model. More study is required to fix the model's flaws. The present approach doesn't account for temperature-sensitive items since it assumes that only one product type is being delivered. And while the enhanced genetic algorithm did reveal some benefits in the data analysis, it's possible that it's not the best option for every distribution type. So, future studies may investigate other optimization techniques and consider a broader variety of characteristics.

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