Membrane Technology
ISSN (online): 1873-4049

# Research on Robot Membrane Material Selection and Distribution Route Optimization on College Campuses

**Junchao Yang***

*School of Account, Inner Mongolia University of Finance and Economics, Hohhot 010051, China*

**Corresponding Author.*

**Abstract:**

An e-commerce logistics park, as a hub for e-commerce logistics, possesses the traits of high task volume and intensive package delivery. It is inefficient and dangerous to rely solely on manual work. Thus, there is some practical significance and benefit in figuring out how to implement cutting-edge delivery techniques to boost the delivery effectiveness of e-commerce logistics parks. This study combined the features of the e-commerce logistics and distribution environment, identified and eliminated the three robot types that are currently suitable for intelligent distribution, built an evaluation index system to assess the robot model selection scheme appropriate for e-commerce logistics and distribution. To assess the robot model selection strategy, we built an entropy weight-material element expansion model and computed the weighted correlation degree and proximity to various grades of the three robot kinds and five assessment grades, as well as the degree of proximity with various grades, determined the distribution robot model. Following example verification, the research presented in this paper can successfully conduct a reasonable and scientific evaluation of the distribution robot selection and can offer specific references for the more thorough decision-making process of robot selection for logistics and distribution in e-commerce parks.

**Keywords:** delivery robot, membrane material; entropy weighted-fuzzy element-to-set operators model, selection evaluation

## INTRODUCTION

The demand for online shopping in China is growing steadily due to the country's thriving e-commerce industry and the country's citizens' improving quality of life year after year. This has resulted in rapid sales growth and high profits for many e-commerce businesses. The entire chain of "third profit source" logistics needs to be further improved in order to boost enterprise income and lower distribution costs if the cost reduction and efficiency of the entire logistics system are to be maintained based on maintaining the original model at this point in the steady and rapid growth of social retail sales [1]. Additionally, people's expectations for their online buying experiences are steadily rising. The main challenge facing the entire e-commerce and logistics sector is how to deliver goods to customers as fast and efficiently as possible while achieving low carbon emissions and green transportation while accommodating the needs of numerous customers with varying arrival times [2].

The burden for delivery manuals rises along with the gap in delivery workers due to the increasing geometric growth trend of the quantity of express delivery orders. As the amount of physical delivery work increases, delivery staff may get more exhausted, and there may be more traffic accidents or collisions during the distribution process, putting their safety at risk. The increased workload also results in higher labor costs, which raises the financial pressure on rapid delivery businesses. As a result, nations are creating unmanned sorting, handling, and distribution companies. Mechanized automation and intelligent logistics distribution systems are especially crucial for creating a low-cost, safe, quick, and efficient system [3]. Numerous domestic and international e-commerce platforms have started to focus on studying autonomous robot delivery. Amazon started testing the delivery robot Scout across the United States in 2019. China Post has deployed unmanned robots across more than 300 kilometers in various locations throughout China. Jingdong has also made significant efforts to study unmanned robots. Beijing launched China's first fleet of unmanned delivery cars in May 2021, with the vehicle code "JD0001". The autonomous delivery robot from Suning is capable of delivering packages. The first unmanned delivery robot in China that can communicate with elevators is called "Wolong No.1". Robots or unmanned vehicles for distribution have been considered as a viable solution to future express delivery problems [4].

As the idea of unmanned distribution gains traction, unmanned distribution technology advances daily, and research on e-commerce logistics distribution using distribution robots and unmanned logistics vehicles in an e-commerce logistics park has steadily gained popularity. Unmanned logistics distribution can be separated into two categories based on the distribution environment: indoor logistics distribution and outdoor logistics distribution. While the latter has a more secure and enclosed distribution environment and typically uses mobile robots to complete duties, the former primarily uses unmanned vehicles and unmanned distribution robots to do distribution activities in an open environment. Major domestic and international logistics companies and e-commerce have long recognized the market's hot spot and the value of autonomous robot distribution, and they have been conducting extensive research in related disciplines [5]. The real data and experience of logistical situations may be perfectly applied to product research and development because of the robust use of customers and terminals. It has conducted several unmanned distribution research and development and application mode scenarios and has been at the forefront of unmanned distribution technology. With a number of machine interaction features, such as the implementation of the popular interactive features of scanning code and scanning face and the cloud interaction mode of audio lighting, Ali Cainiao Logistics' unmanned delivery vehicle has been in the public eye since 2018. In addition to Alibaba, Meituan, Jingdong, and other giants that occupy the daily logistics e-commerce, the new generation of start-up technology e-commerce companies, such as White Rhino and Neolithic, are also vying for the vacancies and hot spots in the field of unmanned distribution, and the overall business model is generally the overall solution of "vehicle + algorithm" [6,7].With the algorithm's continuous improvement, unmanned distribution occupies a big and often used space and market. In addition to more companies focused on unmanned delivery, the technology is rapidly advancing. Scholars mostly focus on optimizing the path distribution of unmanned vehicles [8,9].

The selection of autonomous distribution vehicles is also a critical issue for the entire e-commerce logistics park, especially given the present market for more unmanned vehicles and intelligent robots. The investment in unmanned vehicles and intelligent robots is often characterized by a great quantity and a variety of forms. The selection of unmanned vehicles or intelligent robots can effectively evaluate the economic performance of unmanned distribution equipment [10], as well as give a more green and convenient operation and maintenance evaluation in terms of low-carbon [11]. A limited body of literature has investigated unmanned distribution devices based on the minimum regret value hypothesis [12] and overall distribution group performance, with some success. Some researchers developed multi-criteria models to evaluate unmanned vehicles in an unpredictable environment [13] and carried out UAV selection judgments. Morteza combined with time window [14] and Matthieu combined with battery performance investigated UAV selection [15], and the relevant research in the aforementioned literature have made some progress. However, selecting and evaluating robots in e-commerce parks remains unusual. The primary study focus of this work is the selection of robots in e-commerce parks. The goal of this study is to first examine the existing condition and characteristics of the e-commerce logistics park, and then to develop the index system by screening relevant variables. Finally, the entropy weight - matter element extension model is used to assess the types of robots best suited for the park's logistics.

## E-COMMERCE LOGISTICS PARK DISTRIBUTION ROBOT SELECTION EVALUATION INDEX SYSTEM CONSTRUCTION

E-commerce park logistics distribution differs from other types of logistics distribution due to the park's distinct setting and consumer groupings. To accommodate the sophisticated logistics distribution activities, the e-commerce park is normally spacious, with an easy-to-identify layout and a reasonably tranquil atmosphere. Furthermore, the park's numerous facilities are typically built in separate regions. In some areas, the building density is rather high, and the road conditions vary. As a result, park distribution robots must meet fundamental characteristics such as low noise, small size, and stable driving. In addition to the fundamental needs listed above, given the scarcity of robot charging stations in the park and the difficulty of solving the charging station adaption problem, a robot equipped with charge stations is more convenient and ideal for e-commerce. Based on the preceding investigation, typical types of distribution robots on the market were gathered and examined, and three types were chosen for e-commerce parks: Type A, Type B, and Type C. These three types of robots produce the least amount of operating noise of any category, and their noise level is comparable to that of a normally calm environment. Additionally, the robot's size may accommodate expedited delivery and is smaller than the maximum size of traffic on the road. Its broad ground clearance makes it appropriate for a variety of road conditions and offers good driving stability. Using the entropy weight-matter element extension model, this chapter evaluates the robot model selection scheme for distribution path optimization in the text that follows. It does this by choosing the best robot model for distribution in the e-commerce park from the three types of robots mentioned above, combining the current state of express delivery, road conditions, population density, and delivery time collected from school surveys.

The evaluation index system for selecting robot models in the park is made up of a number of variables that might reflect the characteristics of the park's distribution robots. These indicators describe the parameters of the three types of distribution robots and serve as the foundation for future evaluations. This work develops the assessment index system using the following principles:

(1) Evaluation indicators should be combined with the actual situation of e-commerce park distribution

When creating the evaluation index system for selecting robot models in the park, the characteristics of the park's distribution are integrated with the many parameter indicators of intelligent distribution robots. The system uses a minimal number of accurate indications to reflect the properties of intelligent distribution robots in a systematic and complete manner, eliminating the complication created by the inclusion of irrelevant indicators.

(2) Principle of availability

When developing an index system for the park's robot model selection, the availability and feasibility of the indicators must also be considered. The simplicity of getting indicator data, high precision, and acceptability of indicators as evaluation criteria are critical foundations for improving evaluation accuracy. If data for indicators that are difficult to get are missing, their reference value will be considerably lowered, which is not helpful to the progression of following evaluations.

(3) Principle of objective scientificity

When developing an index system, the scientificity and objectivity of the indicator values are critical. The quantitative study of evaluation items using objective and real indicator values lowers the impact of subjectivity on evaluation findings. That is, in the evaluation index system for the selection of robot models, the majority of the indicator characteristics are chosen as quantitative indicators, ensuring the objectivity of the assessment results as well as the application and economy of the chosen robots.

The research object of this paper is: Among the common types of distribution robots collected and analyzed on the market, Class A, Class B, and Class C robots have the following characteristics: being relatively quiet in noise level, meeting the size requirements for carrying express delivery, being smaller than the maximum road traffic size, having a large ground clearance, being suitable for various road conditions, and having strong driving stability. These robots are ideal for the distribution environment of e-commerce parks.

Indicators such as rated load capacity, battery capacity, battery mileage consumption, maximum endurance mileage, overall machine weight, size, maximum speed, minimum passing width, minimum turning radius, minimum ground clearance, noise, movement error, collision avoidance safety, auxiliary interaction function, charging pile adaptability, charging rate, and artificial intervention convenience are the main ones chosen in this paper based on the previously mentioned goals. The following are the detailed descriptions:

1) Rated load capacity: The typical maximum load capacity, expressed in kilograms, that the park distribution robot is capable of carrying when distributing. It is a favorable indicator since the greater it is, the more efficiently the park distributes its resources.

2) Battery capacity: Battery capacity: The amount of electrical charge, expressed in Ah, that the park distribution robot's integrated battery can hold. It is a favorable indicator since the higher it is, the longer the distribution period in the park.

3) Battery mileage consumption: The number of miles the park distribution robot can travel per kWh of battery power consumed during the distribution process, measured in km/kWh. The higher this indicator, the longer the distance the robot can travel without charging in the park, making it a positive indicator.

4) Maximum endurance mileage: The longest distance the park distribution robot can travel on a single charge with a full battery during the distribution process, measured in km. The greater the maximum endurance mileage, the longer the robot can continue to distribute in the park, making it a positive indicator.

5) Overall machine weight: The total weight of the park distribution robot’s body. The heavier the overall machine weight, the less convenient it may be during the distribution process. Additionally, in the event of unexpected situations during distribution, the heavier weight may lead to more severe accidents and injuries, reducing safety, making it a negative indicator.

6) Size: The dimensions of the park distribution robot’s body, including its length, width, and height, with the total volume measured in m^3. The larger the length or width of the park distribution robot’s body, the higher the requirements for the distribution environment, and the more prone to congestion, reducing body flexibility. The higher the height, the worse the safety during distribution, making it a negative indicator.

7) Maximum speed: The highest speed that the park distribution robot can reach during the distribution process, measured in km/h. The higher the maximum speed, the higher the efficiency during the park distribution process, making it a positive indicator.

8) Minimum passing width: The smallest width that the park distribution robot can pass through during the distribution process, measured in mm. The larger the minimum passing width, the narrower the width the robot can pass through during distribution, resulting in higher requirements for the roads, fewer navigable paths, and fewer deliverable customer points, making it a negative indicator.

9) Minimum turning radius: The radius from the outer steering wheel to the center of the turning circle when the park distribution robot is traveling at its minimum stable speed during the distribution process, measured in meters. The larger the minimum

turning radius, the more space the robot requires to turn, reducing the flexibility of the park distribution robot, making it a negative indicator.

10) Minimum ground clearance: The height from the lowest point of the chassis to the ground when the park distribution robot is fully loaded during distribution, measured in mm. The larger the minimum ground clearance, the lower the requirements for the roads during distribution, making the distribution process safer, making it a positive indicator.

11) Noise: The sound level produced by the park distribution robot during the distribution process, measured in decibels. The louder the noise, the greater the impact on pedestrians nearby and customers in buildings, and the greater the disturbance to the park environment, making it a negative indicator.

12) Movement error: The discrepancy between the set position and the actual position of the park distribution robot during the distribution and interaction process. The larger the movement error, the higher the error rate of the robot during distribution, the worse the distribution efficiency, and the lower the task completion perfection, making it a negative indicator.

13) Collision avoidance safety: The system included in the park distribution robot's body to prevent accidents during distribution, generally including remote control anti-collision design, collision sensor emergency stop system, and VUC with heartbeat protection, temperature protection, and current protection. Converted into a percentage in the indicator evaluation, the higher the collision avoidance safety, the safer the park distribution robot during distribution, making it a positive indicator.

14) Auxiliary interaction function: The interactive functions of the park distribution robot with customers and the distribution service platform during the distribution process, including audio and light prompts upon arrival, cloud recording of walking paths, and remote shouting functions, measured in units. The higher the auxiliary interaction functions, the more interactive functions provided to customers, and the higher the customer satisfaction, making it a positive indicator.

Table 1. Evaluation Index System for Park Robot Model Selection

| Indicator Layer | Unit | Trend |
|---|---|---|
| Rated Load Capacity $A_1$ | Kilograms (kg) | Positive |
| Battery Capacity $A_2$ | Ampere-hours (Ah) | Positive |
| Battery Mileage Consumption $A_3$ | Kilometers per kilowatt-hour (km/kWh) | Positive |
| Maximum Endurance Mileage $A_4$ | Kilometers (km) | Positive |
| Overall Machine Weight $A_5$ | Kilograms (kg) | Negative |
| Size $A_6$ | Cubic meters ($m^3$) | Negative |
| Maximum Speed $A_7$ | Kilometers per hour (km/h) | Positive |
| Minimum Passing Width $A_8$ | Millimeters (mm) | Negative |
| Minimum Turning Radius $A_9$ | Meters (m) | Negative |
| Minimum Ground Clearance $A_{10}$ | Millimeters (mm) | Positive |
| Noise $A_{11}$ | Decibels (dB) | Negative |
| Movement Error $A_{12}$ | Centimeters (cm) | Negative |
| Collision Safety $A_{13}$ | Percentage (%) | Positive |
| Auxiliary Interaction Function $A_{14}$ | Count | Positive |
| Charging Pile Adaptability $A_{15}$ | Percentage (%) | Positive |
| Charging Duration $A_{16}$ | Hours (h) | Negative |
| Artificial Intervention Convenience $A_{17}$ | Percentage (%) | Positive |

15) Charging pile adaptability: The degree of compatibility between the park distribution robot and the charging pile during charging, measured in %. The higher the adaptability, the more convenient the charging process for the distribution robot, and the higher the charging efficiency, which is beneficial for the maintenance of the robot's body, making it a positive indicator.

16) Charging duration: The longest time taken for the park distribution robot to recharge after completing a delivery task, measured in hours. The longer the charging duration, the longer the maximum downtime of the park distribution robot, making it a negative indicator.

17) Convenience of manual intervention: In the distribution process of the park distribution robot, the convenience of backstage manual intervention, the virtual road network to avoid straying, the windows client remote control, the APP mobile phone client remote control and other functions, the unit is %, are positive indicators.

The aforementioned indicators, covering aspects such as the intelligent robot's endurance, operational metrics, load capacity, and convenience of use, construct the evaluation index system for the selection of robot models in the park, as shown in Table 1.

## CONSTRUCTION OF ENTROPY WEIGHT MATTER ELEMENT EXTENSION EVALUATION MODEL

The matter-element extension model and the entropy weight approach are combined in the entropy weight matter-element extension model. This model primarily uses the entropy weight method to calculate the weight of each index in the index system, the matter-element extension model to evaluate the evaluation object, and the model selection scheme to determine the distribution robot's model in the e-commerce park. An entropy weight matrix is created using the index values of each object to be evaluated in the entropy weight technique, which is an objective way to determine weights. Weight calibration, which reflects the relative relevance of several indicators, is accomplished through quantitative computation. This method uses the variability of indicator data to assign weights to indicators [16], without relying on expert experience, and is widely used in weight determination in multiple fields [17]. The approach involves building a judgment matrix, normalizing it to find the indicators' information entropy, and then using that information to calculate the indicators' entropy weight [18]. The matter-element extension model was proposed by Cai Wen, a Chinese scholar. This model combines qualitative and quantitative methods. Through a series of quantitative processing and calculation of the indicator value, it determines the correlation degree and distance between the object to be evaluated and each grade, finally gives the closeness of the object to be evaluated, and determines the qualitative grade [19,20].The flowchart of the model implementation is shown in Figure 1 [21]:

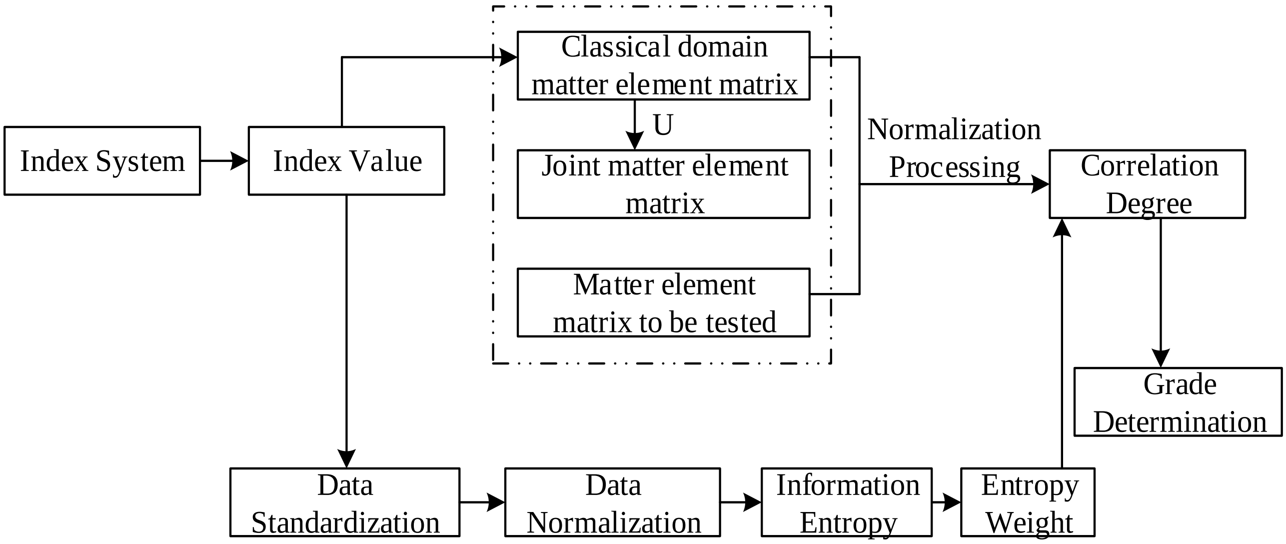


Figure 1. Implementation flowchart of entropy weight matter element extension model

### Determine the classical domain, nodal domain, and test element

Assuming that the object to be evaluated $N$ has a feature set $A$, $A=\{A_1,A_1,\cdots A_n\}$, and the numerical set corresponding to the feature set $A$ is $V$, $V=\{V_1,V_2,\cdots,V_n\}$, then the ordered triplet $R=(N,A,V)$ composed of $N$, $A$ and $V$ is the basic element of the object to be evaluated, abbreviated as matter element. The representation of the matter element matrix is as follows: the classical domain matter element matrix, the nodal domain matter element matrix, and the object element matrix to be tested will be expanded based on this equation.

$$R=(N,A,V)=\begin{pmatrix} N & A_1 & V_1 \\ & A_2 & V_2 \\ & \cdots & \cdots \\ & A_n & V_n \end{pmatrix} \tag{1}$$

(1) Determine the classical domain matter element matrix

The classical domain element matrix is mainly composed of the evaluation level of the object to be evaluated $N_j(j=1,2,\cdots,m)$, the feature set of the object to be evaluated $A$, and the range of feature values of the feature set $A$ at each evaluation level $j$, $V_j\left(V_j=<a_j,b_j>\right)$. The representation of the classical domain element matrix is shown in the following equation.

$$R_j=(N_j,A,V_j)=\begin{pmatrix} N_j & A_1 & V_{j1} \\ & A_2 & V_{j2} \\ & \cdots & \cdots \\ & A_n & V_{jn} \end{pmatrix}=\begin{pmatrix} N_j & A_1 & <a_{j1,}b_{j1}> \\ & A_2 & <a_{j2,}b_{j2}> \\ & \cdots & \cdots \\ & A_n & <a_{jn,}b_{jn}> \end{pmatrix} \quad j=1,2,\cdots,m \tag{2}$$

Among them, $R_j$ is the classical domain element matrix of the first $j$ evaluation level, and $<a_{j,}b_j>$ is the range of values of the feature set $A$ at the first $j$ evaluation level.

(2) Determine the nodal element matrix

The nodal element matrix is the union of the classical nodal element matrix, consisting of the object to be evaluated $N$, the feature set $A$ and the overall value range of the feature set quantities $V_N$ ,where $V_N=V_1\cup V_2\cup\cdots\cup V_m$ .The representation of the nodal element matrix is shown in the following equation.

$$R_N=(N,A,V_{Ni})=\begin{pmatrix} N & A_1 & V_{N1} \\ & A_2 & V_{N2} \\ & \cdots & \cdots \\ & A_n & V_{Nn} \end{pmatrix}=\begin{pmatrix} N_j & A_1 & <a_{N1,}b_{N1}> \\ & A_2 & <a_{N2,}b_{N2}> \\ & \cdots & \cdots \\ & A_n & <a_{Nn,}b_{Nn}> \end{pmatrix} \tag{3}$$

Among them, $R_N$ is the nodal element matrix, and $<a_{N,}b_N>$ is the overall range of values for the feature set $A$.

(3) Determine the matrix of the test element to be tested

Composed of the object to be evaluated $N$, the feature set $A$, and the values of different objects to be evaluated $V$, denoted as *R0*, its specific representation is shown in the following equation.

$$R_0=(N_0,A,V_i)=\begin{pmatrix} N_0 & A_1 & V_1 \\ & A_2 & V_2 \\ & \cdots & \cdots \\ & A_n & V_n \end{pmatrix} \tag{4}$$

(4) Standardization processing

In order to accurately reflect the situation of real data and eliminate the bias caused by numerical attribute differentiation, the classical domain element matrix and the test element matrix mentioned above are normalized, and the following equation is obtained:

$$R_j^{'} = (N_j, A, V_j^{'}) = \begin{pmatrix} N_j & A_1 & V_{j1}^{'} \\ & A_2 & V_{j2}^{'} \\ & \cdots & \cdots \\ & A_n & V_{jn}^{'} \end{pmatrix} = \begin{pmatrix} N_j & A_1 & <\frac{a_{j1}}{b_{N1}}, \frac{b_{j1}}{b_{N1}}> \\ & A_2 & <\frac{a_{j2}}{b_{N2}}, \frac{b_{j2}}{b_{N2}}> \\ & \cdots & \cdots \\ & A_n & <\frac{a_{jn}}{b_{Nn}}, \frac{b_{jn}}{b_{Nn}}> \end{pmatrix} \quad j = 1, 2, \ldots, m \tag{5}$$

$$R_0^{'} = (N_0, A, V_i) = \begin{pmatrix} N_0 & A_1 & \frac{V_1}{b_{N1}} \\ & A_2 & \frac{V_2}{b_{N2}} \\ & \cdots & \cdots \\ & A_n & \frac{V_1}{b_{Nn}} \end{pmatrix} \tag{6}$$

Among them, $R_j^{'}$ is the classical domain element matrix of the normalized $j$ evaluation level, and $R_0^{'}$ is the normalized test element matrix.

**Determination of Weight by Entropy Weight Method**

This article uses the entropy weight method to determine weights, and the specific implementation steps are as follows:

(1) Standardize data using maximum and minimum methods.

$$x_{ik}^{'} = \begin{cases} \dfrac{x_{ik} - min(x_{ik})}{max(x_{ik}) - min(x_{ik})} & x_{ik} \text{ is positive} \\ \dfrac{max(x_{ik}) - x_{ik}}{max(x_{ik}) - min(x_{ik})} & x_{ik} \text{ is negative} \end{cases} \tag{7}$$

Among them, $x_{ik}$ is the actual value of the $i$ th feature of the $k$ th object to be evaluated, and $x_{ik}^{'}$ is the standardized value of the $i$ th feature of the $k$ th object to be evaluated.

(2) Normalize the standardized indicator data.

$$r_{ik} = \frac{x_{ik}^{'}}{\sum_{k=1}^{K} x_{ik}^{'}} \tag{8}$$

Among them, $r_{ik}$ is the proportion of the normalized value of the $i$ th feature quantity of the $k$ th object to be evaluated.

(3) Calculate information entropy

$$H_i = -\frac{1}{\ln K} \sum_{k=1}^{K} r_{ik} \ln r_{ik} \tag{9}$$

Among them, $H_i$ is the information entropy of the $i$ th feature.

(4) Calculate the weight of indicators

$$w_i = \frac{1-H_i}{\sum_{i=1}^{n}(1-H_i)} \tag{10}$$

Among them, $w_i$ is the entropy weight of the $i$ th feature.

**Establish correlation functions and determine levels**

By establishing a correlation function, the correlation degree between the tested element and the classical domain element, as well as the nodal domain element, can be calculated more accurately. The final correlation level can be obtained using objective calculation formulas.

(1) The distance between the measured object element and the classical domain value.

$$D_j(v,v_j^{'}) = \left| v - \left(\frac{a_{j1}}{b_{N1}} + \frac{b_{j1}}{b_{N1}}\right)\Big/2 \right| - \left(\frac{b_{j1}}{b_{N1}} - \frac{a_{j1}}{b_{N1}}\right)\Big/2 \tag{11}$$

Among them, $D_j(v,v_j^{'})$ represents the distance between the object to be evaluated and the classical domain value of the first $j$ evaluation level.

(2) Calculate the feature correlation between the test element and the classical domain element.

$$K_j(V) = 1 - \sum_{i=1}^{n} w_i D_j(v,v_j^{'}) \tag{12}$$

Among them, $w_i$ is the entropy weight of the feature $A_i$.

(3) Determine the membership level of the object to be evaluated. Let $K_j = \max\{K_j(V)\} \quad j = 1,2,\ldots,m$, determine that the object under test belongs to level j.

$$\overline{K}_j(V) = \frac{K_j(V) - \min_j K_j(V)}{\max_j K_j(V) - \min_j K_j(V)} \tag{13}$$

$$j^* = \frac{\sum_{j=1}^{m} j\overline{K}_j(V)}{\sum_{j=1}^{m} \overline{K}_j(V)} \tag{14}$$

Among them, $j^*$ represents the characteristic value of the tested element in the level evaluation, which is used to determine the closeness of the tested element towards adjacent levels.

**EXAMPLE ANALYSIS OF MODEL SELECTION EVALUATION OF DELIVERY ROBOTS IN E-COMMERCE PARKS**

(1) In this paper, the intelligent delivery robot model selection scheme is categorized into five grades: excellent, good, medium, qualified, and poor, $j = 5$. The values of $j$ from 1 to 5, correspond to these five grades, respectively. There are 17 indices in the

index system, as detailed in section 3.2. Consequently, the five evaluation grades of the robot's applicability, along with the 17 evaluation indices and their corresponding evaluation metrics, form the classical domain object matrix. The five evaluation levels of robot applicability, the 17 evaluation indicators, and the corresponding eigenvalue ranges for each indicator collectively constitute the classical domain object matrix. Here, $R_1$ represents the classical domain object matrix for the excellent level, $R_2$ for the good level, $R_3$ for the medium level, $R_4$ for the qualified level, and $R_5$ for the poor level. Additionally, $A_1 \sim A_{17}$ denote the 17 indicators within the index system.

The final matrices of classical domain elements across various grades are presented in the following equation:

$$R_1 = \begin{pmatrix} N_1 & A_1 & (56,60) \\ & A_2 & (20.00,30.00) \\ & A_3 & (15,20) \\ & A_4 & (10,12) \\ & A_5 & (35,50) \\ & A_6 & (0.0506,0.3531) \\ & A_7 & (13,18) \\ & A_8 & (300,550) \\ & A_9 & (0.818,0.923) \\ & A_{10} & (125,130) \\ & A_{11} & (30,31) \\ & A_{12} & (3.8,5.2) \\ & A_{13} & (0.9,1) \\ & A_{14} & (4.25,5.00) \\ & A_{15} & (0.9,1) \\ & A_{16} & (3.5,4) \\ & A_{17} & (0.92,0.98) \end{pmatrix} \quad R_2 = \begin{pmatrix} N_2 & A_1 & (51,55) \\ & A_2 & (14.00,19.99) \\ & A_3 & (12,14) \\ & A_4 & (9,10) \\ & A_5 & (51,63) \\ & A_6 & (0.3532,0.5169) \\ & A_7 & (10,12) \\ & A_8 & (551,720) \\ & A_9 & (0.924,1.053) \\ & A_{10} & (120,124) \\ & A_{11} & (32,34) \\ & A_{12} & (5.3,7.8) \\ & A_{13} & (0.80,0.89) \\ & A_{14} & (3.00.4.24) \\ & A_{15} & (0.82,0.89) \\ & A_{16} & (4.1,4.5) \\ & A_{17} & (0.86,0.91) \end{pmatrix} \quad R_3 = \begin{pmatrix} N_3 & A_1 & (46,50) \\ & A_2 & (10.00,13.99) \\ & A_3 & (10,11) \\ & A_4 & (7.5,8.4) \\ & A_5 & (64,78) \\ & A_6 & (0.5170,0.7579) \\ & A_7 & (8,9) \\ & A_8 & (721,850) \\ & A_9 & (1.054,1.354) \\ & A_{10} & (110,119) \\ & A_{11} & (35,37) \\ & A_{12} & (7.9,8.5) \\ & A_{13} & (0.76,0.79) \\ & A_{14} & (2.35,2.99) \\ & A_{15} & (0.70,0.81) \\ & A_{16} & (4.6,4.9) \\ & A_{17} & (0.76,0.85) \end{pmatrix}$$

$$R_4 = \begin{pmatrix} N_4 & A_1 & (36,45) \\ & A_2 & (8.00,9.99) \\ & A_3 & (7,9) \\ & A_4 & (6.8,7.4) \\ & A_5 & (79,89) \\ & A_6 & (0.7580,0.9735) \\ & A_7 & (6,7) \\ & A_8 & (851,1200) \\ & A_9 & (1.355,1.697) \\ & A_{10} & (100,109) \\ & A_{11} & (38,40) \\ & A_{12} & (8.6,10.5) \\ & A_{13} & (0.61,0.75) \\ & A_{14} & (1.50,2.34) \\ & A_{15} & (0.6,0.69) \\ & A_{16} & (5.0,5.3) \\ & A_{17} & (0.66,0.75) \end{pmatrix} \quad R_5 = \begin{pmatrix} N_5 & A_1 & (25,35) \\ & A_2 & (7.00,0.79) \\ & A_3 & (5,6) \\ & A_4 & (5.0,6.7) \\ & A_5 & (90,120) \\ & A_6 & (0.9736,1.1512) \\ & A_7 & (4,5) \\ & A_8 & (1201,1600) \\ & A_9 & (1.698,2.373) \\ & A_{10} & (90,99) \\ & A_{11} & (41,55) \\ & A_{12} & (10.6,12.5) \\ & A_{13} & (0.40,0.60) \\ & A_{14} & (0.00,1.49) \\ & A_{15} & (0.50,0.59) \\ & A_{16} & (5.4,5.6) \\ & A_{17} & (0.55,0.65) \end{pmatrix}$$

(2)A section-domain object element matrix, denoted as $R_N$ , is created by combining the corresponding metrics of the intelligent delivery robot with the overall range of eigenvalue quantities of these metrics. This section-domain object element matrix is a concatenation of five classical domain object element matrices. The expression for $R_N$ is presented below.

$$R_N = R_1 \cup R_2 \cup R_3 \cup R_4 \cup R_5 = \begin{pmatrix} N & A_1 & (25,60) \\ & A_2 & (7.00,30.00) \\ & A_3 & (5,20) \\ & A_4 & (5,12) \\ & A_5 & (35,120) \\ & A_6 & (0.0506,1.1512) \\ & A_7 & (4,18) \\ & A_8 & (300,1600) \\ & A_9 & (0.818,2.373) \\ & A_{10} & (90,130) \\ & A_{11} & (30,55) \\ & A_{12} & (3.8,12.5) \\ & A_{13} & (0.4,1) \\ & A_{14} & (0,5) \\ & A_{15} & (0.5,1) \\ & A_{16} & (3.5,5.6) \\ & A_{17} & (0.55,0.98) \end{pmatrix}$$

(3) The matrix of the objects to be measured consists of three classes of intelligent delivery robots, a feature set denoted as $A$ , and quantitative values $V$ for the various robots. Below, the third to fifth columns of the matrix represent the specific quantitative values of different metrics for classes A, B, and C robots, respectively.

$$R_0 = \begin{pmatrix} N_0 & A_1 & 55 & 60 & 50 \\ & A_2 & 13.00 & 24.00 & 20.00 \\ & A_3 & 12 & 8 & 10 \\ & A_4 & 8 & 9.6 & 10 \\ & A_5 & 35 & 100 & 60 \\ & A_6 & 0.0792 & 1.092 & 0.54 \\ & A_7 & 8 & 8 & 15 \\ & A_8 & 600 & 1000 & 800 \\ & A_9 & 1 & 2 & 1 \\ & A_{10} & 100 & 120 & 110 \\ & A_{11} & 38 & 42 & 30 \\ & A_{12} & 7 & 10 & 8 \\ & A_{13} & 0.75 & 0.8 & 0.9 \\ & A_{14} & 3 & 3 & 3 \\ & A_{15} & 1 & 0.9 & 1 \\ & A_{16} & 5.2 & 4.5 & 4 \\ & A_{17} & 0.85 & 0.76 & 0.76 \end{pmatrix}$$

(4) Specification processing, based on equations (5) and (6), involves determining the upper and lower limits of each indicator value range for the classical domain object element. The quantitative value of the object element to be measured is divided by the upper limit of the domain section. This unification of the classical domain and the order of magnitude of the object element provides a foundation for the subsequent calculation process.

(5) Calculate the weight of each indicator in the indicator system using the equations (7) to (10) provided above. From the matrix of the elements of the object to be measured, it can be observed that the auxiliary interaction function of each robot has the same numerical value among the indicators. Consequently, this indicator cannot differentiate the level of each robot selection scheme.

Therefore, in this paper, the weight of this indicator is set to 0, while the weights of the remaining indicators are determined using the entropy weight method. Table 2 shows the results of the weighting of the indicators for the three categories of objects to be appraised.

Table 2. Indicator weights

| indicators | weights | indicators | weights |
|---|---|---|---|
| rated capacity $A_1$ | 0.0542 | minimum turn radius $A_9$ | 0.0476 |
| capacity of battery $A_2$ | 0.0505 | min. ground clearance $A_{10}$ | 0.0542 |
| battery mileage depletion $A_3$ | 0.0542 | noise $A_{11}$ | 0.0629 |
| maximum mileage $A_4$ | 0.0483 | motion accuracy $A_{12}$ | 0.0499 |
| overall weight $A_5$ | 0.0509 | containment $A_{13}$ | 0.0629 |
| dimension $A_6$ | 0.0528 | auxiliary interaction functions $A_{14}$ | 0.0000 |
| maximum velocity $A_7$ | 0.1289 | charge post $A_{15}$ | 0.0476 |
| minimum passing widths $A_8$ | 0.0542 | charging duration $A_{16}$ | 0.0517 |
| minimum turn radius $A_9$ | 0.0476 | human intervention approach $A_{17}$ | 0.1289 |

(6) Use the equation (11) above to calculate the distance $D_j(v,v_j)$ between the park delivery robots and each evaluation class. The specific values are presented in Table 3 below, using class C robots as an example:

Table 3. Distance between class C robots and classical domain measures

| indicators | $D_1(v,v_1)$ | $D_2(v,v_2)$ | $D_3(v,v_3)$ | $D_4(v,v_4)$ | $D_5(v,v_5)$ |
|---|---|---|---|---|---|
| $A_1$ | 0.1000 | 0.0167 | 0.0000 | 0.0833 | 0.2500 |
| $A_2$ | 0.0000 | 0.0003 | 0.2003 | 0.3337 | 0.4003 |
| $A_3$ | 0.2500 | 0.1000 | 0.0000 | 0.0500 | 0.1500 |
| $A_4$ | 0.0000 | 0.0083 | 0.1333 | 0.2167 | 0.2750 |
| $A_5$ | 0.0833 | -0.0250 | 0.0333 | 0.1583 | 0.2500 |
| $A_6$ | 0.1624 | 0.0201 | -0.0200 | 0.1894 | 0.3767 |
| $A_7$ | -0.1111 | 0.1667 | 0.3333 | 0.4444 | 0.5556 |
| $A_8$ | 0.1563 | 0.0500 | -0.0313 | 0.0319 | 0.2506 |
| $A_9$ | 0.0324 | -0.0223 | 0.0228 | 0.1496 | 0.2941 |
| $A_{10}$ | 0.1154 | 0.0769 | 0.0000 | 0.0077 | 0.0846 |
| $A_{11}$ | -5.6E-17 | 0.0364 | 0.0909 | 0.1455 | 0.2000 |
| $A_{12}$ | 0.2240 | 0.0160 | -0.0080 | 0.0480 | 0.2080 |
| $A_{13}$ | -5.6E-17 | 0.0100 | 0.1100 | 0.1500 | 0.3000 |
| $A_{14}$ | 0.2500 | 0.0000 | 0.0020 | 0.1320 | 0.3020 |
| $A_{15}$ | 5.55E-17 | 0.1100 | 0.1900 | 0.3100 | 0.4100 |
| $A_{16}$ | -5.6E-17 | 0.0179 | 0.1071 | 0.1786 | 0.2500 |
| $A_{17}$ | 0.1633 | 0.1020 | 0.0000 | 0.0102 | 0.1122 |

(7) The closeness $K_j(V)$ between the three types of robots and each evaluation level is calculated using equation (12) above. The level is calculated using equation (13), as shown in Table 4.

Table 4. Proximity between the three types of robots and each evaluation level

| proximity | $K_1(V)$ | $K_2(V)$ | $K_3(V)$ | $K_4(V)$ | $K_5(V)$ | grades | $j^*$ |
|---|---|---|---|---|---|---|---|
| A | 0.8780 | 0.9371 | 0.9395 | 0.8694 | 0.7592 | moderate | 2.4760 |
| B | 0.7926 | 0.8626 | 0.9032 | 0.9145 | 0.8606 | eligible | 3.5071 |
| C | 0.9340 | 0.9431 | 0.9136 | 0.8345 | 0.7196 | favorable | 2.2804 |

From the closeness results presented above, it is evident that among the three types of robots, Class C robot $K_2 = \max\{K_j(V)\}$, which represents the evaluation results of the Class C intelligent delivery robot, performed well. In contrast, Class B robot $K_4 = \max\{K_j(V)\}$, representing the evaluation results of the Class B intelligent delivery robot, received a qualified rating, while Class A robot $K_3 = \max\{K_j(V)\}$, which reflects the evaluation results of the Class A intelligent delivery robot, received a medium rating. Therefore, the model and parameters of the Class C robot are more suitable for the road conditions of the e-commerce park and its related requirements.

## CONCLUSIONS

E-commerce parks, as concentrated regions for online shopping, have become the main point for e-commerce and express delivery service businesses, creating a massive market opportunity. Logistics distribution within these parks is an important part of the overall logistics chain, especially for end users. This article investigated the distinct characteristics of the logistics distribution environment in e-commerce parks and picks three types of robots now available on the market that are most suited to intelligent distribution inside these parks. We created a model selection program for park distribution robots by incorporating the principles of designing an evaluation index system. The evaluation scheme used an entropy weight-objective topology model to determine the relationship between the three types of robots and the five evaluation criteria, as well as their proximity to various performance grades. This technique identified the maximum proximity, allowing us to classify the model selection scheme for park delivery robots. After processing and computing the index data for the three robot classes, the C class robot's evaluation grade was judged to be good, the B class robot's evaluation grade was qualified, and the A class robot's evaluation grade was medium.

## REFRENCES

[1] Mohamed Dawood Shamout, Salima Hamouche, Malek Bakheet Elayan, Adnan M Rawashdeh, Hamzah Elrehail, Dana Alshwayat. Modeling the moderating role of institutions on logistics-environment nexus in developed and developing economies. Energy & Environment, 2024, 35 (7): 3441-3462.

[2] Xiufang Ou, Bingbin Chen. The research on green logistics management strategy in the perspective of ecological environment protection. International Journal of Environment and Sustainable Development, 2025, 24 (1): 58-68.

[3] Mukherjee Subhodeep, Nagariya Ramji, Mathiyazhagan K., Baral Manish Mohan, Pavithra M.R., Appolloni Andrea. Artificial intelligence-based reverse logistics for improving circular economy performance: a developing country perspective. The International Journal of Logistics Management, 2024, 35 (6): 1779-1806.

[4] Hongyan Dui, Huanqi Zhang, Xinghui Dong, Songru Zhang. Cascading failure and resilience optimization of unmanned vehicle distribution networks in IoT. Reliability Engineering and System Safety, 2024, 246 110071.

[5] Zhao Jiao, Hu Hui, Han Yi, Cai Yao. A review of unmanned vehicle distribution optimization models and algorithms. Journal of Traffic and Transportation Engineering, 2023, 10 (4): 548-559.

[6] MONTOYA A, GUéRET C, MENDOZA J E, et al. A multi-space sampling heuristic for the green vehicle routing problem. Transportation Research Part C, 2016, 70: 11128.

[7] FROGER A, MENDOZA J E, JABALI O, et al. Improved formulations and algorithmic components for the electric vehicle routing problem with nonlinear charging functions. Computers & Operations Research, 2019, 104: 256-294.

[8] Inyoung Kim, Donghyo Kang, Harim Jeong, Soomok Lee, Ilsoo Yun. Method of Evaluating Multiple Scenarios in a Single Simulation Run for Automated Vehicle Assessment. Sensors, 2023, 23 (19):36-38.

[9] AGGARWAL D, KUMAR V. Performance evaluation of distance metrics on Firefly Algorithm for VRP with time windows. International Journal of Information Technology, 2019, 13(6): 1-8.

[10] Parque Victor, Honobe Kazuhiro, Miura Satoshi, Miyashita Tomoyuki. On Vehicle Evaluation and Design Using Data Envelopment Analysis with Hierarchical Concepts. Proceedings of the Design Society: International Conference on Engineering Design, 2019, 1 (1): 1225-1234.

[11] Ling Jian, Li Yong, Li Jingyuan, Yan Yan. Research on Production Vehicle Evaluation Method of China VI OBD for Light-Duty Vehicles. IOP Conference Series: Materials Science and Engineering, 2020, 774 012144-012144.

ISSN (online): 1873-4049

[12] Peng Honggang, Xiao Zhi, Wang Mengxian, Wang Xiaokang, Wang Jianqiang. An integrated decision support framework for new energy vehicle evaluation based on regret theory and QUALIFLEX under Z-number environment. Information Sciences, 2023, 647.

[13] Dong-Ling Xu, Anil Kumar Maddulapalli, Qiuping Yang, Xinlian Xie, Jian-Bo Yang. Uncertainty and Preference Modelling for Multiple Criteria Vehicle Evaluation. International Journal of Computational Intelligence Systems, 2010, 3 (6): 688-708.

[14] Morteza Montazeri-Gh, S. Yaser Jazayeri-M, Mahdi Soleymani. Vehicle ride evaluation based on a time-domain variable speed driving pattern. Int. J. of Vehicle Design, 2008, 47 (1/2/3/4): 81-101.

[15] Matthieu Dubarry, Nicolas Vuillaume, Bor Yann Liaw, Thomas Quinn. Vehicle Evaluation, Battery Modeling, and Fleet-testing Experiences in Hawaii. Journal of Asian Electric Vehicles, 2007, 5 (2): 1031042.

[16] QIANG F, YUROU S, LEI W. Risk Assessment of Import Cold Chain Logistics Based on Entropy Weight Matter Element Extension Model: A Case Study of Shanghai, China. International Journal of Environmental Research and Public Health, 2022, 19(24): 18692.

[17] HUIYAO Z, XIANTANG Z, HUI Y, et al. Comprehensive evaluation of shaped charge blasting effect of rock roadway based on entropy-weighted matter-element extension model. Arabian Journal of Geosciences, 2021, 14(8): 1-12.

[18] HUAN J, MA D, WANG W, et al. Safety-state evaluation model based on structural entropy weight–matter element extension method for ancient timber architecture. Advances in Structural Engineering, 2020, 23(6): 1087-1097.

[19] ZHAO G, DI H, BAI H, et al. A cable health assessment method based on multi-agent and matter-element extension model. Sustainable Energy Technologies and Assessments, 2023, 56: 103108.

[20] KAILEI L, HAN B, XIANG Y, et al. Cooperative Efficiency Evaluation System for Intelligent Transportation Facilities Based on the Variable Weight Matter Element Extension. Sustainability, 2023, 15(3).

[21] LAPORTE G, GENDREAU M, POTVIN J Y, et al. Classical heuristics for the vehicle routing problem. International Transactions in Operational Research, 1999, 7(4-5): 285-300.