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# Random Regret Minimization Model for Variable Destination-Oriented Path Planning

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**ABSTRACT** How should travelers be guided to change destinations and choose routes when they change their initial destination after being informed that the reception capacity is saturated and that the road ahead is congested? Using quasi-experimental methods, this paper explores this problem from the perspective of regret theory. We propose the regret index to classify the regret level and develop a random regret minimization model for variable destination-oriented path planning. Then, an improved ant colony algorithm based on the destination-path regret value is designed to estimate the model and to recommend alternative destinations and new paths to travelers. Finally, the results show the following: (1) The regret index can measure the regret level of travelers' decision-making, determine the minimum attribute difference tolerate threshold and regret threshold, and has a strong correlation with destination selection behavior. (2) In the case of the uncertain destination and paths, path planning depends not only on the minimum distance between Origin-Destination (OD), but also on destination's regret value. The research results provide reference for designing anticipated regret information to improve travelers' intentions to change destinations, which will reasonably guide travelers to change their decision and rationally arrange their travel plan. On the macro level, traffic volume is guided to different destinations, so as to balance destination reception capacity and reduce traffic jam.

**INDEX TERMS** Traffic guidance, path planning, variable destinations, regret theory, improved ant colony algorithm.

## I. INTRODUCTION

Path planning involving uncertain destinations and routes is a worthy issue. When the current road is congested, navigation always recommends alternative routes, ignoring the traveler's psychology. Travelers often regret their original destinations and have a poor travel experience due to irrational travel plan or information change of road conditions, parking, and dining in time (road congestion to the destination or saturation of reception capacity). For instance, when travelers obtain information that the reception capacity of the initial destination is saturated while jaunt or shopping, they experience regret and have intentions to change their destination and replan their path. The target groups are travelers with variable destinations, excluding the demand population of deterministic destinations, i.e. it's a study about re-planning of paths with individual's invariable travel purpose, but variable destinations. This paper considers the situation where the travel demand of the destination is large or the road to the destination is congested. Even if the shortest path is provided to the traveler, the traveler will not tolerate the travel time and regret for the destination.

Path planning of variable destination needs to screen out variable destination sets and choose the most satisfied path from many alternative paths to minimize the anticipated regret of changing destinations. Regret theory holds that travelers' choice depends not only on the physical utility of the choice itself, but also on feelings of regret or rejoice after comparing the physical utility of the choice with the physical utility of another alternative [1]. Chorus *et al.* developed the Original Random Regret Minimization model (Original RRM) and introduced it into the

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analysis of travel decision-making behavior [2]. The Original RRM model assume that the total regret is equal to the maximum value of the sum of attribute regret in the comparison of options, and adopt the independent and identically distributed (IID) assumption of Multinominal Logit Model (MNL), thus, the Original RRM model can well capture the semi-compensation effect. However, Chorus substituted ''Logarithm'' for ''Double Max'' function in the Original RRM model and proposed a Classic Random Regret Minimization Model (Classic RRM) using ''continuously differentiable function'' [3]. Then, the RRM model has been used to various options in the transportation sector [4], such as travel information acquisition options, parking lot selection, shopping locations, route selection [5]–[9]. Recent research involves car-sharing decisions, the choose of renewable energy solutions and evacuation travel behavior [10], [11]. Thus, variable destination path planning can use the feelings of regretful travelers.

If the difference in deterministic utility between the alternative is less than a certain threshold, it can assume that individuals consider or judge that the alternatives are the same. Whereas, the RRM model cannot solve this problem, Georgescu-Roegen argued that individuals perceive differences between two commodities only when attribute differences exceed some necessary minimum [12]. Jang *et al.* hold that the Original RRM model only depends on negative emotions called regret (semi-compensatory decision rules), but this assumption may be extreme, because the minimum attribute regret of the Original RRM model can only be zero, and the impact of substantially increase in an attribute of the choice cannot completely offset the impact of substantially decrease in another attribute. Therefore, Jang proposes a regret-rejoice minimization model, which uses rejoice of an attribute to completely compensate regret of another attribute. The concept of minimum threshold of attribute difference is proposed based on RRM model [13], [14].

There are commonly used path planning algorithms, including Dijkstra and its improved algorithm [15], A* and its improved algorithm [16], bat algorithm [17], ant colony algorithm [18] and genetic algorithms [19]. However, these are path planning algorithms for a given end point, and the question of how to plan paths still needs further study for variable destinations.

In summary, current research involves the following problems in path planning and RRM model: (1) At present, many researches ignore travelers' tolerance for certain factors and this is a non-compensatory behavior [20]. For example, travelers do not consider spend a lot of travel time on routes, that is, travelers have tolerance thresholds for the central attributes. (2) Many studies have adopted the RRM model to choose paths based on the rule of minimizing regret, but when the minimum regret value is larger than a certain threshold, travelers cannot make a choice in route selection, that is, the minimum regret value exceeds travelers' acceptance ability. (3) There are no studies on the combination selection of variable destination and path planning of variable destinations. It does not consider that travelers will change their decisions and provide information guidance for travelers from the dynamic changes.

Following the findings of existing research, this paper proposes to use regret index to measure the degree of decision makers' psychological regret and to classify travelers' regret degree based on the tolerance threshold of travelers for critical attributes, We combine travelers' psychological regret with the actual destination distance, and recommend different destinations to travelers through regret degree index under different scenes. Secondly, the random regret model for variable destinations-oriented path planning is constructed, and the minimum attribute difference threshold and the minimum regret threshold are determined. Finally, an improved ant colony algorithm for estimating the model is designed by taking the minimum regret impedance of the destination-path as the decision criterion.

## II. EXPERIMENT AND REGRET INDEX

Anticipated thinking can affect people's emotions and behaviors [21], and anticipated regret can provide a framework for solving problems: We test the effect of anticipated regret on changing destinations by allowing subjects to imagine that they have irrationally planed their route, causing a loss of time and queues on the way to travel or shop. Do subjects from intentions to change their destination? Is the probability of alternative destinations increased under the stimulus of the provision of anticipated regret information?

Basic Hypothesis: Providing anticipated regret information stimuli can increase the probability of changing travel destinations.

### A. EXPERIMENTAL DESIGN

This study uses quasi-experimental methods and hypothetical scenarios to control the anticipated regret. A total of 65 undergraduates participated in the experiment: 70% of participants were aged 21-24. Adopting scales from purchase behavior research [22], [23], we measure the subjects' impulses to change generated, psychological conflicts, and intentions to change destinations.

Scenario simulation experiment: This involves allowing the subjects to imagine that they are in a virtual congested road. First, we provide the information stimulus and congestion condition: A chain restaurant has attractive discounts; so, you want to drive to chain restaurant 1. However, you are stuck 5 kilometers away from the original destination (approximately 17 minutes, and the congestion time is uncertain). Then, you consider that there are also chain restaurants 2 and 3 in other places. At this time, the subjects are measured in regard to their impulses to change destinations in this situation. Then, we introduce the impeding factor, according to Fig.1(a): At this point, you notice that it takes 20 minutes to drive to alternative destination, and you have to work after 60 minutes (assuming 30 minutes of dining). At this time, the subjects are measured in regard to their psychological conflict and intention to change destinations.

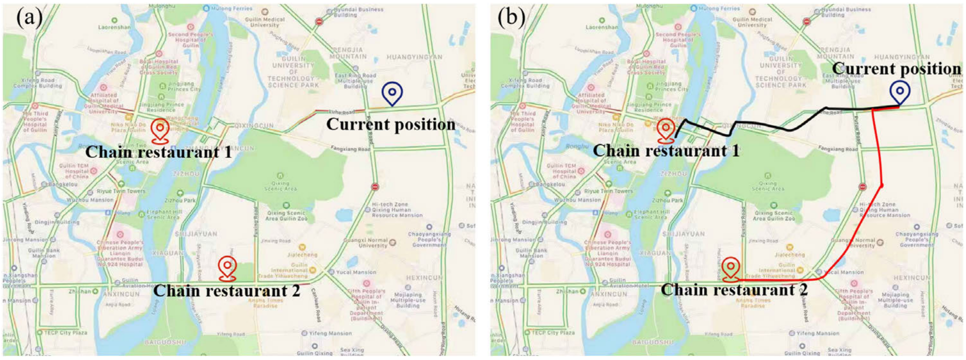



**FIGURE 1.** (a)-Subjects are informed of current traffic congestion and provided with alternative destinations. (b)-Providing anticipated regret information result in the psychological conflict of the subjects.

**TABLE 1.** Basic properties of variables and the probability of regretting and rejecting the original destination.

| Constructs | Generate the Impulse | Psychological Conflict | Initial Intentions | Final Intention | Cronbach α | MV | SD |
|---|---|---|---|---|---|---|---|
| Generate the Impulse | - | | | | 0.67 | 4.17 | 0.71 |
| Psychological conflict | 0.14 | - | | | 0.80 | 3.21 | 1.00 |
| Initial Intentions | $0.66^{**}$ | -0.16 | - | | 0.75 | 3.78 | 0.77 |
| Final Intention | $0.55^{**}$ | 0.29 | $0.51^{**}$ | - | 0.87 | 4.03 | 0.89 |
| Expected congestion time (min) | | probability of regretting the original destination | | | probability of rejecting the original destination | | |
| 3 | | 0.02 | | | 0.00 | | |
| 8 | | 0.65 | | | 0.02 | | |
| 15 | | 0.98 | | | 0.97 | | |

* p<0.05, ** p<0.01

On this basis, we introduce anticipated regret information regarding that recommend routes by navigation, according to Fig.1(b): Ahead, the roads are jammed, and the congestion time is uncertain. However, the drive to the alternative destinations is clear, and holding on to wait without changing destinations might take more time and higher costs. At this time, the subjects' intentions to change destinations are measured.

Then, without introducing the impeding factor, we inform travelers of the expected congestion time to the original decision destination in the experiment, selecting three time nodes (e.g., 3 minutes, 8 minutes, 15 minutes), and analyze whether travelers regret the original destination under different congestion times and whether they will reject the original destination, judge the state of travelers regret for the original destination without comparing with other alternatives.

The experimental results show that the travelers have the idea to change destinations mainly in situations involving impulses to change destinations and psychological conflicts. Their impulsive psychology with regard to changing destinations should be used reasonably, and we can provide stimulus information to cause psychological conflicts that realize traffic guidance. Table 1 presents correlation coefficient, mean value, standard deviation and Cronbach's $\alpha$ coefficient of each variable and the probability of regretting and rejecting the original destination.

We compared the final intention to change destinations under anticipated regret stimuli with the initial intention to change destinations without the information stimulus using a paired sample t-test. The results showed that the mean of the initial intention to change destinations was 3.74. After introducing the anticipated regret information, the mean of final intention to change destinations was 4.03, $t(64) = -3.002$, $p < 0.01$, indicating a significant difference. Thus, the hypothesis is supported, and anticipated regret information stimuli can increase the probability of changing travel destinations. Without comparison with other alternatives, travelers will have different regret perception for different congestion times when going to the same destination. When the congestion time is short, the traveler will firmly choose the original destination, and when the congestion time exceeds a certain value, the traveler will lose patience and give up the original destination. The choice and abandonment of the original decision do not depend on the attribute comparison with the alternative.

### B. ORIGINAL RRM MODEL INTRODUCTION

Studies have shown that RRM modle assumes that individuals will minimize anticipation when choosing alternatives [2] and that it can replace Random Utility Maximization (RUM) decisions. The logarithmic function in Classic RRM model unduly expresses regret, when the attribute difference is 0, the regret value is ln (2), which is inconsistent with reality [3]. Chorus suggested subtracting ln (2) from the logarithmic function, however, this extra calculates the rejoice and hypothesis rejoice having influence on the decision-making process, but it is no longer the model with only regrets as originally assumed [5], [24].

Theoretically, individuals cannot handle the results of many comparisons, in uncertain decision-making, so the Original RRM model may be appropriate [3], [25]. The random regret utility expression of the Original RRM model of individual alternative $i$ is obtained by the formula in Eq. (1), and the probability expression $P_i$ of alternative $i$ is obtained by the formula in Eq. (2):

$$\begin{aligned} RR_i &= R_i + \varepsilon_i \\ &= \max_{j\neq i}\{\sum_{k=1,\ldots,K} \max\{0, \beta_k \cdot (x_{jk} - x_{ik})\}\} + \varepsilon_i \quad (1) \end{aligned}$$

$$P_i = \frac{\exp(-R_i)}{\sum_{j\in M}\exp(-R_i)} \quad (2)$$

where, $R_i$ is the observed regret and the sum of the regret values obtained by comparing the k-th attribute between alternative $i$ and other alternatives $j$; $\beta_k$ is an attribute-related coefficient; $x_{ik}$ and $x_{jk}$ is the attribute values of the k-th attribute of the choice alternative $i$ and other alternatives $j$, respectively; $\varepsilon_i$ is the perceptual random error terms, which are independent of each other and conform to the same Gumbel distribution.

### C. DETERMINATION OF ATTRIBUTE THRESHOLDS AND CLASSIFYING REGRET LEVEL

The Original RRM model ignores the non-compensation behavior of travelers, i.e. the alternative exceeding the threshold of critical attributes (e.g. travel time) will not be chosen [26]. When an actual attribute value is greater than the maximum attribute value that psychological can bear, it will feel the limits of regret and will not choose the alternative $i$; when the actual attribute value is less than the psychological minimum perceived value, that individual will not feel regret. In consideration of all alternatives, the threshold value of the attribute is indicated the maximum attribute value that the individual can tolerate for a certain minimum attribute value is $x^{rs}_{\min,ink}$ in an ideal state (e.g., the minimum travel time is 30 minutes, the maximum tolerance time of the individual is 10 minutes, and 40 minutes is the attribute threshold value). The threshold value of the critical characteristic attribute $k$ of the choice alternative $i$ for the individual $n$ between $rs$ is obtained by the formula in Eq. (3).

$$x^{rs}_{\min,ink} + a^{rs}_{ink} \le x^{rs}_{ink} \le b^{rs}_{ink} + x^{rs}_{\min,ink} \quad (3)$$

where, $b^{rs}_{ink} + x^{rs}_{\min,ink}$ is the upper limit of the attribute threshold, and the actual attribute value should be less than this value; $b^{rs}_{ink}$ is the upper tolerance limit of the individual to the attribute value of the scheme; $x^{rs}_{\min,ink} + a^{rs}_{ink}$ is the lower limit of the attribute threshold, and the actual attribute value should be greater than this value; $a^{rs}_{ink}$ indicates the lower tolerance limit of the individual to the attribute value of the scheme.

In order to better measure and reflect the degree of decision makers' psychological regret, we propose a new concept of regret index, which is defined as the ratio of the actual attribute value and the maximum attribute threshold value of the alternative $i$ for the individual $n$ between $rs$, then it is recorded as $\delta_{ink}$, as shown in formula (4):

$$\delta_{ink} = \frac{x^{rs}_{ink}}{x^{rs}_{\max,ink}} = \frac{x^{rs}_{ink}}{x^{rs}_{\min,ink} + b^{rs}_{ink}} \quad (4)$$

where, $x^{rs}_{ink}$ is the actual attribute value (e.g. actual travel time); $x^{rs}_{max,ink}$ is the upper limit of the attribute threshold, $x^{rs}_{max,ink} = x^{rs}_{\min,ink} + b^{rs}_{ink}$.

Different alternative has different regret index for different attributes. The regret index $\delta_{ink}$ is used to control the attribute value not to exceed the range that individual psychology can bear. Based on the above quasi-experiments, to reflect the psychological regret degree of decision makers, and to screen out the set of alternatives that can be considered (i.e. the set of variable destinations that can be recommended), we can assume that three levels of regret are divided.

(1) $\delta_{ink} \ge 1$ is defined as "Extreme regret stage ?".

When the actual attribute value is greater than or equal to the maximum threshold value of the attribute value $x^{rs}_{ink} \ge x^{rs}_{\max,ink}$, the regret perception reaches the limit, the individual does not consider the $i$ alternative again, and does not compare the attribute values of the $i$ alternative and other alternatives one by one;

(2) $\frac{x^{rs}_{\min,ink}+a^{rs}_{ink}}{x^{rs}_{\min,ink}+b^{rs}_{ink}} < \delta_{ink} < 1$ is defined as "Perceptual regret stage II".

When the actual attribute value is less than the attribute value maximum threshold and greater than the attribute value minimum threshold $x^{rs}_{\min,ink} + a^{rs}_{ink} < x^{rs}_{ink} < x^{rs}_{\min,ink} + b^{rs}_{ink}$, when the attribute value is within the threshold, the alternative $i$ will be intend, but regret perception will also be generated;

(3)$\delta_{ink} \le \frac{x^{rs}_{\min,ink}+a^{rs}_{ink}}{x^{rs}_{\min,ink}+b^{rs}_{ink}}$ is defined as "No regret stage I".

When the actual attribute value is less than or equal to the attribute value minimum threshold $x^{rs}_{ink} \le x^{rs}_{\min,ink} + a^{rs}_{ink}$, the individual choice alternative $i$ without regret perception.

### D. DETERMINATION OF ATTRIBUTE DIFFERENCE TOLERANCE THRESHOLDS

Only when the attribute difference exceeds a certain necessary minimum value can the individual perceive the difference between the two schemes, as shown in formula Eqs. (5)(6). Jang *et al.* [13] holds that attribute difference tolerance threshold $\Delta^{rs}_{ink}$ will not change over actual attribute value $x^{rs}_{ink}$, so it has a threshold ratio, whether 1000min or 10min, the attribute difference tolerance $\Delta^{rs}_{ink}$ is equivalent.

$$x^{rs}_{jnk} - x^{rs}_{ink} > \Delta^{rs}_{ink}|\beta_k > 0 \quad (5)$$

$$x^{rs}_{jnk} - x^{rs}_{ink} < \Delta^{rs}_{ink}|\beta_k < 0 \quad (6)$$

However, the actual attribute value $x_{ink}^{rs}$ can affect the decision-making result. When the attribute difference between the alternative and the another alternative is equal, individuals with larger attribute values may feel less regret (e.g., travelers are more unable to accurately distinguish the real difference between 1020 minute and 1000 minute paths relative to 30 minute and 10 minute paths), because individuals have different perceptions of the attribute difference. The greater the actual attribute value $x_{ink}^{rs}$, the less sensitive perception of the difference between the two alternatives for the individual. Therefore, the attribute difference tolerance threshold $\Delta_{ink}^{rs}$ is defined the percentage of the lower tolerance limit of the attribute value and the upper tolerance limit of the attribute value for the alternative by the individual with actual attribute value as formula Eq.(7),

$$\Delta_{ink}^{rs} = \frac{a_{ink}^{rs}}{x_{\min,ink}^{rs} + b_{ink}^{rs}} \cdot x_{ink}^{rs} = a_{ink}^{rs} \cdot \delta_{ink} \tag{7}$$

according to Eq. (7), the higher the regret level, the worse the perception of the attribute difference between the two alternatives, i.e., the greater the allowable threshold for attribute difference.

## III. MODEL DEVELOPMENT

In this study, it is assumed that traffic, parking, shopping and other information can be obtained and can be fed back to travelers in a timely manner, and the error of information prediction is acceptable in the big data era of information sharing based on the 5G Internet of Things. When the changed destination and path are unclear, the replanning of the route aims not only to minimize the links impedance but also to consider the strategy of minimizing regret over choosing the destination and the path. The question of how to recommend destinationsto travelers based on their regret psychology and to choose the path with the minimum regret are the key problems under the uncertain environment.

Rigid travel demands and non-rigid travel demands have great differences in the willingness to change destinations. Individuals with rigid travel demands will not change the destination and choose the destination no matter what the travel time is, so they are less sensitive to tolerance time, while individuals with non-rigid travel demands have greater uncertainty about the destination and have lager sensitive to tolerance time.

We consider the influence of regret psychology for the change of destination and path planning, and use regret function to reflect the influence of travelers' different regret degrees for the change of destination. We develop a Variable Destination Random Regret Model (VDRRM) to reasonably guide travelers to change destinations. Fig.2 shows a model framework of anticipation module and recommending destination module and path planning module.

### A. DETERMINATION OF ALTERNATIVE DESTINATION SETS

In this paper, regret index can be used to pre-judge the current regret degree of travelers' psychology to the original decision-making, and to select a set of travel destinations with variable choices. If the regret index of the actual characteristic attribute value $k$ when the traveler chooses the original decision is the "No regret stage I", then he/she does not change the travel destination; If the regret index of the traveler when selecting the original decision is " Perceptual regret stage II", it means that he/she may change his/her travel destination. The location at this time is decision point $r$, and the set of variably selected destinations includes the original decision and other alternatives. When the regret index of the traveler choosing the original decision is "Extreme regret stage III", he/she has already exceeded the attribute threshold and will not intend to choose the original decision again. The position at this time is the decision point $r$, and the set of alternative destinations only includes other alternatives except for the original decision. Therefore, if the decision point $r$ is not in the range of regret stages II and III, it is not suitable as a variable decision point.

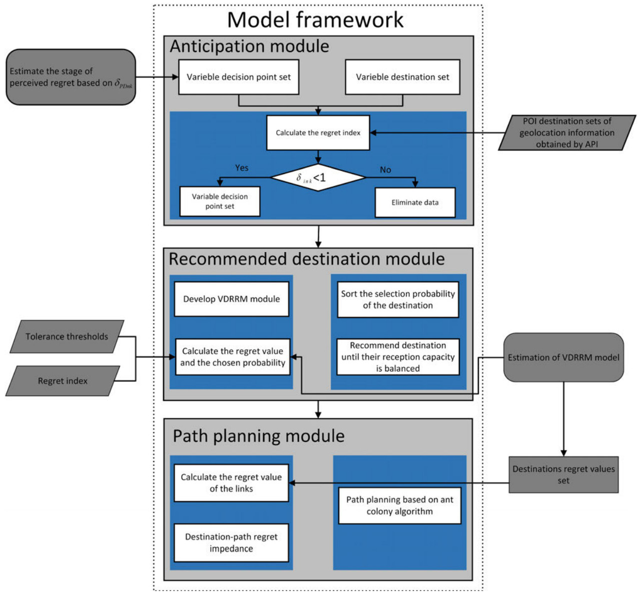



**FIGURE 2.** **Model framework.**

The target group is traveler with variable destinations, excluding rigid destination demand that schools, home and office places and so on of individual. The original destination (PD) can be classified into four types: catering, tourist attractions(jaunt), shopping malls and parking lots. The corresponding point of interest (POI) information is obtained by successively using the subclass with the same name as the PD (denoted as SD), the subclass with a different name from the PD (denoted as DD) and the middle class of the PD (denoted as MD) as filtering attributes. These related destinations are formed into an initial selection set **Q**, which elements be infinite elements including the original decision PD, and geographic location information of this elements can be obtained from API, as shown in Fig.3(a).

*Condition 1:* If traveler is at decision point $r$ and the regret index of an attribute of a destination in the original selection set **Q** is greater than or equal to 1, then the destination is

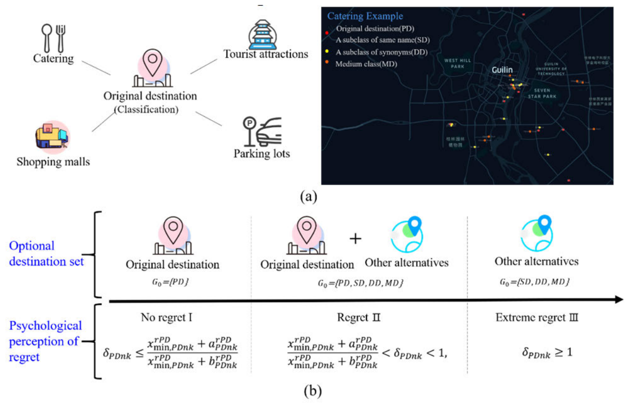



**FIGURE 3. (a)- Variable destination classification and screening attributes of initial set; The left picture shows four types of optional destinations. The right picture is the visualization of POI information of the initial set, which is selected by taking restaurants as an example and taking the SD, DD and MD of the original destination (KFC) name as attributes in Guilin city; (b)- Traveler has three stages of psychological regret between the decision point and the original destination, and the distribution of optional destination sets $G_0$.**

eliminated, $\delta_{jnk} \ge 1, j \in \mathbf{Q}$. According to condition 1, the optional destination set is selected and denoted as $G_0$. The traveler's psychology to the original decision at the decision point $r$ is "No regret stage I" what is no need to recommend destination to the traveler and in " Perceptual regret stage II", we can recommend the destinations including the original decision to travelers, and in "Extreme regret stage III", we recommend the destinations to travelers except the original decision, as shown in Fig.3(b).

### B. DEVELOPING OF VARIABLE DESTINATION REGRET FUNCTION

At present, many be proposed models under the uncertain environment of dynamic traffic flow, the regret value always changes over traffic flow. However, considering the attribute difference tolerance threshold, the regret value will not significantly change over traffic flow, resulting in frequently changing destinations in a short time. In this paper, the regret index of the original decision is used to prejudge whether travelers generate regret perception of the original destination at the decision point $r$ and whether it exceeds the extreme regret perception and stimulate them with anticipated regret information to guide their travel.

This section develops a variable destination random regret minimization function $R_s$ that adds attribute differences tolerance threshold $\Delta^{rs}_{snk}$ and attribute preference parameters $\beta_k$ to jointly influence decision-making as formula Eqs.(8) $\sim$ (9). The attribute differences tolerance $\Delta^{rs}_{snk}$ increase with regret index $\delta_{snk}$ of the alternative $s$. By $\delta_{snk}$ measuring the regret degree of the traveler's reselection destination $s$, the regret value of the reselection destination $s$ is minimized at the reasonable threshold.

$$\min R_s = \max_{\substack{j,s\in G_0\\ j\neq s}} \{ \sum_{k=1,\ldots,K} \max\{0, \beta_k \cdot [(x_{jk} - x_{sk}) - \Delta^{rs}_{snk}]\}\} \tag{8}$$

According to regret index, the model can be divided into three functions.

Segment 1:

$$R_s = 0, \delta_{snk} \le \frac{x^{rs}_{\min,snk} + a^{rs}_{snk}}{x^{rs}_{\min,snk} + b^{rs}_{snk}} \tag{9}$$

Segment 2:

$$\begin{aligned} R_s = \max_{\substack{j,s\in G_0,\\ j\neq s}} \{ & \sum_{k=1,\ldots,K-n} \max\{0, \beta_k \cdot [(x_{jk} - x_{sk}) - a^{rs}_{snk} \cdot \delta_{snk}]\} \\ & + \sum_{k=K-n,\ldots,K} \max\{0, \beta_k \cdot (x_{jk} - x_{sk})\}\}, \\ & \frac{x^{rs}_{\min,snk} + a^{rs}_{snk}}{x^{rs}_{\min,snk} + b^{rs}_{snk}} < \delta_{snk} < 1 \end{aligned} \tag{10}$$

Segment 3:

$$\begin{aligned} R_s = \max_{\substack{j,s\in G_0,\\ s\neq PD,\\ j\neq s}} \{ & \sum_{k=1,\ldots,K-n} \max\{0, \beta_k \cdot [(x_{jk} - x_{sk}) - a^{rs}_{snk} \cdot \delta_{snk}]\} \\ & + \sum_{k=K-n,\ldots,K} \max\{0, \beta_k \cdot (x_{jk} - x_{sk})\}\}, \delta_{PDnk} \ge 1 \\ & \text{and } \frac{x^{rs}_{\min,snk} + a^{rs}_{snk}}{x^{rs}_{\min,snk} + b^{rs}_{snk}} < \delta_{snk} < 1 \end{aligned} \tag{11}$$

Refer to (9), where $\delta_{snk} \le \frac{x^{rs}_{\min,snk} + a^{rs}_{snk}}{x^{rs}_{\min,snk} + b^{rs}_{snk}}$ indicates that the chosen destination $s$ is not regretful. The travelers' psychological perception of the alternative destination $s$ at the decision point position is determined through the regret psychological level. This regret value for choosing alternative $s$ can be determined is 0 without comparing with other alternatives; Refer to (11), where the regret value of the segment is equal to the sum of the regret values of $K - n$ central attributes and $n$ non-central attributes, $\frac{x^{rs}_{\min,snk} + a^{rs}_{snk}}{x^{rs}_{\min,snk} + b^{rs}_{snk}} < \delta_{snk} < 1$ indicates that travelers in this interval are at the stage of perceivable regret for all destinations in the set, and the regret value is calculated by comparing two attributes; Refer to (12), where $\delta_{PDnk} \ge 1$and$\frac{x^{rs}_{\min,snk} + a^{rs}_{snk}}{x^{rs}_{\min,snk} + b^{rs}_{snk}} < \delta_{snk} < 1$ indicates the regret perception of the original decision has reached the limit, and the original decision is no longer used as a selection set of variable destinations. Only regret values of variable destinations except the original decision are calculated.

Van proposed the concept and formal measurement of regret depth. The degree of regret minimization depends on the estimated scale parameter $\mu$ and differences in attributes [24], but there is a lack of parameters describing the regret value of model alternatives in the normal range. When the minimum regret value in the alternative scheme is greater than a certain threshold value min $\{R_s, R_i, \ldots\} > y$, its value also exceeds the regret value of travelers' psychology, thus cannot make decisions. In this paper, the threshold of the minimum regret value is determined in the extreme regret stage through the division of regret grades.

The probability of travelers to choose variable destinations is obtained through Eqs.(2) $\sim$ (12). The probability values are sorted from large to small, and the top five destinations are selected as recommended destinations. We recommend these five destinations to travelers on congested roads until the reception capacity of the destinations is balanced. The main purpose for travelers to change their destinations is to guide the traffic volume to different destinations, so as to achieve a balanced allocation of resources. Traffic guidance for variable destination can divert traffic from demand and relieve traffic congestion by "inducing traffic demand to increase".

### C. PATH SEARCHING

#### 1) DESTINATION-PATH REGRET IMPEDANCE

In this paper, the decision point position $r$ is the new starting point and the variable destination $s$ is the ending point to re-plan the path. For the path planning of a new "OD", it is necessary to select the path among the many possible paths that best matches the traveler's preference, minimizing the value of anticipated regret over changing destinations. The overlapping link is divided into the overlapping link of destinations and the overlapping link of paths: ① In $< r, s >$, there are multiple destinations sharing the link in. It is necessary to consider that regret values of multiple destinations jointly affect the links; ② In $< r, s >$, there are multiple paths that share the links. it is assumed that there are $f(f \in \{1, 2, \ldots, 5\})$ destinations that share link $a$, $x_i(i = 1, 2, ..f)$ indicates the i-th destination of the overlapping link, denoted as $G_1$, and $x_i \in G_1$.

It is assumed that the traveler's path to each alternative destination is the minimum route in actual time, and the minimum path's actual travel time greater than the minimum travel time in ideal state. The above destination regret value is calculated based on the shortest path obtained by traditional path search. It only considers the impedance and regret of the path, does not consider the regret of other destinations, and cannot guide the path to the travelers. In this section, the minimum path is searched by taking the minimum regret impedance of destination-path as the decision criterion for the case ① and ②.

The regret impedance $R_{t_a}$ of link $a$ is defined as taking the proportion of each link impedance to the link impendences of all paths $c_y^{rx_i}$, multiplying by the regret value $R_{x_i}$ of the destinations for each overlapping link and the proportion coefficient of regret influence of alternative destination $s$ on link $a$. The impedance is distributed according to the weight of the selection probability of the optional destination, the greater the choice probability of the destination, the greater the influence on the section impedance. $c_y^{rx_i}$ and $R_{t_a}$ are obtained by the formula in Eqs.(12) $\sim$ (13).

The regret value of path:

$$R_{c_y} = \frac{c_y^{rx_i}}{\sum\limits_{y \in Y} c_y^{rx_i}} \cdot R_{x_i} \tag{12}$$

The regret value of link:

$$\begin{aligned} R_{t_a} &= \sum_{y \in Y} \sum_{i=1,\ldots,f} \frac{1}{z_i} \cdot \frac{t_a}{c_y^{rx_i}} \cdot R_{c_y} \cdot \omega \\ &= \sum_{y \in Y} \sum_{i=1,\ldots,f} \frac{1}{z_i} \cdot \frac{t_a}{\sum\limits_{y \in Y} c_y^{rx_i}} \cdot R_{x_i} \cdot \omega \end{aligned} \tag{13}$$

where $\mathbf{Y}$ indicates the number of paths to destination $x_i$; $c_y^{rx_i}$ indicates the impedance on the $y - th(y \in Y)$ path from the OD to destination $x_i$ and containing decision point $r$ at which the traveler chose to destinations; $t_a$ indicates the impedance function of link $a$; $R_{x_i}, R_{c_y}, R_{t_a}$ indicates the regret value of the destination of the $i - th$ overlapping link, regret value of the route of the $y - th$ overlapping link, and regret value of link $a$, respectively; $z_i$ is the path of link $a$ shared by $z_i(z_i \in \mathbf{Y})$ in the same destination; $\omega$ represents the proportion coefficient of regret influence of destination s on link $a$, when link $a$ is the common section of multiple destinations; $\omega$ is the weighted sum of the selection probability $P_{x_i}$ of the common destination, $\omega = \frac{P_{x_i}}{\sum\limits_{i=1,\ldots,f} P_{x_i}}$.If link $a$ does not share destination, then $x_i = s$, $\omega = 1$.

#### 2) ANT COLONY ALGORITHM FOR MINIMUM REGRET VALUE

Chorus *et al.* proposed path selection for random regret minimization to select routes according to the minimum impedance of the path based on the known OD. However, the perception of regret also affects the choice of destination. In what follows, we design an improved ant colony algorithm for the pheromone update aspect to solve the path planning model by taking the least regret impedance of the destination-path as the decision criterion refer to (2) $\sim$ (17).

Ant k (k = 1, 2, …, m) calculates the status transition probability based on each link's pheromone concentration and the link's heuristic information. The current ant k passing nodes is recorded using the taboo tabuk, and the link sets adjust dynamically with the tabuk evolutionary process. The state transition probability of ant k moving from node a to b at time t is Eq. (14),

$$P_{ab}^k = \begin{cases} \dfrac{\tau_{ab}^{\alpha}(t) \cdot \eta_{ab}^{\beta}}{\sum\limits_{c \in allowed_k} \tau_{ac}^{\alpha}(t) \cdot \eta_{ac}^{\beta}} & c \in allowed_k \\ 0 & otherwise \end{cases} \tag{14}$$

where, $allowed_k$ indicates the node that the ant is allowed to select next; $\tau_{ab}(t)$ indicates the pheromone concentration on the link $< a, b >$ at time t; $\eta_{ab}(t) = 1/R_{t_a}$ indicates the expected degree of the ant moving from node a to b. $R_{t_a}$ is regret impedance of the link $a$ between the two nodes a and b, when it is larger, the $\eta_{ab}(t)$ is smaller, and selected probability $p_{ab}^k(t)$ of this link is smaller; $\alpha$, $\beta$ respectively indicates the importance of the heuristic pheromone and the importance of the pheromone. Taking the regret value as decision criterion, the ant pheromone update formula is improved in

**TABLE 2.** Correlations of difference minimum travel time and travel purpose and tolerance time.

| | | Tolerance time | Travel purpose | Minimum travel time |
|---|---|---|---|---|
| Tolerance time | Pearson Correlation | 1 | .001 | .980** |
| | Sig.(2-tailed) | | .943 | .000 |
| | N | 4104 | 4104 | 4104 |
| Travel purpose | Pearson Correlation | .001 | 1 | .000 |
| | Sig.(2-tailed) | .943 | | 1.000 |
| | N | 4104 | 4104 | 4104 |
| Minimum travel time | Pearson Correlation | .980** | .000 | 1 |
| | Sig.(2-tailed) | .000 | 1.000 | |
| | N | 4104 | 4104 | 4104 |

Eqs. (15) ∼ (17).

$$\tau_{ab}(t+1) = (1-\rho)\cdot\tau_{ab}(t) + \Delta\tau_{ab}(t) \tag{15}$$

$$\Delta\tau_{ab}(t) = \sum_{k=1}^{m}\Delta\tau_{ab}^{k}(t) \tag{16}$$

$$\Delta\tau_{ab}^{k}(t) = \begin{cases} \dfrac{Q}{R_{t_a}} \\ 0 \end{cases} \tag{17}$$

where, $\Delta\tau_{ab}^{k}(t)$ indicates pheromone concentration of the k-th ant on the road segment $< a, b >$ between time t and t+1, and it is related to the regret value of the passed links, The algorithm flow is shown in Fig.4, and set the initial time pheromone $\tau_{ab}(t) = 0$, ant-quantity k = 0.

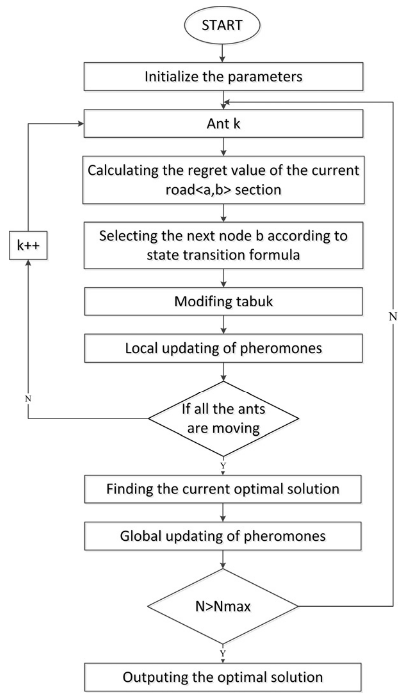



**FIGURE 4.** Flow chart of an improved ant colony algorithm.

## IV. CASE STUDY

In the following, we illustrate the above path planning by assuming that from $G_0$ selects destinations with attributes of catering, having the original decision PD (KFC), and using the subclass with the same name as the PD, denote as SD ($S_1$: Another KFC), the subclass with a different name from the PD, denoted as DD ($S_2$: McDonald's, $S_3$: Burger King), and the middle class of the PD, denoted as MD ($S_4$: Chinese food). In this paper, the four variable decision points $r$ are selected in the congested section between the original starting point O and the original decision PD; i.e. the four different points of the minimum travel time are the new starting point to the original decision (when the minimum travel time under the ideal state is 90 min, 60 min, 30 min and 20 min, respectively, the decision point $r$ is selected). The actual travel time from decision point $r$ to each type of destination is defined as PD $> S4 > S1 > S3 > S2$. Based on this principle, we acquired the departure time and expected arrival time of the new "OD" in the morning and evening peak hour using Amap in Guilin on May 19, 2019. We conducted an SP survey about change destinations, which includes two attributes: Travel time TT and Destination preference M.

### A. DETERMINATION OF ATTRIBUTE THRESHOLD

For non-rigid travel purposes, this paper conducts a survey with the crucial attribute of travel time tolerance threshold. The subjects of the survey are drivers in Guilin CBD and tourist attractions. The survey method is to allow drivers to choose the longest tolerable travel time for the shortest travel time. The survey time is July 2020, and 684 valid questionnaires were gotten. The survey results are shown in Fig.5, Fig.5(a) is the threshold distribution of travel time, and Fig.5(b) is Pareto chart analysis of upper and lower limits of tolerance time thresholds for different minimum travel times. The non-rigid travel demands of the respondents were divided into four travel destinations: catering, shopping, parking and jaunt. There are 171 questionnaires for each type of travel destination to analyze the correlation between minimum travel time, travel destination and individual tolerance time, as shown in Table 2 and Fig.5(a) on the right. It can be seen from the analysis results that different minimum travel times have a strong correlation with the individual tolerance time, and the minimum travel time has a greater impact on the individual tolerance time.There is no correlation between individual tolerance time and travel destination,

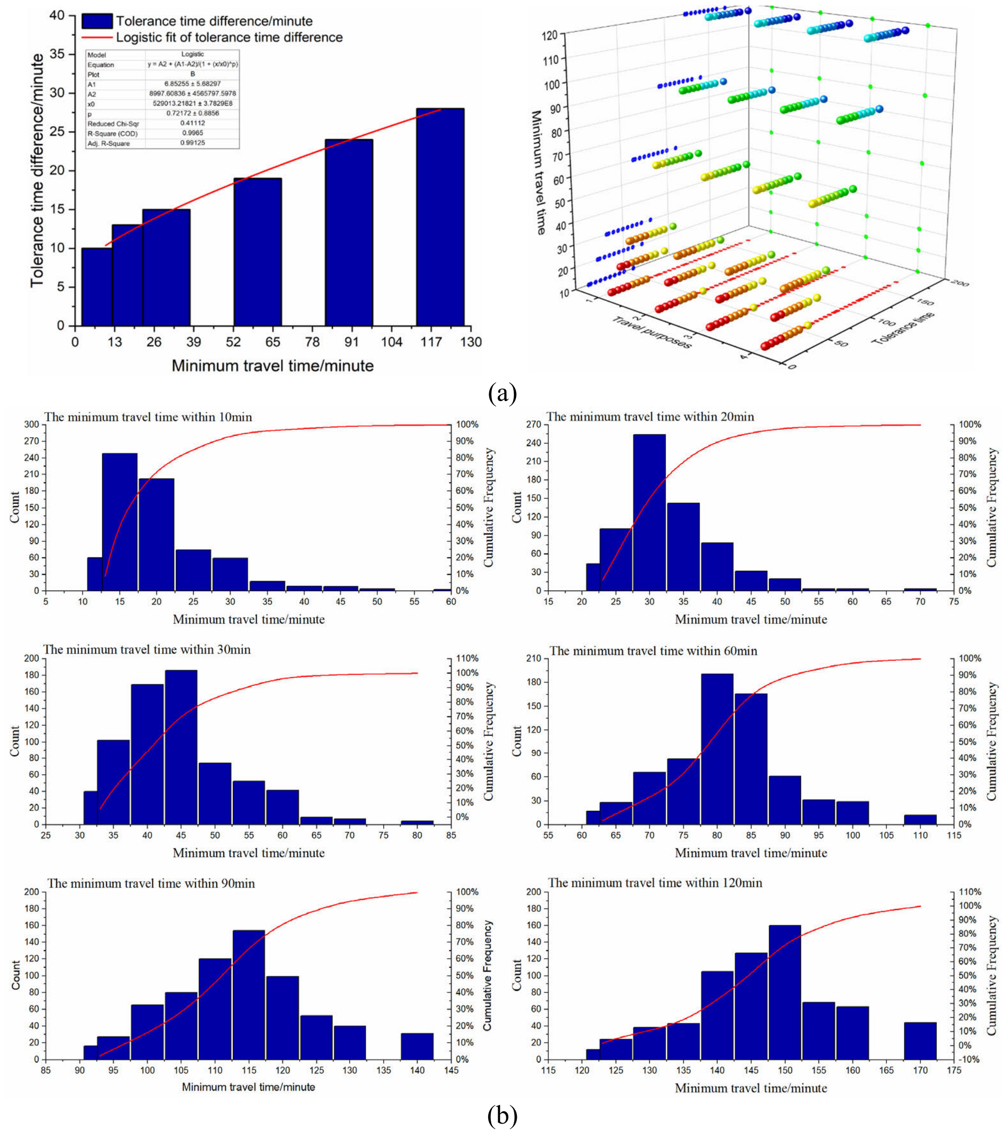



**FIGURE 5.** **(a)-Distribution of travel time threshold; (b)-Pareto chart analysis of upper and lower limits of tolerance time threshold for different minimum travel time.**

that is, non-rigid travel destination has little influence on individual tolerance time.

As can be seen from Fig.5(a) on the left, the "tolerance time difference" refers to the difference between the average value of the maximum time that the driver can tolerant and the minimum travel time given by the questionnaire. The histogram shows the distribution of tolerance differences for different minimum travel times. With the increase of the minimum travel time, the tolerance time difference increases continuously. The $R^2 = 0.99$ of the logistic fitting function shows that the data over 99% can be interpreted by the model.

The Fig.5(b) shows that the greater the minimum travel time, the greater the tolerance threshold for travel time, the less sensitive the perception of time difference, and the more evenly distributed the choice of the maximum tolerance time. According to Pareto law, the maximum tolerance time of 80% is the upper limit of the tolerance threshold $b_{ink}^{rs}$, and the maximum tolerance time of 20% is the lower limit of the tolerance threshold $a_{ink}^{rs}$. For example, when the minimum travel time is 30 min, the upper limit of the tolerance threshold is 50 min and the lower limit is 35 min, which means 80% of travelers can tolerate up to 35 minutes and 20% of travelers can tolerate up to 50 minutes. The upper and lower limits of the attribute threshold for different minimum travel times and the tolerance threshold are shown in Table 3.

In practical application, we can determine the individual time tolerance threshold according to the tolerance threshold table corresponding to the minimum travel time between the current position and the destination.

### B. MODEL PARAMETER ESTIMATION

Refer to Table 3, the results of calculating regret index of different decision points for each destination are shown in Table 4. When the decision-making point is within the

**TABLE 3.** Upper and lower limits of attribute threshold and tolerance threshold for different minimum travel time.

| Minimum travel time(min) | 10 | 20 | 30 | 60 | 90 | 120 |
|---|---|---|---|---|---|---|
| $a_{ink}^{rs}$ | 5 | 5 | 5 | 10 | 10 | 15 |
| $b_{ink}^{rs}$ | 15 | 15 | 20 | 25 | 30 | 35 |
| Attribute tolerance threshold | $15 \le x_{ink}^{rs} \le 25$ | $25 \le x_{ink}^{rs} \le 35$ | $35 \le x_{ink}^{rs} \le 50$ | $70 \le x_{ink}^{rs} \le 85$ | $100 \le x_{ink}^{rs} \le 120$ | $135 \le x_{ink}^{rs} \le 155$ |

**TABLE 4.** Regret index and attribute difference threshold of different decision points for each destination.

| Destination | $r_1$ | | $r_2$ | | $r_3$ | | $r_4$ | |
|---|---|---|---|---|---|---|---|---|
| | $\delta_{ink}$ | $\Delta_{ink}^{rs}$ | $\delta_{ink}$ | $\Delta_{ink}^{rs}$ | $\delta_{ink}$ | $\Delta_{ink}^{rs}$ | $\delta_{ink}$ | $\Delta_{ink}^{rs}$ |
| PD | 0.975 | 9.750 | 0.965 | 9.650 | 0.960 | 4.800 | 0.943 | 4.715 |
| $S_1$ | 0.850 | 8.500 | 0.871 | 8.710 | 0.900 | 4.500 | 0.828 | 4.140 |
| $S_2$ | 0.835 | 8.350 | 0.840 | 4.200 | 0.860 | 4.300 | 0.857 | 4.285 |
| $S_3$ | 0.859 | 8.590 | 0.860 | 4.300 | 0.880 | 4.400 | 0.886 | 4.430 |
| $S_4$ | 0.892 | 8.920 | 0.894 | 8.940 | 0.900 | 4.500 | 0.914 | 4.570 |

**TABLE 5.** Parameter estimation of the model.

| Decision point | Variables | Original RRM | | Variable Destination RRM | |
|---|---|---|---|---|---|
| | | Parameter | t-stat | Est | t-stat |
| $r_1$ | Travel time | -0.595 | -5.367 | -0.524 | -5.393 |
| | Mark | 0.022 | 1.436 | 0.023 | 1.484 |
| $r_2$ | Travel time | -0.559 | -4.522 | -0.513 | -4.523 |
| | Mark | 0.005 | 0.259 | 0.006 | 0.337 |
| $r_3$ | Travel time | -0.034 | -4.705 | -0.030 | -4.705 |
| | Mark | -0.017 | -0.787 | -0.014 | -0.629 |
| $r_4$ | Travel time | -0.056 | -4.958 | -0.055 | -4.964 |
| | Mark | -0.093 | -2.296 | -0.093 | -2.297 |
| Final log likelihood | | -245.714 | | -245.693 | |
| Rho-square | | 0.223 | | 0.223 | |
| AIC | | 507.429 | | 507.387 | |
| BIC | | 522.548 | | 522.506 | |

range of regret stages II, travelers will feel regret to PD, but they will still insist on their original decision-making. Therefore, this paper assumes that travelers' preference for the PD is classified as (50, 40, 30, 20) according to the decreasing location of the decision-making point. The parameter estimation method is Python Biogeme [27] maximum likelihood estimation. We obtained 196 online respondents for 4 decision points, and the results of estimating the parameters of the model are shown in Table 5.

Variable destination RRM model puts forward the regret index to distinguish the stage of traveler's regret. When the traveler is satisfied with the travel time of the original destination, there is no need to compare other alternatives, that is, there is no regret for the choice of the original destination. However, when the traveler is extremely dissatisfied with the travel time of the original destination, the regret value of the original destination will not be considered. This cannot be reflected in original RRM model. Two models are analyzed for elasticity. The direct elasticity is defined as the change in the selection probability of alternative $i$ when the value of the $l$ utility variable of alternative $i$ was changed by 1%. According to the research of Wen *et al.*, the direct elasticity of the $l$ utility variable in MNL model is deduced [28], $(1 - P_n)\beta X_n$, and the results were shown in Table 6. The tolerance threshold of the variable destination RRM model is added to amend the perception difference.

According to Table 5, the VDRRM model has a slightly better fitting effect than the Original RRM model, and the significance level is approximately equal between different models. In addition, the VDRRM model also introduces regret index to the model to quantify the regret degree of travelers. As the decision point is further away from the original decision, the travel time preference attribute $\beta_{\text{time}}$ first gradually increases and then decreases, showing a quadratic function $y = -0.0002x^2 + 0.03x - 1.04$, $R^2 = 0.99$ relationship with the minimum travel time. When the OD scale is especially large (the minimum travel time is large), the $\beta_{\text{time}}$ becomes insensitive and disliked. The changed destination should not only consider the degree of psychological regret of the traveler's decision point, but also consider the scale of

**TABLE 6.** Elasticities comparison between original RRM model and variable destination RRM model about travel time.

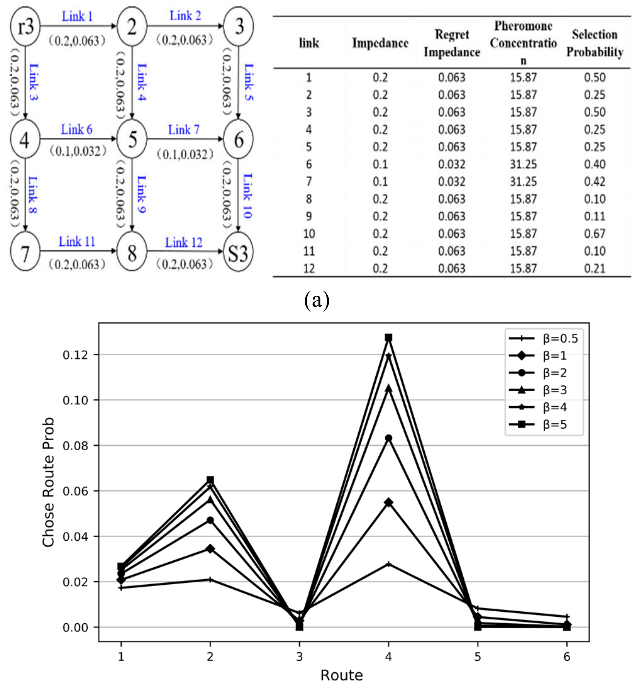
| Decision point | Destination | Original RRM | Variable Destination RRM |
|---|---|---|---|
| | | Attributes | |
| | | Travel time | Travel time |
| r1 | PD | -18.45 | -16.68 |
| | S2 | -9.99 | -5.17 |
| | S3 | -13.49 | -12.69 |
| | S4 | -15.50 | -14.73 |
| | S5 | -17.69 | -16.08 |
| r2 | PD | -26.08 | -24.12 |
| | S2 | -21.37 | -20.53 |
| | S3 | -14.04 | -9.47 |
| | S4 | -18.19 | -18.13 |
| | S5 | -24.12 | -21.56 |
| r3 | PD | -2.56 | -2.26 |
| | S2 | -2.28 | -2.02 |
| | S3 | -0.97 | -0.81 |
| | S4 | -0.92 | -0.84 |
| | S5 | -2.27 | -2.02 |
| r4 | PD | -6.23 | -6.12 |
| | S2 | -5.46 | -5.35 |
| | S3 | -2.98 | -2.31 |
| | S4 | -2.76 | -1.37 |
| | S5 | -5.48 | -5.37 |

the new "OD" of that destination. The destination attraction preference attribute $\beta_{\text{mark}}$ is positive at the decision points r1 and r2, and negative at r3 and r4, which indicates that the closer the destination attraction preference attribute $\beta_{\text{mark}}$ is to the original decision.

The elasticity analysis of travel time of Original RRM model and VDRRM model is shown in Table 6.The addition of the regret index reduces the elasticity of the model in each case. Because in Original RRM model, it is assumed that the individual regrets due to the small attribute difference, but not in the VDRRM model. For example, in the Original RRM model, at the decision point r2, the probability of choosing alternative destination S3 would be reduced by 14.04% for every 1% increase in travel time, while it would only be reduced by 9.47% if the tolerance threshold is added. These results provide relevant insights into government or business recommended destinations and traffic management.

### C. PATH SELECTION OF ANT COLONY ALGORITHM

Wang and Niu [29] proposed a distributed path navigation system, using data acquisition and communication technology, the system adopts a hierarchical network design method, and puts forward an improved Dijkstra algorithm to find the optimal path (shortest time or path), path selection is determined according to the minimum time or the shortest distance in real time, and is based on the constant destination. In this paper, the path choice of variable destination is considered, and the influence of the regret value of multiple destinations on the path segment is considered. The path replanning assumes that the traveler changed the destination S2 at time t1, and trips is 22000 (passenger car unit, pcu), the decision point r3($x_{\min} = 60$).There are 12 links and 6 paths in Guilin's the road network according to Fig.6(a),




(b)

**FIGURE 6.** (a)- A road network with 12 links and 6 paths; (b)- The influence of change on path selection probability.

the values of $m, \rho, Q, \alpha, \beta$ in the formula Eqs.(14) $\sim$ (17) and the parameters are set $m = 10, \rho = 0.5, \alpha = 1, \beta = 1, Q = 1$. The calculation of links impedance adopts the function developed by the Bureau of Public Road.

Travelers changed the destination to S2 at time t1, and the regret value $R_{S2}$=0.14 is calculated on the basis of the parameter estimation. According to the improved ant colony algorithm, the regret impedance of 12 links and the initial pheromone concentration of each link are calculated, and the probability of selecting a link at time t1 is calculated as shown in Fig.6(a). Keeping $\alpha$ constant, the pheromone importance degree $\beta$ changes from 1 to 5, and the selection probability changes of the six routes are 1: link <1, 2, 5, 10>, 2: link <1, 4, 7, 10>, 3: link <1, 4, 9, 12>, 4: link <3,6,7,10>, 5: link <3,6,9,12>,and 6: link <3,8,11,12>, as shown Fig.6(b).

The analysis results show that regardless of the value of $\beta$, the optimal path is 4: link <3, 6, 7, 10>. When $\beta$ is gradually increased, the selection probability of the optimal path 4 is gradually increased. The improved algorithm can more quickly search the optimal path without a large $\beta$, and a more reasonable solution can be found in fewer iterations.

### D. RESULTS AND DISCUSSION

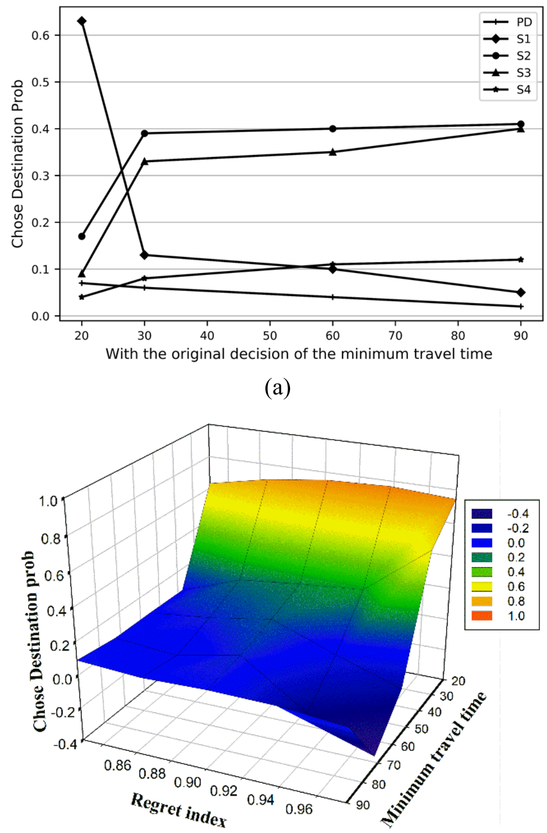
In order to judge whether travelers have regret perception of changing destinations during travel, the influence of regret perception (regret index value) generated at different decision points on destination selection is analyzed. Combined with the above research, the analysis results are shown in Fig.7, Fig.7(a) is the probability of selecting destinations at different decision points, and Fig.7(b) is the probability 3Dmesh diagram of different decision points and regret index.

As can be seen from Fig.7(a):

(1) Since the assumed travel time is fixed in the order of PD $> S4 > S1 > S3 > S2$, travelers choose minimum travel time in the same destination type. At the decision point r1($x_{\min} = 20$), the travelers feel regret, and they still insist on the type of the original destination. Therefore, the probability of selecting S1 is the largest, and the probability of selecting others is the smallest. Even if the travel time of S2 is minimal, it is not as attractive as the PD and S1. Since the degree of attraction of PD is greater than S4, the probability of presenting PD is greater than S4.

(2) As the far away from the original decision and the regret index $\delta_{PDnk}$ increases, the probability of destination selection for SD type and DD type increases and the probability of destination selection for PD type and the same type decreases. At decision point r2($x_{\min} = 30$), the traveler's psychology is regretting the original decision more and more. When there is little difference in the likes of destinations, travelers begin to feel impatient, and they are more inclined to change destinations with the minimum loss of time. Meanwhile, the probability of selecting S2 and S3 increases sharply, while the probability of selecting S1 decreases. Businesses of the same SD type can recommend SD class to attract tourists when travelers arrive at the original decision-making minimum travel time $25 \leq x_{\min} \leq 27.445$ under the ideal state. Similarly, businesses of DD type can recommend DD type when $27.445 \leq x_{\min} \leq 120$.

According to the Fig.7(b), the influence of minimum travel time and regret index on the selection probability can be determined by observing the inclination of the curved surface. The higher the slope, the steeper the slope, indicating the more significant the interaction of both. The higher the regret




(a)

(b)

**FIGURE 7. (a)- the minimum travel time of different original decisions (i.e. the selection probability of each destination at different decision points); (b)- shows the probability 3Dmesh diagram of different decision points and regret index.**

index, the more regretful the driver is about the choice of destination. With the sharp decrease of the change trend of the selection probability, its color also shows a trend of fading, which indicates that the regret index can measure the regret degree of travelers to change their decision.

In summary, When the minimum travel time is lesser, travelers prefer to choose PD or SD destinations. When the minimum travel time is about 30 minutes, travelers mainly consider choosing the destination with the minimum loss of time. The regret index can identify travelers' stage of perception of regret at different decision points, measure travelers' regret degree over changing decisions, determine the minimum regret threshold, and have a high correlation with destination selection behavior.

## V. CONCLUSION

In this paper, a path planning random regret model was constructed for variable destinations, this model includes actual time regret perception prediction, a random regret minimization model for variable destination-oriented path planning and an improved ant colony algorithm solution model. The contributions of this work are as follows.

First, extant regret theory lacks an explanation for the psychological activities of changing destinations [4]. It is proven by experiments that in a congested queue, travelers mainly have the idea to change destinations in the context of impulses to change destinations and psychological conflicts. Existing studies ignore the traveler's tolerance limit for certain factors [13], [24], [30], while the actual attribute value will affect the decision result. When the attribute difference between the alternative $i$ and the alternative $j$ is equivalent, the larger the attribute value, the less regretful the individual may feel.

We have determined the upper and lower limits of tolerance threshold and tolerance threshold for different crucial attributes, and classified the degree of regret of decision makers into three levels, i.e. "None regret stage I", "Perceived regret stage II" and "Extreme regret stage III". The regret index can identify the regret perception stage of travelers at different decision points, and it has a high correlation with destination selection behavior.

Second, the variable destination random regret minimization model VDRRM is developed, and the minimum attribute difference tolerance threshold and regret threshold are determined. Travel decisions are jointly influenced by preference parameter $\beta_k$ and regret index $\delta_{ink}$, the probability of selecting each alternative is calculated through the model, and the destination is recommended according to the probability. The results show that preference parameter $\beta_k$ becomes insensitive and disliked when OD scale is especially large (i.e., minimum travel time becomes large). The changed destination should not only consider the degree of psychological regret of the traveler's decision point, but also consider the scale of the new "OD" of that destination. Travelers in the second stage of perceived regret will prefer PD or SD type destinations closer to the original decision. When the minimum travel time is about 30 minutes, travelers will mainly reconsider choosing the destination with the minimum loss of time. In the case of traffic jam at the climax of self-driving tour on major holidays, the government can judge the degree of psychological regret for decision-making according to the traveler's current location r and the travel time of the original decision-making destination PD, and recommend the destination with the highest probability to the traveler, when the regret stage is II and III. Businesses can also recommend themselves to travelers to attract tourists. The destination reception capacity will be balanced after changing, recommendation also will be stopped, people's travel demand will be judged and distributed in advance, and overall and coordinated planning will be carried out, which will effectively improve travel efficiency.

Third, The path selection mentioned in many studies is determined in real time according to the minimum time or the shortest distance, and is based on the constant destination [18], [29]. The improved ant colony algorithm proposed in this paper considers the path choice of variable destinations and the influence of the regret value of multiple destinations on the path. In the actual situation, the shortest distance does not necessarily involve the smallest loss. Therefore, this paper changes the traditional ant colony algorithm to target the shortest path but takes the destination-path regret value as the decision criterion of the planning path. The pheromone update of the ant colony algorithm is improved by the regret impedance factor of links. The results show that the ants rely on the pheromone importance degree $\beta$ search path. The improved algorithm can search the optimal path faster without a large $\beta$, and a more reasonable solution can be found in fewer iterations.

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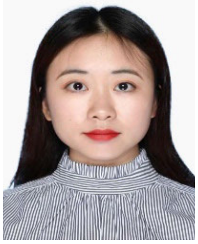

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