Research Article

Optimal Route Selection Decision-Making Based on Intelligent Network

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Modern intelligent network provides a lot of convenience for the development of the society, especially for some practical NP-hard optimal problems. In this paper, we study a game case which is a problem of optimal strategy of desert crossing based on intelligent network and then propose an optimal route selection decision-making. We construct some dynamic multiobjective network problems and use heuristic algorithm to solve the two problems in four levels in the paper. The innovation of this paper lies in the optimal route selection strategy which considers different environment conditions and their own situations. The cross research between the practical engineering problems and mathematics is applied flexibly in this article. Moreover, the strategy given in this paper is a general direction rather than a specific result, which is also in line with the characteristics of diversity of the game optimal results.

1. Introduction

Intelligent network is a good choice to solve some specific problems. The optimization algorithm based on intelligent network has good performance in solving the optimal route selection decision-making problems. In practical routing problems, we often abstract them as network optimization problems. Therefore, we need to find the optimal route from a source network node to the destination node. It has been widely applied to many fields, such as the Traveling Salesman Problem (TSP), distributed resource allocation optimization in 5G network [1], and traffic engineering for 5G network [2].

In the past decades, lots of researchers were devoted to apply intelligent network to solve some actual NP-hard optimal problems [3] and many interesting results were obtained [4–9]. The existing optimal route selection decision-making problems can be classified into three aspects based on intelligent network. The first class is based on genetic algorithm [4, 10, 11]. The second one is based on ant colony optimization algorithm [5, 6, 12]. And, the last aspect is based on neural network [7–9]. Many excellent results [13–17] have been achieved on the abovementioned intelligent algorithms and their improved algorithms and have made wide applications in the aspect of the optimal route selection [15–17] at the present stage. At the same time, it is one of the best solutions to transform the special practical problems into the general graph theory problems.

Furthermore, intelligent network algorithms refer to some relatively novel algorithms and theories in engineering practice. All of those algorithms and technologies make the applications fast and safe. However, it is necessary to learn the existing mature algorithms to make up for their weaknesses because the demands for actual 5G network development change rapidly.

The global mobile data traffic in intelligent network is expected increasing by exponential growth in the modern society. Intelligent network can easily ascribe as a modern optimal problem to be an NP-hard problem because the modern optimal problem is always a nonlinear multi-objective and multiconstraint optimization problem. There are some mature intelligent algorithms to solve it, such as genetic algorithm and ant colony optimization algorithm. However, the convergence of these algorithms is limited by
the network size. Therefore, this is an interesting and challenging problem.

In this paper, a case study is motivated by a game of desert crossing. In this case, we use the intelligent network data traffic to solve the desert crossing problem and explore the optimal route detection decision-making. And, we also give different strategies for different problems in different levels.

The main contributions of our research are summarized as follows:

(1) Compared with the existing works, we use intelligent network data traffic to play games for the first time. This is a cross-cutting combination of mathematical and engineering problems.

(2) Different optimal strategies are given for different problems in their corresponding levels. And, the rapid and optimal route selection decision-making is made in this paper. The remaining sections of this paper are arranged as follows. In Section 2, we present the related work and current state-of-the-art of this paper. In Section 3, problem description of the case study is introduced. In Section 4, the proposed problem is modeled and solved mathematically. Section 5 is the simulation validation and the analysis of the results. Finally, Section 6 concludes the paper and gives a discussion on the advantages and the disadvantages of improvement.

2. Related Work

According to intelligent network optimization problem, the existing optimization algorithms can be classified into probabilistic algorithms [4–6, 10–12] and logical algorithms [7–9, 18, 19] in the present stages. All of those algorithms have a great requirement for the improvement of algorithm efficiency.

Intelligent network is applied to various predictions. Liu et al. [20] have proposed a prediction of fuel consumption and emissions for diesel engine vehicles under intelligent network environments. Galeschuck [21] uses time-series prediction with neural networks to research into the exchange rate. Gnana Sheela and Deepa [22] have proposed a neural network algorithm based on the hybrid computing model to predict wind speed commendably. Nikolov et al. [23] have proposed a passive data rate estimation method which leverages commonly available parameters of commercial modems with application in intelligent transportation systems. Sun et al. [24] have proposed persistent traffic predictions through vehicle-to-infrastructure communications in cyber-physical road systems.

Network optimization based on intelligent network is also applied to many aspects. In particular, scholars have combined intelligent network with the objective optimization method to build the model. Fletcher et al. [25] have used multiobjective optimization to solve the nonspecialized ensemble classifier problem. Wang et al. [26] have proposed an efficient sorting multiobjective optimization framework for sustainable supply network optimization and decision-making. Tian et al. [27] have proposed traffic engineering in partially deployed segment routing over IPv6 network with deep reinforcement learning. Li et al. [28] have proposed a self-organizing reciprocal modular neural network.

In terms of route strategy selection, there are also a lot of research studies [29–40]. Among them, there are many studies on TSP [34–37]. Peng et al. [38] have proposed a selection for large-scale SVM training. Zhou et al. [39] have proposed a selection for offloading cellular traffic through mobile networks. H. Xia et al. [40] have proposed an efficient semantic-aware service discovery mechanism for large-scale Internet of Things.

In recent years, more and more researchers have used intelligent network algorithm to solve some practical problems. Meo [41] has proposed an approach to predict the intensity of trust and distrust relations in online social networks (OSNs). Kasim [42] has proposed an efficient and robust deep learning based on distributed denial of service attacks. Hareedy et al. [43] have minimized the number of detrimental objects in multidimensional graph-based codes.

At the same time, more and more researchers have created new algorithms to solve optimal decision problems. Lei et al. [44] have used the QUALIFLEX method, which is a relatively novel multiple attribute group decision-making (MAGDM) technique, to obtain the optimal alternative. Lei et al. [45] also have provided the probabilistic linguistic (PL-MAGDM) with incomplete weight information. Wei et al. [46] have developed the COPRA model to solve the MAGDM under single-valued neutrosophic 2-tuple linguistic sets (SVN2TLSs). Dong et al. [47] have provided a cosine similarity-based QUALIFLEX approach MCDM with HFLTSS. Wan and Dong [48] have provided a comprehensive and systematic introduction to the ranking methods for interval-valued intuitionistic fuzzy sets, multicriteria decision-making methods with interval-valued intuitionistic fuzzy sets, and group decision-making methods with interval-valued intuitionistic fuzzy preference relations.

3. Problem Description of a Case Study

In this section, we will give a case to study the optimal strategy of desert crossing based on intelligent network. And, the problem is formulated as a mathematical problem which combines the actual route selection decision-making and undirected-graphs with networks. The level means some constrains and the problem means the objective function. The details are described as follows.

3.1. Definition of Symbols. The used notations and the meanings of the symbols related to the formulated optimization problem are sketched in Tables 1 and 2.

3.2. A Case. In order to better describe the case problem, we introduce the following game of desert crossing. There is a player in a desert and he has the desert map. The player can use the given initial funds to buy a certain amount of water, food, and other daily supplies for his optimal desert crossing.
The funds or resources can be replenished in some mines and villages, and the weather will be different on his crossing way. Therefore, the optimal problem is the player reaches the destination within the specified time and with the remaining money, as much as possible.

We make the following assumptions for the game problem:

(i) The initial condition is the player at the starting point on Day 0. The player must reach the destination before the deadline date, and then, the desert crossing game is over.

(ii) Crossing the desert requires water and food, and both of them are measured with boxes. The total weight of water and food should not exceed the maximum weight per day. If water or food is exhausted before reaching the destination, the game fails.

(iii) The weather has three conditions in each day: “sunny,” “hot,” and “sandstorm.” The weather is the same in all areas of the desert.

(iv) The player can travel from one point to another adjacent place or keep staying at the present point. When the weather is “sandstorm,” the player must stay at the present point.

(v) When a player is staying at one point for one day, the amount of resources is called basic consumption, and the consumption is twice than the basic consumption when walking.

(vi) The player can buy water and food with the basic price at the starting point on Day 0 with their initial funds. The player can return the remaining water and food at half of the basic price per box when he arrives at the destination.

(vii) When the player stays in the mine, he can obtain some funds through mining, and the amount of funds obtained by mining in one day is called basic income. If the player chooses to mine, the amount of resource consumption is twice than the basic consumption; if not, the amount of consumed resources is the basic consumption. No mining is allowed on the day when player arrives at the mine. Mining is allowed on “sandstorm” days in the meanwhile.

(viii) When passing through or staying in the village, the player can buy water and food. However, the price is twice than the basic price per box.

### 3.2.1. Description of Levels

#### Level 1

1. Parameter setting: see Table 3.
2. Weather condition: see Table 4.
3. Map: see Figure 1.

#### Level 2

1. Parameter setting: it is the same as Level 1
2. Weather condition: it is the same as Level 1
3. Map: see Figure 2

#### Level 3

1. Parameter setting: see Table 5.
2. Weather condition: there will be no “sandstorm” for 10 days.
3. Map: see Figure 3.

#### Level 4

1. Parameter setting: it is almost the same as Level 3, but the differences are shown in Table 6.
2. Weather condition: there is less “sandstorm” in 30 days.
3. Map: see Figure 4.

### 3.2.2. Problems

Based on the above assumptions, the following two problems are considered to solve.

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**Table 1: Notations.**

| Symbols | Parameters                  |
|---------|-----------------------------|
| \( C \) | Final remaining funds       |
| \( D \) | Deadline                    |
| \( M_w \) | Maximum weight             |
| \( F \)  | Remaining of food           |
| \( W \)  | Remaining of water          |
| \( C_1 \) | Basic income               |
| \( C_2 \) | Cost of purchasing resources |
| \( C_3 \) | Mining revenue             |
| \( d \)  | Weight of water per box     |
| \( e \)  | Weight of water per box     |
| \( a \)  | Cost at the starting point on day 0 |
| \( b \)  | Cost when passing through or staying in the village |
| \( c \)  | Money of returning the remaining water and food |
| \( f \)  | Days of mining              |

**Table 2: Notations.**

| Symbols | Parameters                  |
|---------|-----------------------------|
| \( g \) | Basic income               |
| \( q_1 \) | Income from mining in sunny day |
| \( q_2 \) | Income from mining in hot day |
| \( p \)  | Probability of sunny weather |
| \( Q_i \) | Mathematical expectation of walking consumption |
| \( i \)  | The number of days         |
| \( t \)  | The number of game days    |
| \( j \)  | The location on the map    |
| \( m \)  | The number of points on the map |
| \( S_v \) | State                      |
| \( A \)  | A group of actions         |
| \( P_{sa} \) | Transition probability     |
| \( R \)  | Reward function            |
| \( V_f \) | Value function             |
| \( Q^\pi(s, a) \) | The value function of action |
| \( \omega \) | The feasible region        |
| \( \mu \) | The number of times that event A occurs |
| \( p' \) | The probability that event A occurs in each test |
Problem 1. There is one player and all weather conditions are known in advance during the whole game period. The problem is to give the best desert-crossing strategies in Level 1 and Level 2, respectively.

Table 3: Parameter setting.

| Description                           | Value   |
|---------------------------------------|---------|
| Maximum weight                        | 1200 kg |
| Initial funds                         | 10000 $ |
| Deadline (D)                          | 30 days |
| Basic income (C1)                     | 1000 $  |
| Basic consumption in "sunny" (water)  | 5 boxes |
| Basic consumption in "sunny" (food)   | 7 boxes |
| Basic consumption in "hot" (water)    | 8 boxes |
| Basic consumption in "hot" (food)     | 6 boxes |
| Basic consumption in "sandstorm" (water) | 10 boxes |
| Basic consumption in "sandstorm" (food) | 10 boxes |
| Basic price (water)                   | 5 $/box |
| Basic price (food)                    | 10 $/box|
| Resources weight (water)              | 3 kg    |
| Resources weight (food)               | 2 kg    |

Table 4: Weather condition.

| Date   | 1  | 2  | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  |
|--------|----|----|-----|-----|-----|-----|-----|-----|-----|-----|
| Weather| Hot| Hot| Sun  | Sand | Sun | Hot | Sand | Sun | Hot | Hot |
| Date   | 11 | 12 | 13  | 14  | 15  | 16  | 17  | 18  | 19  | 20  |
| Weather| Sand| Hot| Sun  | Hot  | Hot  | Hot  | Hot  | Hot  | Sand | Hot |
| Date   | 21 | 22 | 23  | 24  | 25  | 26  | 27  | 28  | 29  | 30  |
| Weather| Sun| Sun| Hot  | Sun  | Sand | Hot  | Sun  | Sun  | Hot  | Hot |

This is the abbreviation of “sunny.” bThis is the abbreviation of “sandstorm.”

Problem 2. There is one player and the player only knows the weather in current day, so he can decide the action of the current day. Similar to Problem 1, the problem is to give the best strategies in Level 3 and Level 4, respectively.

4. Problem Formulation and Mathematical Modeling

In order to better describe the established model, we turn the above desert-crossing problems into network optimization problems based on intelligent traffic network. Think of the
places in the maps as connecting communication nodes in the network, where special nodes are villages and mines. We abstract those places as interconnected network nodes and maps as undirected graphs.

Based on the above transformation, Figures 5–8 are the new undirected network graphs 1–4 of Maps 1–4, respectively. Figure 6 is the new undirected network graph of Map 2.

In the network, “S,” “M,” “V,” and “E” are the abbreviations of “start,” “mine,” “village,” and “end,” respectively. And, the weight of the network edge represents the number of network nodes between the two linked nodes.

### 4.1 State Space Analysis

The state variable $S_v$ contains four integer components. $i$ and $t$ are the numbers of days and game days, respectively:

1. $0 \leq i \leq t$. \hfill (1)
2. $i \leq j \leq m$. \hfill (2)

$W$ and $F$ are the numbers of boxes of water and food:

$$M_w = W \times d + F \times e \leq \text{weight limit}, \quad W \geq 0, \, F \geq 0,$$

where the maximum weight is $M_w$ and $d$ and $e$ represent the weights of water and of food per box, respectively.

Above all,

$$S_v = (i, j, W, F) \in N^4, i \leq t, j \leq m, W \times d + F \times e \leq \text{Weight Limit}. \hfill (3)$$

The size of the state variable $S_v$ is

$$|S_v| = t \times m \times \frac{d}{2} \times \frac{e}{\text{Weight Limit}} \hfill (4)$$

When $t$ is 30 and $m$ is 64, $|S_v|$ is 230,000,000. The space complexity is acceptable to a computer.

### 4.2 Problem 1

#### 4.2.1 Establishment of the Model

The flowchart of the player decision is shown in Figure 9.

This is a Markov decision process, consisting of four tuples $M = (S_v, A, P_{sa}, R)$, where $S_v$ represents states, $A$ represents a group of actions, $P_{sa}$ is a transition probability, and $R$ is a reward function. Then, the definition of value function $V_f$ is

$$V_f^*(s, A) = E_x \left[ \sum_0^\infty y^t R_t | S_0 = s \right]. \hfill (6)$$
Figure 5: Undirected network graph 1.

Figure 6: Undirected network graph 2.

Figure 7: Undirected network graph 3.

Figure 8: Undirected network graph 4.
In $V^f_j(s, A)$, the fixed value $\pi$ and $s$ are given. The action $A$ is

$$A = \pi(s),$$

(7)

which is given by $\pi$ and $s$.

At the next moment, $S$ will be transferred to $s'$ with probability $P(s'|s, A)$, and $V^f_j(s', A)$ is

$$V^f_j(s, A) = \sum_{s' \in S} P(s'|s, A)[R(s'|s, A) + \gamma V^f_j(s', A)].$$

(8)

Then, we define the value function of action $A$ is

$$Q^f(s, A) = \sum_{s' \in S} P(s'|s, A)[R(s'|s, A) + \gamma V^f_j(s', A)].$$

(9)

The optimal strategy is as follows:

$$\pi^* = \arg\max_{A} \{V^f_j(s, A)\}.$$  

(10)

The purpose is to find $\pi^*$ that can maximize the value function under any initial condition $s$.

Therefore, in order to gain more and more final remaining funds, we construct an objective optimization model to solve the aforementioned optimal problem based on the new intelligent network and then convert all objectives and constraints into network flowing problems. The optimization model represents the optimal scheme determined by linear programming, nonlinear programming, dynamic programming, integer programming, and system science methods. The general optimization model is described by the mathematical language as follows:

$$\max (\min) u = f(x), \ x = (x_1, x_2, \ldots, x_n), \ x \in \omega,$$

s.t. \ $h_i(x) = 0, \ i = 1, 2, \ldots, m,$

$$g_i(x) \geq 0 (g_i(x) \leq 0), \ i = 1, 2, \ldots, p,$$

(11)

where $f(x)$ is the objective function, $x$ is the decision variable, and $\omega$ is the feasible region.

For this problem, the establishment of the model is described as follows.

The optimization constraints are deadline, maximum weight, and living conditions. Assume that the final remaining funds in the network are $C$, the deadline is $D$, and the maximum weight is $M_w$. Therefore, the constraints of living conditions cannot be empty in order to make sure that the player will not fail in the desert crossing game. Assume that the remaining food is $F$ and the remaining water is $W$. Therefore, the optimization model is established and the constraints defining the solutions of our optimization problem are defined as follows. We start with the network constraints:

$$\max C = C_1 - C_2 + C_3,$$

s.t. $D \leq 30$,  

$$M_w = W \times d + F \times e \leq 1200,$$

$$W > 0,$$

$$F > 0,$$

(12)

where $C_1$ represents the basic income, $C_2$ represents the cost of purchasing resources, $C_3$ represents the mining income, $d$ represents the weight of water per box, and $e$ represents the weight of food per box.

The cost of purchasing resources is

$$C_2 = a + b - c,$$

(13)

where $a$ represents the player’s cost at the starting node on Day 0, $b$ represents the player’s cost when passing through or staying in the village, and $c$ represents money of returning the remaining water and food when he arrives at the destination node.

The mining income is

$$C_2 = f \times g,$$

(14)

where $f$ represents the mining days and $g$ represents the basic income.

4.2.2. Description of the Algorithm. In the previous section, we carried out the mathematical modeling for the corresponding network problem. The flowchart of solution is shown in Figure 10. Here, we can use heuristic algorithm to
solve the above dynamic programming problems. We find
the shortest route from the starting node to the destination
node and mark it as the first situation. In the first situation,
we do not consider any additional capital consumption.
Conversely, we consider some incomes on the player’s
crossing way such as mining and mark it as the second
situation. The player needs to buy as much food and water as
possible at the source node and gains as many incomes as
possible on his way within a limited crossing date range.

4.3. Problem 2

4.3.1. Establishment of the Model. For Problem 2, we con-
struct the same objective optimization model as Problem 1.
In order to keep more final remaining funds, we consider the
incomes from mining positive.

According to conditional expectation formula,

\[ E(Y|X = x) = \sum_{y \in Y} yP(Y = y|X = x) \]

\[ = \sum_{y \in Y} \frac{P(Y = y, X = x)}{P(X = x)}. \]  

The incomes from mining on a sunny day are \( q_1 \) and ones
on a hot day are \( q_2 \):

\[ q_1 = 200 - 9 \times 5 - 12 \times 10, \]

\[ q_2 = 200 - 27 \times 5 - 27 \times 10. \]  

Then, define \( p \) as the critical values of positive income
from mining:

\[ p \times q_1 + (1 - p) \times q_2 \geq 0, \]  

where \( p \geq 0.77 \).

In Level 3, the mathematical expectation of walking consump-
tion \( Q_1 \) is

\[ E(Q_1) = (6 \times 5 + 8 \times 10) \times p + (18 \times 5 + 18 \times 10) \]

\[ \times (1 - p) = 270 - 160p. \]  

And, the final remaining funds with the minimum re-
source consumption given from the starting network node is

\[ C = C_1 - 2Q_1 - 0.5 \times (405 - 2Q_1). \]  

In Level 4, assume the probability of sandstorm is 0.1.
The mathematical expectation of walking consumption \( Q_1 \) is

\[ E(Q_1) = 110p + (0.9 - p) \times 270 + 0.1 \times (20 \times 5 + 20 \times 10). \]  

It is the same as Level 3, and the final remaining funds
with the minimum resource consumption given from the
starting node is

\[ C = C_1 - 8Q_1. \]  

4.3.2. Description of the Algorithm. Based on Bernoulli’s law
of large numbers, if \( \mu \) is the number of times that event \( A \)
occurs in \( n \) independent tests and the probability that event
\( A \) occurs in each test is \( p' \), then, for any positive number of \( \varepsilon \),
there is

\[ \lim_{n \to \infty} P\left(\left|\frac{\mu}{n} - p'\right| < \varepsilon\right) = 1. \]  

Randomly, given the probability of sunny days, 5000
simulations are carried out according to Figure 11. And, the
final average value of incomes is taken as the approximate
value.

5. Validation

To validate our study, we employ realistic assumptions and
carry out simulation experiment in four levels.

5.1. Level 1

5.1.1. Results. According to Figure 7, Table 7 is one way (first
situation) of taking the shortest route from the start node to
the end node by using the heuristic algorithm.

According to the above algorithm, Table 8 is another way
(second situation).

Therefore, Figure 12 and Table 8 show the best strategy in
Level 1.

5.1.2. Analysis of the Results. For the second situation, there
are insufficient resources, and the player needs to go to node
\( V \) to buy water or food. Therefore, we consider that, in this
situation, the player does not go to node \( V \) to buy water or
food. Figure 13 records the result of the second situation as
\( A \). In the second situation, we also find that the player has
purchased resources twice in the villages and the purchasing
behavior will reduce the amount of total money inevitably.
Therefore, we assume that the player will find the shortest
route to the destination when this behavior occurs. And, we
use \( B \) and \( C \) to represent the player’s first and second village
purchasing behaviors, respectively.

In Figures 14 and 15, if player chooses \( B \) or \( C \), the game
will be over in 15 days or 19 days, which means the player
fails in the game.

To summarize, we think strategy \( A \) is the optimal
crossing route selection decision-making.

5.2. Level 2

5.2.1. Results. According to the above multiobjective pro-
gram algorithm, Table 9 shows the best desert-crossing
strategy based on intelligent network in Level 2.

5.2.2. Analysis of the Results. For the above results, two other
kinds of suboptimal solutions about the model have been
discussed. In Figures 16 and 17, record the results of Level 2
as \( A \), \( B \), and \( C \), respectively, which have the same definition
as Level 1.

According to Figure 18, \( A \) is the best strategy in Level 2.
5.3 Level 3

5.3.1 Results. In Level 3, we divide the situations into two types. One is no mining and another is mining. Figure 19 is a comparison of them.

As shown in Figure 19, the best strategy in Level 3 is no mining.

5.3.2 Analysis of the Results. Through the simulation experiment, we find that the situation of no mining is better than the other, regardless of the weather. So, the best strategy in Level 3 is no mining on the player’s crossing route.

5.3.3 Algorithm Comparison and Results’ Analysis. In this section, we compare our proposed algorithm with the one in [49] under the same data set.

Table 10 gives the results’ comparison of two algorithms in Level 3, respectively. We can see from Table 10 that there are 9685.9 $ in our proposed algorithm and 9400 $ in [49]. This is because our proposed algorithm not only considers
the use of Markov chain but also tries to bring conditional expectation, mathematical expectation of walking consumption $Q_1$, and Bernoulli’s law of large number to Level 3. However, the algorithm in [49] simply considers the use of Markov chains in Level 3. Therefore, the reliability of the random weather is increased and the result is better.

| Date | Node | Weather | Remaining water | Remaining food | Remaining funds |
|------|------|---------|-----------------|---------------|----------------|
| 0    | 1    | None    | 42 boxes        | 38 boxes      | 9410 $         |
| 1    | 25   | Hot     | 26 boxes        | 26 boxes      | 9410 $         |
| 2    | 26   | Hot     | 10 boxes        | 14 boxes      | 9410 $         |
| 3    | 27   | Sunny   | 0 boxes         | 0 boxes       | 9410 $         |

| Date | Node | Weather | Remaining water | Remaining food | Remaining funds |
|------|------|---------|-----------------|---------------|----------------|
| 1    | 25   | Hot     | 26 boxes        | 26 boxes      | 9410 $         |
| 2    | 26   | Hot     | 10 boxes        | 14 boxes      | 9410 $         |
| 3    | 27   | Sunny   | 0 boxes         | 0 boxes       | 9410 $         |

| Date | Node | Weather | Remaining water | Remaining food | Remaining funds |
|------|------|---------|-----------------|---------------|----------------|
| 1    | 25   | Hot     | 26 boxes        | 26 boxes      | 9410 $         |
| 2    | 26   | Hot     | 10 boxes        | 14 boxes      | 9410 $         |
| 3    | 27   | Sunny   | 0 boxes         | 0 boxes       | 9410 $         |

Table 7: The best strategy and the remaining resources of the first situation in Level 1.

Table 8: The best strategy of the second situation in Level 1.

Table 9: The best strategy under Level 2.

Figure 12: Comparison of final remaining funds in two situations in Level 1.

Figure 13: Comparison of remaining funds.

Figure 14: Comparison of remaining water.

Figure 15: Comparison of remaining food.
5.4. Level 4

5.4.1. Results. In Level 4, we divide the situations into four types. The first one is no mining behavior (first situation). The second one is only mining behavior (second situation). The third one is mining behavior after purchasing behavior (third situation). And, the last one is purchasing behavior after mining behavior (fourth situation). Figure 20 shows the result comparison of four situations.

As shown in Figure 20, the best strategy in Level 4 is listed in Table 11.

5.4.2. Analysis of the Results. The curves in Figure 20 are analyzed as follows.

For the first situation, no mining behavior means just traveling in the constructed network. There are only a few
days in travel crossing and not sensitive to weather conditions. Therefore, the influence of $p$ on the value of final remaining funds is small and the curve is relatively stable and basically has no fluctuation.

For the second situation, the mining incomes are high when the weather is bad, and the mining times and average incomes will increase when the weather getting better. The growth trend of the curve is close to the conic, as shown in Figure 20.

For the third situation, the player takes more days to buy food and water compared with the second situation. The resource consumption is much greater than its mining incomes and it is far less cost effective. However, when the weather becomes better, crossing time is important due to lack of the obvious resource constraints. This will lead the cost effect to spend extra time on the way. And, we can see the curve is lower than other strategies in Figure 20.

For the fourth situation, the player takes more days to buy food and water after mining compared with the second and third situations. The resource consumption is much greater than its mining incomes when the weather is bad and it is far less cost effective. The incomes increase rapidly when the weather gets better, and the player has the highest final remaining funds when the weather is suitable for his crossing.

Therefore, the curve is like “S.” Therefore, we can see from the simulation results that the first situation is not the optimal desert-crossing strategy for any $p$. When $p$ is uncertain, there are many values of $p$ corresponding to second situation as the optimal strategy.

5.4.3. Algorithm Comparison and Results’ Analysis. In this section, we compare our proposed algorithm with the one in [49] under the same data set.

Table 12 gives results of two algorithms in Level 4, respectively. We can see from Table 12 that there are more than 13193 $ when the probability of sunny weather $p > 0.05$ in our proposed algorithm and 13070 $ in [49]. The reasons for the algorithm improvement are described in Section 5.3; moreover, our proposed algorithm considers $p$ is uncertain, and there are many values of $p$ corresponding to second situation as the optimal strategy. This shows that we not only are comprehensive but also have good results.

6. Conclusion and Future Work

In this paper, we solve the optimal desert-crossing strategy for one player. We give some reasonable assumptions and practical situations and turn the problem into an intelligent network problem. The strategies obtained in the paper have strong adaptability under specified conditions. Then, we construct dynamic multiobjective network problem and use heuristic algorithm for solving the two problems in four levels. The established model has high portability and is suitable for some network NP-hard problems. Moreover, the optimal route selection decision-making based on intelligent network given in this paper is a general direction rather than a specific result. That is to say, intelligent network was high performance in finding and making optimal strategies.

Future works and research directions will be devoted to apply the above studies to other NP-hard problems by using dynamic programming, genetic algorithm, and particle swarm optimization according to the Markov chain. And, more solutions can be obtained by increasing the random times, thus making the range of solutions more applicable.

Data Availability

The data used to support the findings of the study are available within the article.

Conflicts of Interest

The authors declared that they have no conflicts of interest to this work.

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