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A method for determining parameter weight early warning model based on reinforcement learning ☆

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ABSTRACT

To solve the problem of low efficiency of early warning in public security emergencies, this paper proposes a method for determining parameter weight in public events early warning model which was based on reinforcement learning. Firstly, using the calibrated conflict early warning label, using reinforcement learning algorithm to build the public early warning event model; secondly, through iterative training to obtain the arrival path of the agent to the abnormal sequence, that is, the public early warning event; finally, by analyzing the weight parameters in the neural network, to determine the early warning event. Simulation showed that under this algorithm, convergence happened when the number of steps was in the range from 500 to 800, 37.5% smaller than that when using the original data. This result of the experiment demonstrated that this method greatly improved the efficiency of early warning for public incidents.

1. Introduction

In recent years, mass emergencies in taxi industry become increasingly severe such as taxi drivers' strikes, appealing to higher authorities for help, and conflicts. Meanwhile, the emerging of "internet plus" models has brought about new forms of conflicts. Incomplete statistics show that large-scale unconventional emergencies resulted from taxi drivers' boycotts of taxi e-hailing platforms have erupted in China's sixteen cities since May 2015. In the area of China's urban public transport, the conflict between traditional way of taxi roadside hailing and the internet-based taxi e-hailing has been increasingly sharp. Emergencies in taxi industry thus have become a difficult problem and headache for management departments of local governments. Jinan City Public Transport Management and Service Center was the first one to have been sued by a taxi e-hailing platform operator in China's taxi industry. The urgency of such emergencies is that it may trigger larger-scale conflict nationwide. Reality shows that complete traditional way of experience-based management, simple punishments like fines and confiscation of property, and post-event responses now cannot cope with relevant mass emergencies in an effective and timely manner. Therefore, it is undoubtedly highly valuable both theoretically and practically to construct an early warning model to prevent such conflicts with information about conflict triggering by finding the correlation between key factors and emergencies and digging up possible potential emergencies from considerable time series generated by traveling cars.

Threats to Public security are not presented instantly but evolve with time. If signals of faults could be captured before the occurrence of events, the early warning system for threats can detect anomaly as soon as possible and take early warning measures after comparing abnormal data with normal ones [1]. Hence, how to make use of considerable historical data to obtain parameter weight in public events and to predict the occurrence probability of public events is the technical issue of this paper.

Analyzing major factors of emergencies can not only help clarify the birth of conflicts, but also and more importantly throw light upon effective early warning for conflicts. In-depth studies on internal factors of mass emergencies assist in constructing an initial index system for such emergencies. As simple linear relationship between data is transformed into complex nonlinear one, the causal relationship prevalent in small data times to instruct decision making has evolved to correlation analysis for prediction. Exploration of causes has thus changed to correlation searching [1].

The advantages of the proposed method in this paper for determining parameters of the early warning model are as follows:

First, public events were denoted by time series, which were then dimensionally reduced. After the dimension reduction, the time series met the principle of no false negative [2], which meant that the treated

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data still satisfied the lower bound lemma:

$$D_F(q,s) \le D(q,s) \tag{1}$$

The Euclidean distance between time series after the treatment of dimension reduction should not be longer than their original distance. In the above lemma, q denoted query sequence; s, random series in the time series cluster; D_F, the distance between two spatial time series after dimension reduction; and D, the real distance between the two time series.

Second, reinforcement learning was integrated into the public events early warning, and training and learning were conducted to improve the accuracy of weight parameters.

Third, experiments in this paper were realized by devised hardware, which increased the speed of agent exploring and searching.

This paper began with an introduction of related research. The second section gave priority to the method for determining parameter weight. It was then followed by the presentation of experiment results and concluded with a summary of the study and a vision for future research.

2. Relevant research

Early warning index systems and emergency early warning mechanisms have been a research topic for many scholars all over the world. The following presented some selected and relevant viewpoints and research results.

Research on early warning index systems for public crises and early warning models have long started in western countries, and western economists, sociologists, and scholars in politics have already contrived a series of social risk index systems [3]. For example, American professor F. T. Haner proposed national risk assessment index, also known as "Forland Index", which comprehensively reflected political, economic, and social risks. At the same time, numerous indexes of national stability were put forward one after another, such as political system stability index and social instability index.

From the beginning of 1990s, Chinese scholars turned their attention to early warning index systems and early warning mechanisms and performed a series of research. Sociologist Zhu Qingfang [4], for example, proposed a "comprehensive assessment index system for social development" consisting of over forty sub-indexes in such four aspects as economy, living standards, social issues, and popular will. Song Linfei [5] constructed "China's social risk early warning index system", which had 49 sub-indexes in five risk areas including economy, politics, society, natural environment and international environment. Yan Yaojun [6] conducted an exploratory empirical study and framed "social early warning index system". Li Jiajing [7] presented a taxi early warning system. Hu Sitao [8] took into account taxi supply and demand, cost, environment, and policies in Bengbu city, eastern China's Anhui province, and then established a risk assessment index system for mass emergencies in taxi industry. Existing studies on mass emergencies in taxi industry leaned toward post-event analyses focusing on emergencies' causes, characteristics, and remedies, but few offered quantitative risk assessment for mass emergencies in this industry [8].

As time goes by, taxis produce a large quantity of data in traveling such as their positions in different time, the state of carrying passengers or not, and pausing time. These numerous multi-dimensional time series may contain early warning signals before the happening of emergencies. Therefore, digging up these data in advance of the occurrence of emergencies would undoubtedly play the role of early warning.

Sound denotation methods for time series can improve the efficiency of anomaly detection. Traditional methods include discrete Fourier transform (DFT), discrete wavelet transformation (DWT), dynamic time warping (DTW), and the modified DTW by Movchan [9]. Knorr and RN [10] were the first to put forward distance-based method. However, just as Breunig et al. [11] pointed out, the distance-based method encountered difficulties in treating data of obviously different internal densities. This method either classified the area of low density as anomaly, or failed to detect certain anomalies. Keogh [12] came up with a new method, namely HOT SAX, for anomaly detection. H. J. Kang [13] proposed a GPS-based method for anomaly detection. Dazhi Jiang [14] proposed time series prediction method is the commonly used one for building models for early warning. The best parameters for classification model were explored for the effective prediction. Luca Piciullo [15] proposed the optimal percentile combination to be employed in the regional early warning system, i.e. the one providing the best model performance in terms of success and error indicators, is selected employing the "event, duration matrix, performance" (EDuMaP) method. Hong-Gui Han [16] proposed a data-driven forecasting model was proposed as an important part of this system based on the theory of partial least squares (PLS) and time series multi-step prediction method. Haoyu Wen [17] created time series with time intervals over three orders of magnitude from the raw data, and tested them for early warning signals. Early warning signals can be reliably found only if the time interval of the data is shorter than the time scale of critical transitions in our complex system of interest. The author compared the set of time windows with statistically significant early warning signals with the set of time windows followed by large movements, to conclude that the early warning signals indeed provide reliable information on impending critical transitions. Waheeb et al. [18] presents an interactive visual analytics system and approach. This paper points out that deep learning and two-dimensional dimension reduction technology are used for rapid dimension reduction. Aliet al. [19] Proposed a time series forecasting application based neural network models in multivariate time series. This paper points out that the combination of autoregression and moving average (i.e. error feedback) input model has better prediction performance.

3. Method for determining parameter weight of early warning model

In this section, the emphasis was placed on the method for determining parameter weight. At the beginning, a brief introduction to fractal theory and denotation of time series' position information was given.

3.1. Fractal theory and denotation of multi-dimensional time series' position information

Studying the fractal characteristics of time series can provide analyses and predictions about the features and patterns of time series from a new perspective. The rescaled ranged analysis, also known as R/S analysis, in fractal theory is a statistical method for long-term recording of natural phenomena. It can be used to predict time series with fractal characteristics, find out changing patterns, and predict their developing trends.

Suppose the time range is T and ξt is the observation of natural phenomena at the discrete integer time t, then they can be denoted as followings:

$$\xi_T = \frac{1}{T}\sum_{t=1}^{T}\xi(t) \tag{2}$$

And from the above formula, we can obtain cumulative deviation:

$$X(t,T) = \sum_{u=1}^{t}[\xi(u) - \xi_T] \tag{3}$$

Range:

$$R(T) = \max_{1\le t\le T} X(t,T) - \min_{1\le t\le T} X(t,T) \tag{4}$$

Standard deviation (SD):

$$S(T) = \frac{1}{T}\sum_{t=1}^{T}[\xi(t) - \xi_T]^2{}^{\frac{1}{2}} \tag{5}$$

The experiment-based relational expression:

$$R/S = R(T)/S(T) = (cT)^H \tag{6}$$

Usually, in the rescaled range or R/S, H denotes the Hurst exponent and C denotes constant.

The research object of time series analyses is a series of data which vary with time and are correlated with each other. The major method for time series analyses is to give an approximate description of time series with a proper data model on the basis of data characteristics. R/S analysis is a new method for data treatment and statistical analysis for time series. From Formula (6), we can reach:

$$H = \ln(R/S)/\ln(cT) \tag{7}$$

Therefore, when using R/S analysis to analyze the developing trend of time series, we should start from Formula (7) and the calculated values of $(T, R(T)/S(T))$, when $t = 2, 3, \dots$ to fit Formula (7) using least squares in the double-logarithmic coordinate system $(\ln t, \ln R(T)/S(T))$. Then we obtained the Hurst exponent (H). The relationship between H and the dimension (D) of time series was as follows:

$$D = 2 - H \tag{8}$$

H can be derived from the R/S analysis proposed by Hurst. Then D can be calculated utilizing Formula (8).

In this paper, the collected historical data included those of buses, taxis, and non-motorized vehicles at intersections. To be more specific, the historical data of buses included their longitude and latitude, number of buses, number of stops, arrival and departure time, number of lanes, state of having bus lanes or not, distance between stops, and number of intersections; those of taxis consisted of the longitude and latitude shown by taxis' GPSs in real time, speed, calculated traffic volume in a circle, average speed, and occupying rate; and those of non-motorized vehicles at intersections comprised traffic volume in certain time period, waiting time, and others. They can be denoted in the following equations.

$$S = \{\{\langle B_1, t_1\rangle, \langle T_1, t_1\rangle, \langle N_1, t_1\rangle\}, \dots, \{\langle B_n, t_n\rangle, \langle T_n, t_n\rangle, \langle N_n, t_n\rangle\}\}$$

where, t denoted time; B, the time series of buses; T, the time series of taxis; and N, the time series of non-motorized vehicles.

$$B = \{\{\langle B_{11}, t_1\rangle, \langle B_{21}, t_1\rangle, \langle B_{31}, t_1\rangle, \langle B_{41}, t_1\rangle, \langle B_{51}, t_1\rangle, \langle B_{61}, t_1\rangle, \dots\}, \dots, \\ \{\langle B_{1n}, t_n\rangle, \langle B_{2n}, t_n\rangle, \langle B_{3n}, t_n\rangle, \langle B_{4n}, t_n\rangle, \langle B_{5n}, t_n\rangle, \langle B_{6n}, t_n\rangle, \dots\}\}$$

where, t denoted time, and B_1, B_2, B_3, B_4, B_5, and B_6 denoted respectively buses' longitude and latitude, number of buses, number of stops, arrival and departure time, number of lanes, state of having bus lanes or not, and distance between stops.

$$T = \{\{\langle T_{11}, t_1\rangle, \langle T_{21}, t_1\rangle, \langle T_{31}, t_1\rangle, \langle T_{41}, t_1\rangle, \langle T_{51}, t_1\rangle\}, \dots, \\ \{\langle T_{1n}, t_n\rangle, \langle T_{2n}, t_n\rangle, \langle T_{3n}, t_n\rangle, \langle T_{4n}, t_n\rangle, \langle T_{5n}, t_n\rangle\}\}$$

where, t denoted time, and T_1, T_2, T_3, T_4, and T_5 denoted the longitude and latitude shown by taxis' GPSs in real time, speed, calculated traffic volume in a circle, average speed, and occupying rate respectively.

$$V = \{\{\langle V_{11}, t_1\rangle, \langle V_{21}, t_1\rangle\}, \dots, \{\langle V_{1n}, t_n\rangle, \langle V_{2n}, t_n\rangle\}\}$$

where, t denoted time, and V_1 and V_2 denoted respectively traffic volume in certain time period and waiting time of non-motorized vehicles at intersections.

3.2. Dimension reduction of time series

First of all, normalization of time series' position information was performed by utilizing fractal denotation of the position-based multidimensional time series of the traveling cars. That is to say, the initially gathered time series data were normalized in the dimensions of buses, taxis, and non-motorized vehicles at intersections respectively. After such treatment, the effect of index dimensions was eradicated and the dimension of time series data was equivalent. Thus, indexes of data were comparable. Normalization of original time series data made all indexes in the same numeric level, which was fit for comprehensive comparison and assessment. Features of originally different dimensions of the time series thus could be compared in value. Here, zero-score standardization was adopted to treat the data. Together with the mean and SD of the original data, this method normalized the data. The treated data observed standard normal distribution with their mean being zero and SD one. The conversion function was (X – Mean) / (SD). Of which, mean was that of all sample data and SD was that of the same.

The 3-dimensional data after normalization were converted to 3-tuple data of time period, 2-dimensional road map, and traffic change sequence. The time series of buses, taxis, and non-motorized vehicles were further denoted respectively as follows:

$$B = \{\langle t_1, M_{b1}, F_{b1}\rangle, \dots, \langle t_n, M_{bn}, F_{bn}\rangle\}$$

where, t_i represented a self-defined fixed time period; M_{bi}, road map information of a certain bus top at t_i time period; and F_{bi}, the traffic change past M_{bi} at t_i time period.

$$T = \{\langle t_1, M_{t1}, F_{t1}\rangle, \dots, \langle t_n, M_{tn}, F_{tn}\rangle\}$$

where, t_i represented a self-defined fixed time period; M_{ti}, road map information of a specified route at t_i time period; and F_{ti}, the traffic change past M_{ti} at t_i time period.

$$V = \{\langle t_1, M_{v1}, F_{v1}\rangle, \dots, \langle t_1, M_{vn}, F_{vn}\rangle\}$$

where, t_i represented a self-defined fixed time period; M_{vi}, road map information of a specified intersection at t_i time period; and F_{vi}, the traffic change past M_{vi} at t_i time period.

The 3-tuple data in the three dimensions were integrated. The 3-tuple data of buses were integrated into the 3-tuple data of taxis according to time periods and 2-dimensional road map, and the 3-tuple data of non-motorized vehicles at intersections were combined into the former integrated data of buses and taxis according to 2-dimensional road map. Next, the finally combined 3-tuple data were normalized to construct a 4-dimensional historical data map. Then the time and place of historical conflict early warning were marked in the 3-tuple 4-dimensional historical data map. The dimensions of the mentioned 4-dimensional historical data map were 2-dimensional road map, one-dimensional traffic change sequence, and one-dimensional time series. The time series were finally expressed as follows:

$$S = \{\langle t_1, M_1, F_{btv1}\rangle, \dots, \langle t_n, M_n, F_{btvn}\rangle\}$$

where, t_i represented a self-defined fixed time period; M_i, road map information of a specified place at t_i time period; and F_{btvi}, the traffic change past M_i at t_i time period.

In this paper, fractal method was integrated into the expression of multi-dimensional time series. The fractal expression of time series S was shown as the following equation:

$$S_F = \{\langle M_1, D_{s1}, T_1\rangle, \dots, \langle M_i, D_{si}, T_i\rangle\}$$

where, M_i still stood for the road map information of a specified place at t_i time period; D_{si}, the fractal dimension of traffic change at i time period, or $Ds_i = 2 - \ln(R(n_i)/S(n_i))/\ln(cn_i)$; and n_i, the number of observed points at i sub-segment ($n_i = sr_i - sr_{i-1}$).

Meanwhile, it can be proved that the introduction of fractal denotation made the distance measure formula smaller that the Euclidean one. Given this, we not only retained the fractal features of time series S, but also achieved dimension simplification.

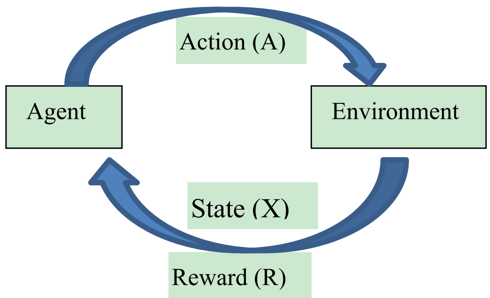

Fig. 1. Construction of the early warning model.

3.3. Defining reinforcement learning-based early warning model

Marked conflict early warning labels and deep Q-learning algorithm in reinforcement learning were utilized to build the model and create agents which were actors in decision making. The 4-dimensional historical data map was the environment. State stood for certain state of the 4-dimensional historical data map. Observation was the agent's observing of such data map. Action was agent's response to the environment, namely its moving direction according to the decision. The model was shown in Fig. 1.

The algorithm was shown in the following:

$$Q(s, a) = r + \gamma(\max(Q(s', a')))$$

where, s represented the current state; a, the action taken at current state; s', the new round of state generated by the current action; a', the next action; and r, the reward brought by the current action.

```
    γ, gamma factor, represented the degree of sacrificing
current profit for long-term one.
  def choose_action(self, observation):
    self.check_state_exist(observation)
    # action selection
    if np.random.uniform() < self.epsilon:
      # choose best action
      state_action = self.q_table.loc[observation, :]
      # some actions may have the same value,
randomly choose on in these actions
      action =
np.random.choice(state_action[state_action ==
np.max(state_action)].index)
    else:
      # choose random action
      action = np.random.choice(self.actions)
    return action
```

The above mentioned deep Q-learning algorithm was to define an agent to search for early warning for public events from the 4-dimensional historical data through the reward and punishment mechanism. When the agent found the marked conflict early warning labels in the time series, corresponding reward was bestowed to the agent. Memory model was used to memorize the path of the agent, which was the uncertain conditions of the occurrence of abnormal series (early warning for public events).

The memory model was as follows:

```
  def check_state_exist(self, state):
    if state not in self.q_table.index:
      # append new state to q table
      self.q_table = self.q_table.append(
        pd.Series(
          [0]*Len(self.actions),
          index=self.q_table.columns,
          name=state,
  )
        )
```

3.4. Determining parameter weight

The moving path of the agent in the 4-dimensional historical data map was the agent's self-explored path according to the reward and punishment mechanism. It thus was characterized by certain randomness and trials, and continuous iteration training was required for the agent to find out a "self-perceived" most correct path. At the end of iteration training, the agent would arrive at a specific path to abnormal series (early warning for public events). Agents which were generated from the iteration training were compared in the aspect of multithreading. The assessment indexes were accuracy rate, searching time, and searching path. The agent whose three assessment indexes were best was chosen. We then utilized the 4-dimensional historical data, namely the combined 3-tuple data of buses, taxis, and non-motorized vehicles at intersections. Finally, we obtained the parameter of the weight by analyzing the weight parameter of neural networks.

The best agents of different threads from the iteration training were gathered together to construct an agent model. The past paths of the agents were defined as agent path model stored in the memory of the agents. As to the generated data every day in real time, they were treated in real time according to the above mentioned collection and treatment of time series. These treated data were referred to as 4-dimensional historical data. When the path model was the same as the 4-dimensional historical data, the agent was applied to move along that same path. If the path was finished and the conditions of the path model were totally satisfied, it then was labeled as abnormal series (early warning for public events).

4. Experiment results

In this experiment, the data were chosen from the public transport of Jinan city, Shandong province, China. To be more specific, the experiment time series data were the traffic series of buses, taxis, and non-motorized vehicles at the intersection of Lishan road and Jiefang road from August 1, 2016 to December 30, 2016. A terminal including processors and computer-readable storage media was devised specially for this experiment. The processor performed instructions and the computer-readable storage media stored instructions which could be uploaded to the processor and apply the method for determining the parameter weight in the public events early warning model based on reinforcement learning.

At first, the time series were normalized and reduced dimensionally according to the normalization and dimension reduction in Section 2. Considering space limitations, details of treatment were skipped here. Next, presupposition of environment was made on the basis of the treated time series. Reinforcement learning was conducted to search for public events of early warning from the 4-dimensional time series according to the reward and punishment mechanism. The agent was rewarded when it found the marked early warning labels. The memory model then memorized the agent's path, which was the abnormal series, namely the uncertain conditions of the occurrence of public events of early warning. Agents which were generated from the iteration training were compared in the aspect of multithreading and the assessment index was the number of convergence steps.

$$C = \frac{(y - a)^2}{2} \tag{9}$$

Where, C is the Cost function, y is the expected output and a is the actual output.

Fig. 2 was the exploration model of agents in the 4-dimensional historical data map. The experiment results were shown in Figs. 3 and 4. Fig. 3 was about the convergence steps the agent took to search for paths in the early warning model based on fractal theory and reinforcement learning. It showed that after training convergence took place when the number of steps was from 500 to 800, which meant the agent reached the destination. After that, it was found that with the increase of training, over fitting happened as demonstrated by the enlarging

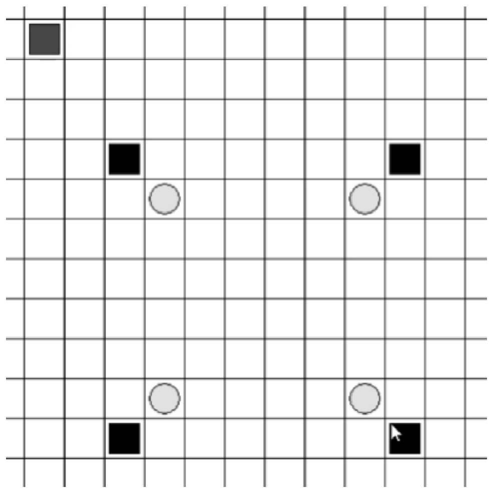

Fig. 2. Exploration model of the agent in the 4-dimensional historical data map.

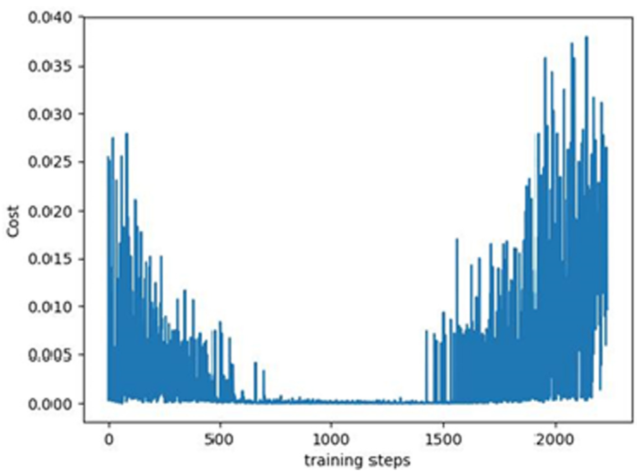

Fig. 3. Convergence steps when adopting the proposed method.

range. In Fig. 3, the x-axis was the number of steps in iteration training and the y-axis was the cost function. Fig. 4 was the convergence steps the agent took to search for paths in the early warning model when fractal theory and reinforcement learning were not applied. It was found that convergence took place when the number of steps was in the range from 800 to 1000. This experiment demonstrated that the application of fractal theory and reinforcement learning were effective in determining the parameter weight in the public events early warning model.

5. Conclusion

People are no longer deceived by false appearances or restricted by the logic of "why". Instead, attention is turned to pure relation and correlation [1]. Data-oriented urban public security early warning systems can monitor, judge, early warn, and control factors of public security events and their evolution. It can also integrate, complete, and share information of public security, and regulate the collection, storage, treatment, spread, usage, and feedback of early warning information. In this way, it can construct a defensive system of early warning for dangers [1]. Theoretically, further research is encouraged in the aspects of early warning mechanisms for public crises and series similarity and anomaly detection in digging time series. At the same time, from the perspective of research and application, deep reinforcement learning will continue to be a hot topic in the field of artificial intelligence

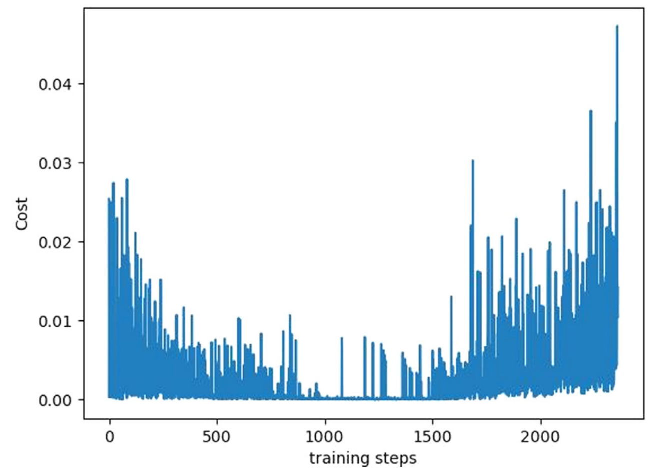

Fig. 4. Convergence steps of the original time series.

because it has great advantages in dealing with complex, multi-faceted and continuous decision-making problems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Meiyu Sun: Conceptualization, Methodology, Software, Validation.

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