Emergency Task Allocation Mechanism Based on Reputation and Region

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Abstract: In the communication network operation and maintenance management system structure, on-site operation and maintenance is at bottom position, and its quality and efficiency play a vital role in the smooth operation of the communication network. For emergencies in on-site scenes, we proposed an emergency task allocation method. We predict the completion by evaluating staff's historical working expressiveness and activeness. Then, we combine the staff's comprehensive reputation and movement pattern to design task allocation and personnel scheduling methods. Experiments proves our mechanism can reasonably allocate unexpected tasks based on accurately evaluating the ability of staff, and improve both allocation successful rate and completion quality. Our emergency task allocation mechanism can effectively improve the quality and efficiency of on-site operation and maintenance, and enhance the anti-damage ability of the communication network.

1 INTRODUCTION

In order to ensure the safe and stable of the communication network, the technical means and measures of on-site operation and maintenance management is extremely necessary (Liu S et al., 2020). The responsibility of operation and maintenance staffs is inspecting and repairing network equipment and infrastructure (Warabino T et al., 2021).

As the increasing business needs of communication network (Chen W et al., 2021), the connection relationship between equipment tends to be complicated (Ren B et al., 2020), so it also increases operation and maintenance difficulty (He L et al., 2021). On-site operation and maintenance's problems such as heavy workload (Yang Z et al., 2021), low task allocation efficiency (Sven T and Sonke D, 2018) and lack of information support (M. Xu et al., 2019) need to be solved urgently.

The task types of on-site operation and maintenance of the communication network are divided into routine task and emergency task. Routine task is the daily inspection (Liang J et al., 2021), and emergency task is the random fault and it usually spread rapidly with the network topology (Yang S et al., 2021). Considering emergency tasks should be solved efficiently and effectively, we optimize the method of selecting staff based on quality and celerity requirement.

Emergency Task Allocation Mechanism based on Reputation and Region (ETARR) we proposed can evaluate the comprehensive reputation and movement pattern of staffs to find the most suitable staff. Comprehensive reputation guarantees the completion quality while movement pattern ensures the completion efficiency. Experiments show that our mechanism improves the management level of operation and maintenance.

2 RELATED WORKS ON QUALITY EVALUATION AND REGION PREDICTION

In terms of quality requirement, the experience and ability of staffs determine the quality of task completion. There are many studies devoted to the precise analysis of user behaviour. Paper (Xiong X, 2020) builds a multi-dimensional panoramic portrait of the user to encode users' primary attributes related interests and behavioural preferences. But this

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method requires the support of massive user data. Trust evaluation based on user behaviour has been studied in many computer science domains including e-commerce, social network, etc (Wu Z et al., 2021). Paper (Zhang L et al., 2020) evaluates the credit of power users based on k-means clustering and Silhouette Coefficient method. Paper (Yang M et al., 2019) proposes a credible evaluation scheme combined with entropy weighting, overcoming the limitations of subjective weight assignation. Paper (Wang H et al., 2018) proposes a dynamic trust model based on time decay factor. When users do not interact for a period, their trust will decrease over time.

In terms of celerity requirement, many researches use deep learning models for path prediction. Paper (Rathore P et al., 2018) proposes a scalable cluster-based and Markov chain-based hybrid framework, suitable for short-term and long-term Trajectory Prediction, and they can handle many overlapping trajectories in dense road networks. Aiming at the problem of poor prediction accuracy caused by sparse trajectory data, paper (Li F et al., 2019) uses Prediction by Partial Matching and Probability Suffix Tree to predict cluster links. Paper (Zhang W et al., 2018) uses a recurrent neural network-based trajectory prediction method, which provides high-precision prediction within one minute. The Long Short-Term Memory (LSTM) model is one of the most used vehicle trajectory prediction models. In order to solve the problem of long-term trajectory prediction in dense traffic, literature (Dai S et al., 2019) proposed a Spatio-Temporal Long Short-Term Memory (ST-LSTM), which embeds spatial interaction into the LSTM model to implicitly measure the interaction between adjacent vehicles. At the same time, paper (Inkyu C et al., 2019) uses LSTM to model the moving information of pedestrians, and maps the position of each pedestrian to a high-dimensional feature space to predict the displacement.

3 REPUTATION-REGION-BASED EMERGENCY TASK ALLOCATION MECHANISM

3.1 Task Allocation Problem Description

Time limitation and accuracy demand is the main characteristic of emergency task. On one hand, emergency tasks have high requirements on the experience and ability of staffs in problem-solving, and on the other hand, it requires staff to arrive at site quickly.

ETARR consists of a comprehensive reputation computation model and a movement-pattern-based regional prediction model. The comprehensive reputation computation model evaluates the ability of staff from expressiveness and activeness. The regional prediction model evaluates the current working status and area, to select the staff who can reach the site with lowest cost.

3.2 Comprehensive Reputation Module

Definition 1. Comprehensive Reputation (CR). It represents the quality and efficiency when the staff deal with tasks. It is divided into working expressiveness (ω_E) with proportion of γ and working activeness (ω_A) with proportion of δ as shown in equation (1).

$$CR = \gamma \cdot \omega_E + \delta \cdot \omega_A \tag{1}$$

Definition 2. Task Reputation (TR). It points 1 to 5 and is given to all participants after one task completed. It stores in the database as a basic indicator of CR.

Definition 3. Working Expressiveness. It refers to the ability of the staff, and it is evaluated by his history TR.

We use LSTM model with "memory unit" to solve the TR sequence problem, and the output is the Working Expressiveness. The input and output of LSTM is in equation (2). Working mechanism of the LSTM model is shown in Figure 1.

$$c_t^{(t-1)}, h_{t-1}^{(t)}, h_t^{(t-1)} \xrightarrow{LSTM\ Block} c_t^{(t)}, h_t^{(t)} \tag{2}$$

Definition 4. Working Activeness. It refers to the enthusiasm of staff, and it is evaluated by the number of tasks he has participated in as shown in equation (3).

$$\omega_A = \frac{\arctan\left(d - \frac{t}{2}\right) + \arctan\,(t/2)}{\frac{\pi}{2} + \arctan\,(t/2)} \tag{3}$$

Where t is the total number of days ($t = 30$ in our experiment), and d is the number of working days of the staff among t.

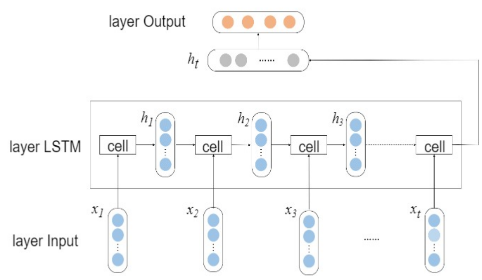

Figure 1: Working mechanism of LSTM model.

3.3 Region Prediction Model Based on Movement Pattern

3.3.1 Staff Active Region Division

When remotely operating and controlling the operation and maintenance conditions, due to the sparseness of GPS data (Aiswarya R and Surendran S, 2020) and the unstable network connections, the locations of personnel are stored discretely and it is difficult to find the trajectory path. Therefore, it is necessary to preprocess the position points, and cluster the movement between position points into the transfer between regions.

The k-means algorithm is a classic clustering analysis method with three steps.

First, initialize. Randomly set k number of position points as the initial centroid $m_j(1 \leq j \leq k)$.

Second, distribution. Calculating the distance between each centroid and every position point x_p in the set, allocate every point to the cluster C_i with the smallest distance squared as shown in equation (4).

$$C_i^{(t)} = \{x_p : \| x_p - m_i^{(t)} \|^2 \leq \| x_p - m_j^{(t)} \|^2, \forall j, 1 \leq j \leq k\} \quad (4)$$

Finally, update. Calculate the mean value of all points in the cluster and use it as the new centroid, as shown in equation (5).

$$m_i^{(t+1)} = (\textstyle\sum_{x_j \in C_i^{(t)}} x_j)/|C_i^{(t)}| \quad (5)$$

Repeat the distribution and update operations until there is no change of the cluster result of active region.

3.3.2 Movement Pattern Computation

Definition 5. Movement Pattern (MP). It means a movement trajectory that can reflect the personalized moving behaviour and location preferences of the personnel in the operation and maintenance site, which helps to predict the location. MP set represents a collection of multiple MPs of different lengths.

We have divided the staff's active region in section 3.3.1. Next, we create the task-region list according to the task location, and the task level is divided according to the difficulty and urgency, to form a double cluster of both the task location and the task level. The range of task level is [1,5]. Considering the TR of personnel, task level is required to be similar but lower than the average value of the TR of who can solve the problem. We believe that tasks of the same level in the same area can be substituted for each other when reflecting the behaviour of staffs. Therefore, we no longer distinguish tasks based on task numbers, but based on regions and levels, so that it is easy to summarize the historical path of personnel.

The Historical Path (P) is defined as a multivariate vector group $(\langle r_1, l_1\rangle, \langle r_2, l_2\rangle, \ldots, \langle r_k, l_k\rangle)$. Where *i-th* item of the vector group represents the information of task t_i, including r_i represents the number of the located area and l_i represents the level.

Define the confidence parameter (CP) of a path, which is positively correlated with the possibility of staff appearing in this path, and the equation is (6). A path is selected as the main path ($path_M$), and a path in the historical path set is selected as the path to be calculated ($path_i$).

$$CP(path_i|path_M) = \begin{cases} \frac{1}{1+\Delta} & path_i \ is\ the\ sub-path\ of\ path_M \\ 0 & path_i\ is\ not\ the\ sub-path\ of\ path_M \end{cases} \quad (6)$$

Where sub-path means the vector groups of $path_i$ is the sub-group of the vector groups of $path_M$, and Δ represents the number of vector groups missing from the sub-path compared with $path_M$.

The core of the region prediction model based on MP is to classify staff's historical path set according to the length of path, and select a MP of each length. The way is calculating CP of each path relative to all historical paths and add them to get the total confidence parameter (CPT). Choose path with the largest CPT in same length as the MP of the length. MPs under all length paths consist the MP set.

3.4 Task Allocation Method Based on Comprehensive Reputation and Region Prediction

3.4.1 Personnel and Task Information List

Table 1 is an example of Personnel Information List. "Path" is used to evaluate MP. "Status" has several options and their meaning is shown in Table 2. "CurrentRegion" is for the static personnel while "AimRegion" is only for the dynamic personnel. "StartTime" refers to the beginning time of the Status.

Table 3 is an example of Emergency Task List putting in OccurTime order.

Table 1: Personnel Information List.

StaffID	StaffName	Path	Status	CurrentRegion	AimRegion	StartTime	CR
0001	Tom	P1	Working	r1	null	14:51	4

Table 2: Meaning and Type of Staff Status.

Status	Description	New Task	Type
Free	he is taking a break and have no task in the future.	suitable	static
Working	he is doing routine task or emergency task.	suitable	
Allocated	He is taking a break or working but have a scheduled task in the future.	not suitable	
Going to Routine	He is on the way to the routine task site.	suitable	dynamic
Going to Emergency	He is on the way to the emergency task site.	not suitable	

Table 3: Emergency Task List.

TaskID	TaskName	Level	Region	OccurTime	Staff
191205001	repair cable	5	r1	11:00	

3.4.2 Task Allocation Algorithm

We consider three main factors when allocate the personnel for emergency task.

1). Personnel active region. In Section 3.3.1, we divide the personnel activity area into a directed graph. In order to simplify the calculation, it is assumed that the distance between adjacent areas is a unit of length. Therefore, we set the time spent on the way between neighbouring regions as $2T$.

2). Staff status. For static personnel, latency depends on the remaining time of current task ($r.jobtime$) and the distance between current area ($r.area$) and emergency task area ($t.area$). For dynamic personnel, after predict the area they will reach, the latency depends on the distance between the area to be reached ($r.pre$) and $m.area$. The equation of latency of personnel going to task site is (7).

$$latency = \begin{cases} distance(r.area, t.area) \times 2T & \text{Status is Free} \\ distance(r.area, t.area) \times 2T - r.jobtime & \text{Status is Working} \\ \infty & \text{Status is Allocated} \\ distance(r.pre, t.area) \times 2T & \text{Status is Going to Emergency} \end{cases} \quad (7)$$

3). Staff reputation. To ensure the completion of the task, it is regulated that the CR of personnel must be greater than or equal to the task level.

Define k as the distance between a certain area and the current emergency task area. R is the set of areas with a distance of k from the emergency task. $minID$ is the ID of staff who is most capable for the emergency task. $minLatency$ is the delay for $minID$ to arrive at the task.

The steps of ETARR are as follows.

Step 1. Initialize the parameters. $k = 0$, $R = \emptyset$, $minID$ and $minLatency$ are the largest integers.

Step 2. Obtain historical staff position point and task location from management system. using the directed graph clustered by point generates historical path set and divides the task region and task level. Get regions which distance k to current emergency task and store them in R;

Step 3. If the latency of distance k is less than $minLatency$, do Step 4. Otherwise do Step 7;

Step 4. Go through static personnel in R. If meet the requirements of CR, calculate $latency$;

Step 5. If the $latency$ is less than $minLatency$, update $minLatency$ and $minID$.

Step 6. If the traversal of staff in the area is completed, $k++$. Otherwise do Step 4;

Step 7. Obtain the dynamic staff set and go through it. If meet the requirements of CR, calculate MP and the difference x between the current time and the start time;

Step 8. Analyse the movement habits and location preferences according to staff's MP, and predict $r.pre$ before calculate $latency$;

Step 9. If the $latency$ is less than $minLatency$, update $minLatency$ and $minID$.

Step 10. If the traversal of dynamic staff is completed, end. Otherwise do Step 7.

4 EVALUATION

4.1 Performance of Working Expressiveness Prediction

Definition 6. Error Rate (Err). The equation is (8), where x_i is the prediction value and y_i is the actual value.

$$Err = \frac{x_i - y_i}{y_i} \times 100\% \quad (8)$$

Figure 2 shows calculation of the error rate between actual value and predict value by LSTM model and Markov model. It can be seen that Err_{LSTM} is almost kept within 10%, while Err_{Mar} is concentrated in 10% to 40%. This is because the Markov model has no memory, and the prediction of next value is only based on the current value. On the contrary, the LSTM model has a long-term memory, which can well match the characteristics that work expressiveness has strongly related to the historical value.

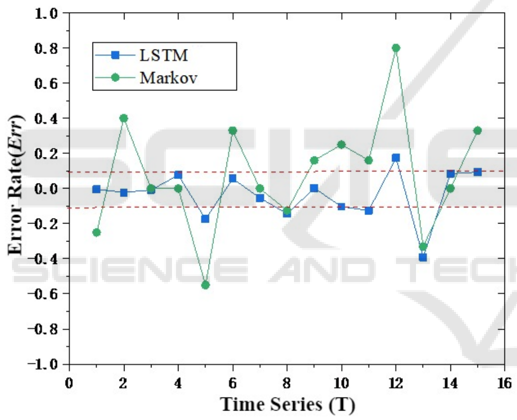

Figure 2: The prediction Error Rate of Working Expressiveness.

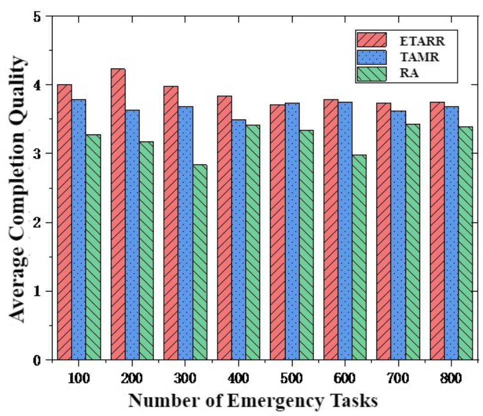

Figure 3: Average Completion Quality of different number of emergency tasks.

4.2 Performance of Emergency Task Allocation

4.2.1 Average Completion Quality

Definition 7. Average Completion Quality (QLT). It refers to the effect of the repairing task, and is evaluated by TR as equation (9).

$$QLT = \frac{\sum_{i=1}^{N} Quality_i}{N} = \frac{\sum_{m=1}^{M}\sum_{k=1}^{K_m} TR_k^m}{N} \quad (9)$$

Where N is the number of completed tasks in a period, $Quality_i$ is the Completion Quality of task i. M is the number of staffs involved in the task, K_m is the number of tasks completed by the *m-th* staff, and TR_k^m is TR obtained by the *m-th* staff after completed task k.

Figure 3 shows the comparison of QLT in three algorithms. The RA does not consider the differences of staffs' ability, and only assigns task to a closer staff randomly. This will lead to some difficult tasks that cannot be successfully completed while some professional staffs spend time doing easy task. But ETARR divides staffs into different expressiveness and activeness, so as to accurately match personnel capability and task difficulty as much as possible.

4.2.2 Allocation Successful Rate

Definition 8. Allocation Successful Rate. It is defined to the proportion of the number of emergency tasks finished successfully to the total number of emergency tasks.

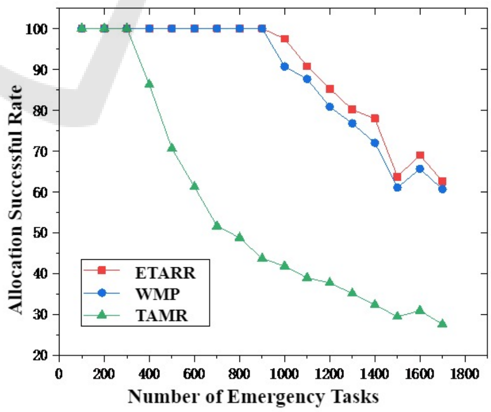

Figure 4: Task Allocation Successful Rate for different number of emergency tasks.

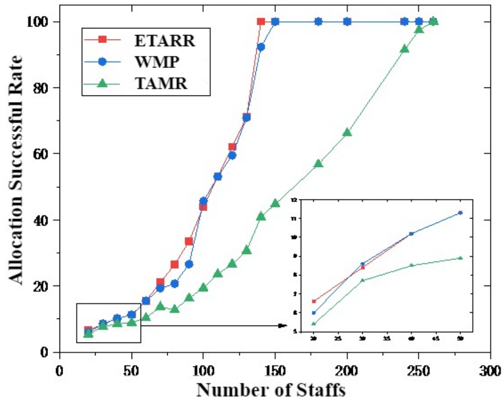

Figure 5: Task Allocation Successful Rate for different number of staffs.

Setting the number of staffs is 150 and number of routine tasks is 1000. As Figure 4 shown, when the number of emergency tasks is less than 900, both ETARR and WMP (Jiang Y et al., 2018) have a high task Allocation Successful Rate. When the number of tasks is greater than 900, the workload of staffs is saturated. Many staffs remain in the "Allocated" state and unable to accept new assignments, resulting in a sharp drop in the successful rate. However, because the ETARR makes full use of the geographical advantages of the nearby region and reduces the staff's time consuming on the road, the staff can complete a little more task.

Setting the number of routine tasks and emergency tasks are both 1000. As Figure 5 shown, when the number of staffs is close to 150, both ETARR and WMP can achieve 100% allocation of emergency tasks, while TAMR requires 250 staffs to achieve this goal. This is because TAMR only considers the task allocation method of static personnel when assigning tasks, but the ETARR takes full advantage of dynamic personnel who can handle emergency tasks in passing.

5 CONCLUSION

Aiming at the emergency tasks in the on-site operation and maintenance of the communication network, we propose an emergency task allocation mechanism based on the comprehensive reputation and area of operation and maintenance staffs. Our mechanism ensures the efficient and effective operation of on-site operation and maintenance, and brings greater benefits to the communication network operation and maintenance system.

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