Software Maintenance Event Tickets Requests For Resolution Recommendation

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Abstract: A trouble ticket is an important information carrier in system maintenance, which records problem symptoms, the resolving process, and resolutions. A critical challenge for the ticket management system is how to quickly deal with trouble tickets and fix problems. Thousands of tickets bouncing among multiple expert groups before being fixed will consume limited system maintenance resources and may also violate the service level agreement (SLA). Thus, trouble tickets should be routed to the right expert group as quickly as possible in order to reduce the processing delay. In this paper, to address the challenge in ticket routing, we exploit three different routing models by mining the combination of problem descriptions and resolution sequences from the historical resolved tickets, and develop the corresponding routing recommendation algorithms to determine the next expert group to solve the problem. To evaluate the performance of routing recommendation algorithms, we conduct extensive experiments on a real ticket data set. The experimental results show that the proposed models and algorithm can effectively shorten the mean number of steps to resolve (MSTR) with a high ratio of the number of successfully resolved tickets to the total number of tickets (RSR), especially for the long routing sequences generated from manual assignments. These models and algorithms have the potential of being used in a ticket routing recommendation engine to greatly reduce human intervention in the routing process.

Keywords: Resolution Recommendation, Sequence Mining, Signature, Trouble Ticket.

I. INTRODUCTION

The quality of modern large-scale IT service delivery highly depends on the underlying IT infrastructure. Although powerful hardware and software tools have been used in modern IT infrastructure, it is still inevitably to suffer from system faults, even system failure, due to software aging [1,2], operation errors, etc. When an event (which is not part of the standard operation of a service that may cause an interruption or a reduction) happens, or when using an IT service, errors, faults, difficulties or special situations (that need attention from system management experts) occur, a trouble ticket is then generated in the ticketing system. The IT infrastructure and Manuscript received ####. The work is partially supported in part by the service delivery management system is responsible for dealing with the trouble tickets in time. In a typical IT infrastructure and service delivery management organization, experts are often organized into groups, each of which has the expertise to solve certain types of problems. Skilled expert groups need to be quickly assigned to bring an abnormal service back to normal because an IT service provider typically signs up a Service Level Agreement (SLA) with their users. However, the increasing complexity of the IT infrastructure and service delivery makes the types of reported troubles diverse. Moreover, the trouble description in a ticket is often vague and may not contain the actual root cause of the trouble. Thus, it is difficult to find a right expert group to solve the trouble. Many of the tickets have to bounce among multiple groups before being transferred to the group with the right expertise. We call the process that a ticket is transferred among various expert groups as the trouble ticket routing. Obviously, if a ticket is mistakenly transferred to an expert group that cannot solve the trouble, it might lead to a long maintenance time and violate the SLA. In real world applications, the number of trouble tickets generated each day is large. Therefore, although manually assigning expert groups has a high accuracy, it suffers from a low efficiency. Rapid problem solving has to rely on the automatic ticket routing based on the accurate ticket routing models. This paper focuses on the study of ticket routing models by analyzing this information from historical trouble tickets in order to address the following problems: 1) How to build the trouble ticket routing model (describing how and why the tickets are transferred and resolved) from historical tickets? and 2) How to apply the trouble ticket routing model to guide the automatic routing process with a high efficiency? Although a few studies [3,4,5] have been reported to deal with these problems, there are still many limitations in existing methods that need further investigation.

For example, a Markov based routing model [3,4] was built based on the resolution sequences of historical tickets. A drawback of the approach is that it is locally optimized and might not be able to find the best routing sequences. Moreover, the approach did not use other important information such as problem descriptions to further enrich the routing model. To overcome these drawbacks, we comprehensively analyze a ticket's problem type, problem description in conjunction with its resolution sequence, and develop three different routing models and the corresponding routing recommendation algorithms. Furthermore, to evaluate the effectiveness and robustness of these models and algorithms, we evaluate our Trouble Ticket Routing Models and Their Applications algorithms on real trouble ticket data sets. The main contributions are summarized as follows:

1) Three routing models and the corresponding routing recommendation algorithms are proposed by mining the combination of problem descriptions and routing sequences to improve the performance of ticket routing.
2) Several groups of experiments are conducted to validate the effectiveness and robustness of our routing models and recommendation algorithms. The experimental results demonstrate that the proposed models and algorithms can effectively shorten the average length of ticket routing sequences, especially for the long routing sequences generated from manual assignment.

II. TROUBLE TICKET ROUTING MODELS

Given a set of historical tickets, since the problem descriptions and resolution sequences of historical tickets provide critical clues as to how and why the tickets are routed and solved by expert groups, they can be used to construct routing models that effectively represent this routing information hidden in historical tickets. Here, we use the combination of problem descriptions and resolution sequences to build routing models. Moreover, because the problem descriptions and the mean number of steps to resolve tickets vary with problem types, it is thus quite difficult to build a unified routing model covering all problem types. This motivates us to build a group of models, each of which corresponds to a specific problem type. In this paper, three kinds of ticket routing models: the group profile (GP), the transfer profile (TP), and the routing network (RN), will be introduced, as shown in Fig1. In particular, the group profile (GP) based routing model only focuses on characterizing the expertise and experience of each expert group, the transfer profile (TP) based routing model only focuses on characterizing the interaction relationships among expert groups, and the routing network (RN) based routing model takes the expertise and experience of all expert groups and the interaction relationships among expert groups into consideration.

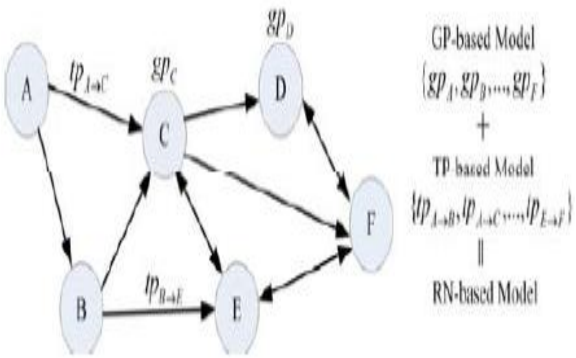

Fig1. Three kinds of ticket routing models.

A. The GP Model

Several expert groups are often involved in an individual routing sequence. Although only the last expert group is a resolver, the intermediate expert groups have rich experience in problem diagnosis and ticket transfer. Thus, in the routing model, we will characterize all expert groups that involve in the routing process from the historical tickets, and introduce the concept of group profile to characterize each expert group in terms of expertise and experience. Before the formal definition of the group profile is given, we describe some extra notations used in the section. We assume that the number of tickets of the problem type m c in the set T is $N=\sum_{m=1}^{M} n_m$. For the tickets of the problem type m c , the number that group l g is chosen as an IEG is (1)

Definition 1. (Group Profile, GP). For a given problem type m c , group l g is one of the expert groups that involve in the routing process for the tickets of the problem type m c . The group profile of group l g is a five-tuple, defined as $gp_l^m=[S_{lm}^1, S_{lm}^2, S_{lm}^3, S_{lm}^4, DW_{lm}^5]$. We refer the set of discriminative domain words of each expert group as a signature.

In summary, the first four components characterize the group routing experience using statistical information from the resolution sequences, while the last component characterizes the group expertise using discriminative words from the problem descriptions. Compared with the first four components, the fifth component is relatively trivial to obtain. If we find a signature that corresponds to each expert group by mining the problem descriptions of tickets resolved by that group, we can recommend an expert group for an incoming ticket based on the signature-based matching approach. Since a group signature is a set of discriminative domain words, we first extract all words from problem descriptions as candidates. Then, we consider two factors to choose discriminative domain words among them, which is conceptually similar to in the traditional vector space model for text mining. The first factor is the number of tickets where a word w occurs, called the document frequency (df) to signify a word's extent of representativeness with respect to a specific group. For the tickets that a group have resolved, we compute the df of a word w by counting the number of tickets that contain the word w in their problem descriptions. The higher the value of the df, the better is the representativeness of the word w . The second factor is a weight function called the inverse group frequency (igf) to signify a word's extent of uniqueness with respect to groups. The higher the value of igf, the higher is the discriminative nature of the word w . Taking these two factors into consideration, we have a discriminative metric for domain words, The group signature discovery algorithm is as shown in Algorithm 1.

Algorithm 1. Group Signature Discovery (GSD)

Input: T: a set of historical tickets, T={t_1,t_2,……,t_N}; V_m^G: a global vocabulary map of a specific problem type c_m, c_m € C; K: a threshold for the number of domain words to characterize a group profile, K = 20 for all cases by default.

Output: Sig_m^G = {sig_{m1}^G,….sig_{ml}^G,..,sig_{mL}^G},

where sig is a vector of K elements at most, sig_{ml}^G = {<w_k, DM(w_k) >}$_{k-1,…..,K}$

Initialize Sig = Ø;
Get distinct words from T as keys of V_m^G, and initialize V_m^G. For each word w, we have <w, (0,……,0,…..,0,0)>;
for i = 1 to N do
    if the problem type of ticket t_i is c_m then
    get the group index l of the resolver group of ticket t_i;
    for each w in ticket t_i do
    get the value df_l^m from V_m^G;
        $df_l^m(w)$++;
    compute $gf^m(w) = \sum_{l=1}^{L} I(df_l^m(w))$, where $I(df_l^m(w)) = 1$ when $df_l^m(w)\geq 1$, and 0 otherwise;
    update the key-value pair with the key w in V_m^G;
    end for
    end if
    end for

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for l = 1 to L do
    sort the key w in the map V_m^G by the descending order using (1);
    select the top-K domain words at most satisfying DM_l^m(w)>0;
    update sig_ml^G using the chosen domain words;
end for
return Sig_m^G;
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Definition 2. (GP Model).

Input: T: a set of historical tickets, a set of historical tickets, $T=\{t_1,t_2,\ldots\ldots,t_N\}$; V^T: a global vocabulary map containing M components $\{V_m^T\}_{m-1,\ldots,M}$; c_m : specific problem type, c_m € C; K: a threshold for the number of domain words to characterize a transfer profile, K = 20 for all cases by default.

B. The TP Model

A transfer profile model characterizes the features of all transfers that involve in the routing sequences of the historical tickets. Similar to the GP model, we also take all expert groups that involve in the routing process for the tickets of a specific problem type into consideration. Thus, for a given problem type m c , we assume that T m is a set of tickets of the problem type and Gm is a set of expert groups that involve in the routing process of the tickets. For any two groups

C. The RN Model

Both the GP model and the TP model are local models. Although both models are built using the combination of problem descriptions and routing transfer, the former focuses on characterizing the problem-solving capacities of expert groups, while the latter focuses on characterizing the interaction behaviors among expert groups. If we take an expert
group and a transfer as a node and an edge of a graph
respectively, the GP model for the nodes can be combined with the TP model for the edges to form the routing network (RN) model, as shown in Definition 5.

Existing System:

Software-defined networking (SDN) innovation is a way to deal with system the board that empowers dynamic, automatically productive system arrangement so as to improve organize execution and observing making it more like distributed computing than conventional system the executives. SDN is intended to address the way that the static engineering of conventional systems is decentralized and complex while current systems require greater adaptability and simple investigating. SDN endeavors to bring together system knowledge in one system segment by disassociating the sending procedure of system bundles from the steering procedure. The control plane comprises of at least one controller which are considered as the cerebrum of SDN organize where the entire insight is joined. Be that as it may, the knowledge centralization has its own disadvantages with regards to security, adaptability and flexibility and this is the principle issue of SDN.

Proposed System:

Controller Placement Strategy:

- It is planned as a blended whole number straight program (MILP). The goal is to limit the most extreme, for all switches, of the whole of the inertness.
- The change to the closest controller with enough limit (first reference controller) and the dormancy from the main reference controller to its nearest controller with enough limit (second reference controller).
- We additionally proposed a summed up model which can be utilized to limit the normal inactivity and expanded it for numerous controller disappointments. Moreover, we exhibited a reenacted strengthening heuristic that proficiently takes care of the issue on enormous scale systems.

IV. APPLICATIONS

We now study the applications of the proposed ticket routing models by developing routing recommendation algorithms. Formally, for a new ticket t of the problem type m c , we use

$$Hop_{(k)}(t) = g_{(1)} \rightarrow g_{(2)} \rightarrow \ldots \rightarrow g_{(k-1)}$$

$$G_{(k)}(t) = \{g_{(1)}, g_{(2)}, \ldots, g_{(k-1)}\}$$

to denote the current resolution sequence of the length k , the set of expert groups involved in the current resolution sequence, and the set of expert groups involved in the model of the problem type m c respectively. The main task of routing recommendation algorithms is to predict an expert group (k) g as a resolver candidate until the right resolver is found using the routing models. Here, we develop three different routing recommendation algorithms based on these three routing models respectively.

The first algorithm is a ranked expert group recommendation algorithm using the GP model, named GPRR. For a given ticket, the algorithm GPRR first ranks all expert groups by computing a score between a new ticket and a group profile, and then recommends an expert group that has the highest score and is never recommended as a candidate to resolve the ticket. The second algorithm is also a ranked routing recommendation algorithm based on the transfer score from the TP model, named TPRR. For a given ticket, TPRR first assigns an expert group as an IEG for the ticket, and then routes it to the next group with the highest transfer score among the neighbors if the current expert group fails to resolve the ticket. The last is a routing recommendation algorithm using the RN model, named RNRR. For a given ticket, RNRR first assigns an expert group as an IEG for the ticket, and then routes it to the next group by considering the combination of the group profile and the transfer profile embedded in the RN model. Note that all three algorithms need to assign an IEG based on the ranked group profiles. Intuitively, the assigned IEG has a great impact on the performance of routing. A straightforward solution is to assign the IEG in a random way.

An alternative approach is to assign the optimal expert group as an IEG using GPRR. On the other hand, the difference of the three algorithms lies in the choice of a resolver candidate when the current expert group fails to be a right resolver. Specifically, GPRR chooses the expert group with the highest group profile score among the unvisited expert groups, TPRR chooses the expert group with the highest transfer profile score among its neighbor expert groups of the visited expert groups, and RNRR chooses the expert group with the highest score that takes the combination of the group profile score and the transfer profile score into account among its neighbor expert groups of the visited expert groups. Moreover, the first two algorithms are not optimized for the end-to-end ticket routing because the models used in these two algorithms are local models, while the last algorithm is a globally optimized one. As a result, the last algorithm should perform better than the first two algorithms. To evaluate the performance of the routing recommendation algorithms, we use two common metrics, the mean number of steps to resolve (MSTR) [3] and the ratio of the number of successfully resovled tickets to the total number of tickets (RSR)[5].

Given a set T m of tickets of the problem type m c , MSTR is defined as:

$$MSTR(T^m) = \frac{\sum_{t_i \in T^m} k_i}{|T^m|}$$

where the number of steps of the ith ticket’s resolution sequence. Ideally, we expect the MSTR is equal to 1, namely the assigned IEG is the RG. In reality, it is a minor case. Thus, our goal is to minimize the MSTR. Besides the metric MSTR,

B. The Algorithm TPRR

The TP model of a specific problem type only captures the historical interaction information among expert groups that ever tried to solve or successfully resolved the tickets of the same problem type. The basic idea of TPRR is that when the current expert group fails to solve a ticket, the TP model can be used to make a transfer decision about which neighbor in the model can be a resolver candidate based on the generated resolution sequence. Formally, for a ticket t of the problem type m c , we use to denote the set of expert groups involved in the current resolution sequence and the set of expert groups involved in the TP model of the problem type m c , respectively. We need to find a neighbor with the maximum weighted score among all neighbors of as a resolver candidate. Here we say that a group j g is a neighbor of another group i g if and only if an edge in the TP model. The weighted score evaluation is similar to the way used in GPRR. We assign a set of weights to two components in the transfer profile.

IV. RESULTS

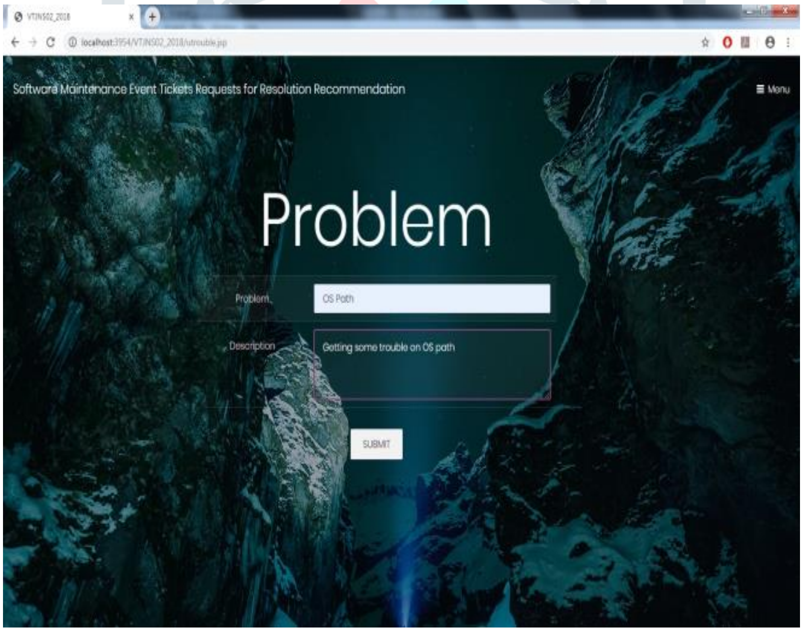

Fig2. Sending Trouble

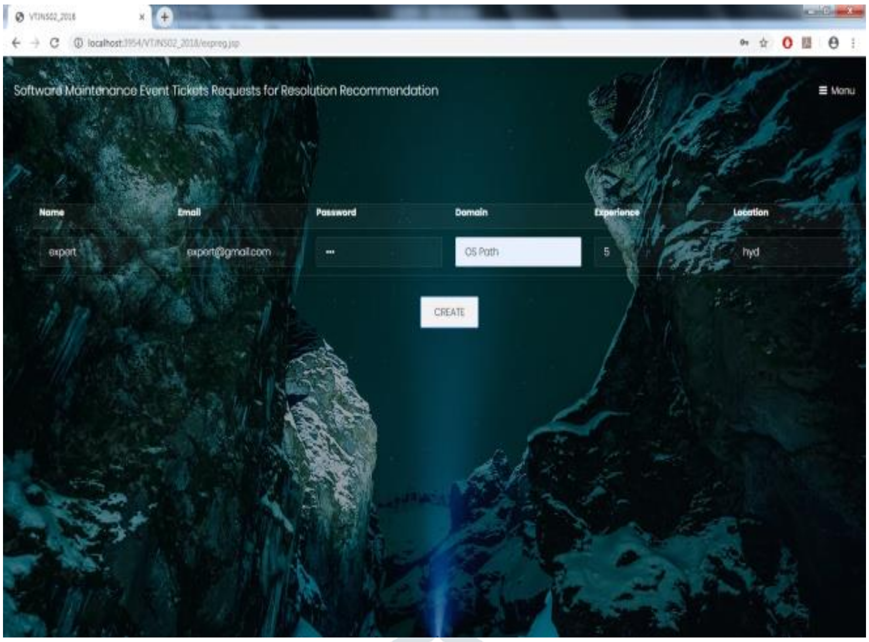

Fig3. Creating Experts

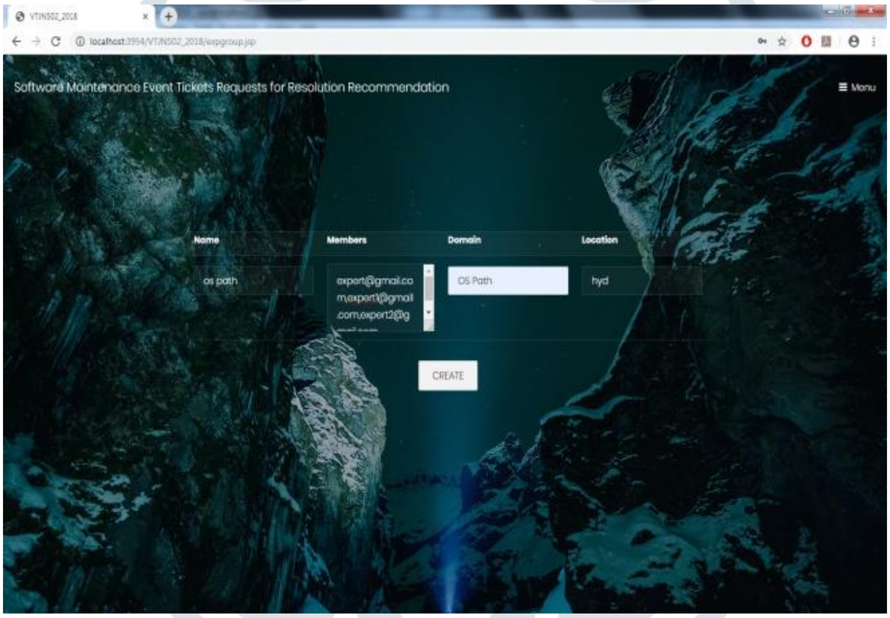

Fig4. Creating Expert Groups

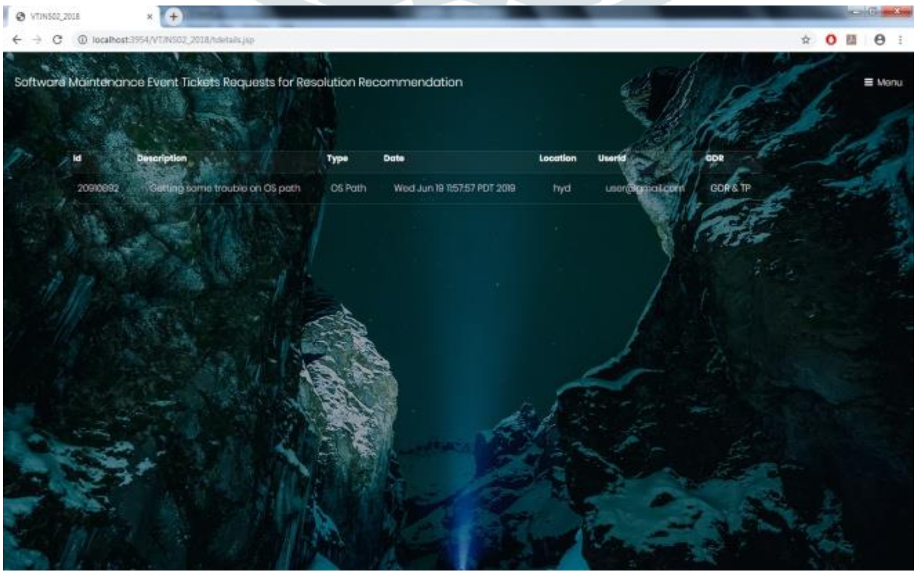

Fig5. Ticket Details

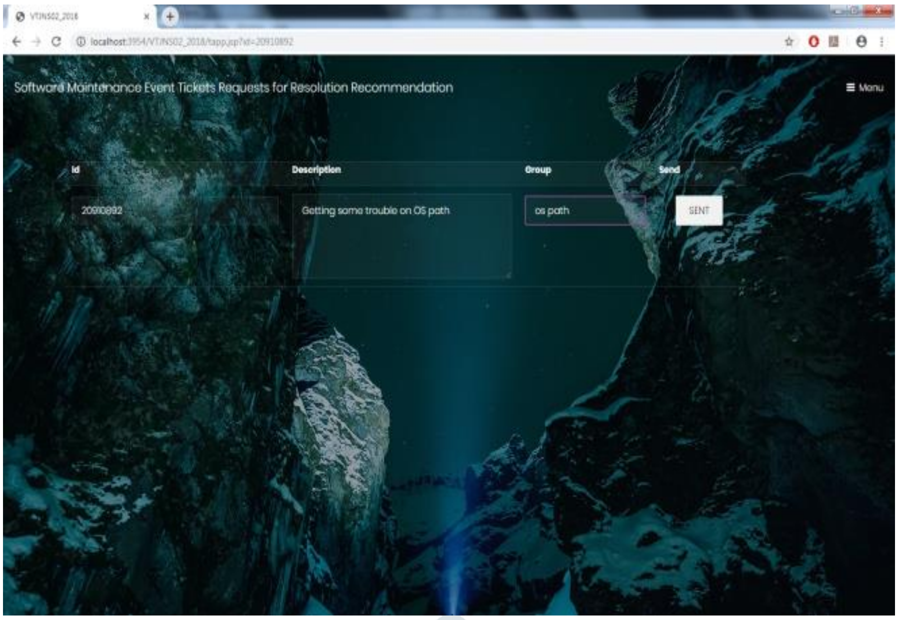

Fig6. Assigning Ticket

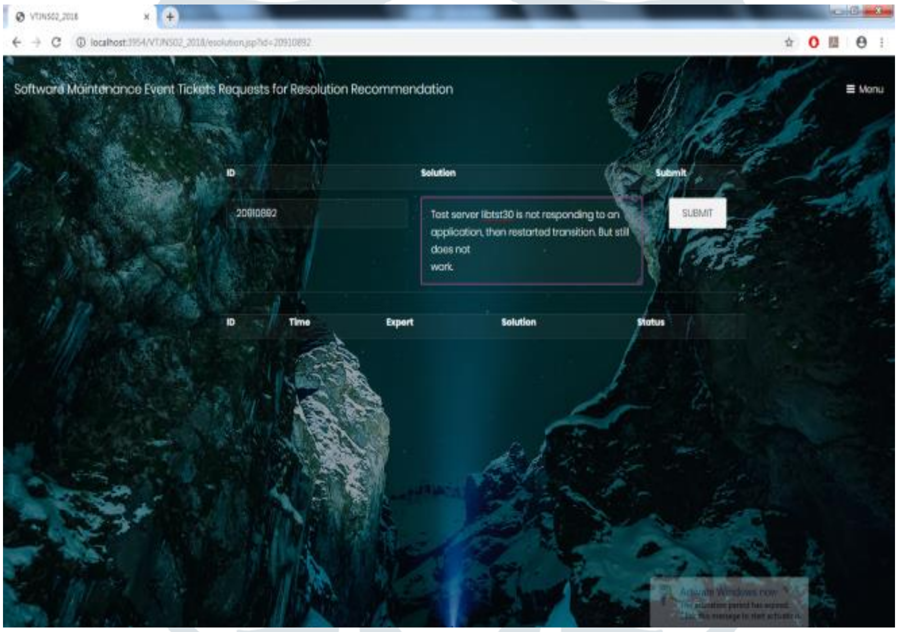

Fig7. Providing Solution

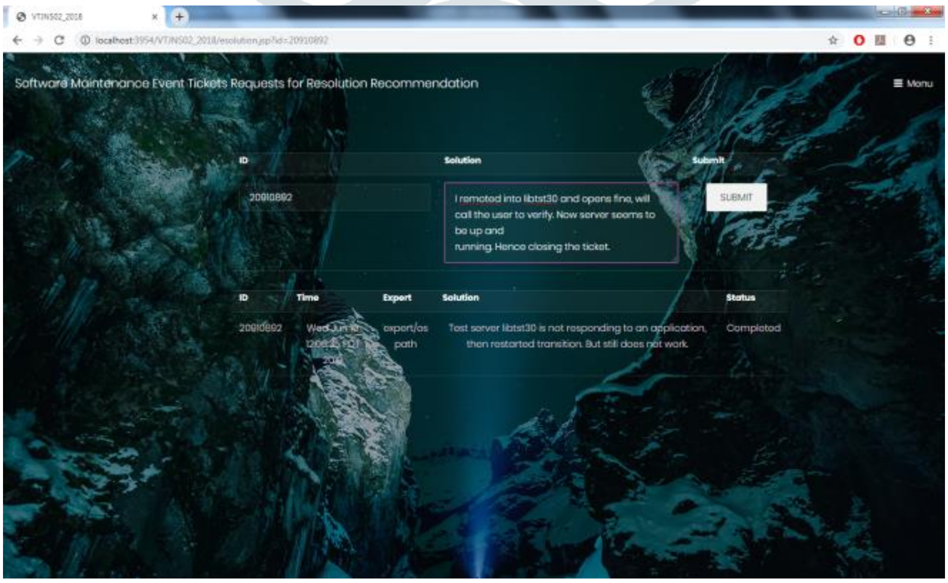

Fig8. Expert Closing the Ticket

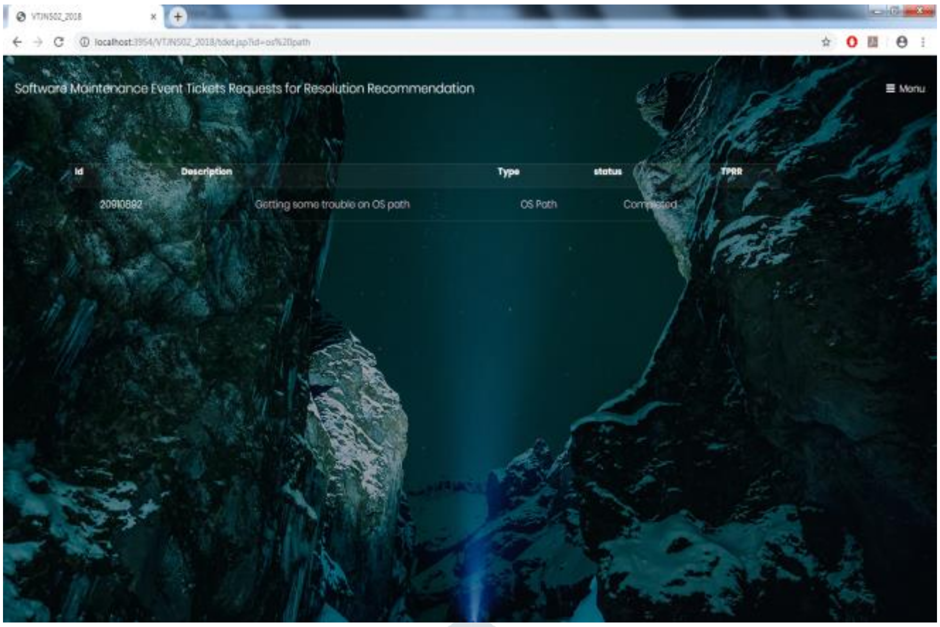

Fig9. Closed Ticket Details

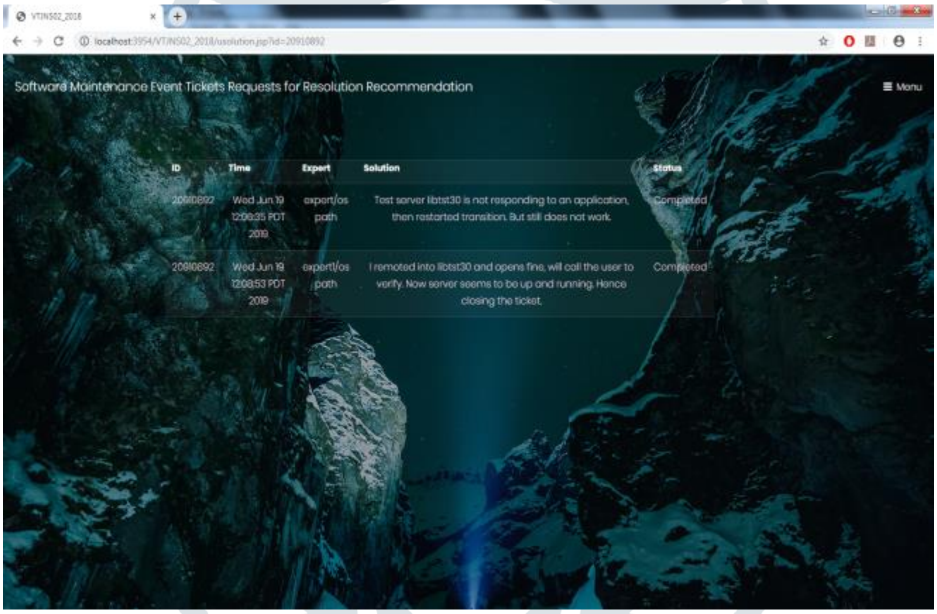

Fig10. User Ticket Information.

V. CONCLUSIONS AND FUTURE WORK

When a critical system exhibits an incident during its operation, system maintenance teams are expected to rapidly assign skilled experts to bring an abnormal service back to normal as short as possible. In a typical ticket management system, the ticket routing is done manually by system administrators to assign an expert or expert group, which is time consuming and error prone, especially when there is a large number of tickets. To deal with this issue in an automated way, this paper proposes three routing models and develops their corresponding routing recommendation algorithms using the combination of ticket problem descriptions and the routing sequences. We also conduct several groups of experiments to evaluate the effectiveness and robustness of the proposed models and algorithms. The experimental results show that the proposed routing models and routing recommendation algorithms can be used to avoid manual routing decision with a high precision accuracy and resolution success rate. Meanwhile, the characteristics of the proposed models and algorithms are summarized in Table 5. The main differences lie in three aspects: the considered ticket information, the next possible candidate and the routing recommendation method. Further, these differences determine that GPRR and RNRR have a good and close performance in terms of MSTR and RSR, and can be used in practice. Moreover, these algorithms can only make one step prediction and select the most probable resolver from their possible candidates.

Moreover, we have some important findings from the result analysis, which can provide promising directions for our future directions to further improve the routing accuracy and resolution success rate. An important finding is that compared with ticket routing sequences, problem descriptions have a greater contribution to routing recommendations although the combination of the ticket problem descriptions and the routing sequences can not only reduce the average steps to resolve tickets, but also increase the resolution rate of the routing algorithms. According to this finding, we should focus on improving the precision of the ticket classification algorithms based on the problem descriptions, because ticket classification is used to assign the initial expert group. Another important finding is that the continuous change of system runtime environments and system services can lead into the gradually decreasing recommendation accuracy and the resolution success rate of the algorithms using the built routing models based on the historical tickets.

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