

Automatic Resolver Group Assignment of IT Service Desk Outsourcing in Banking Business

Padej Phomasakha Na Sakolnakorn*, Phayung Meesad ** and Gareth Clayton***

Abstract

This paper proposes a framework of automatic resolver group assignments of IT service desk outsourcing in banking firms. Recently, service desk technologies have not addressed the problem of performance in resolving incidents dropped due to overwhelming reassignments. This article makes two contributions: (1) data preparation procedures proposed for text mining discovery algorithms; and (2) rule generation from data based on decision tree procedures proposed for knowledge acquisition. In the experiments, we acquired the incident dataset from Tivoli CTI system as text documents and then conducted data pre-processing, data transforming, decision-tree-from-text mining, and decision-tree-to-rules generation. The method of model was validated using the test dataset by the 10-fold cross validation technique. The experimental results indicated that ID3 method could correctly assign jobs to the right group based on the incidents documents in text or typing keywords. Furthermore, the rules resulting from the rule generation from the decision tree could be properly kept in a knowledge database in order to support and assist with future assignments.

Keywords: text mining, decision tree, automatic resolver group assignment, service desk, and outsourcing.

1. Introduction

Beyond the rapid change in technology and competition among the banks in Thailand, therefore, they need to reduce costs and to improve their quality of services by strategic IT outsourcing. The IT outsourcings are understood as a process in which certain service providers, external to organizations, take over IT functions formerly conducted within the boundaries of the firm [1], [2]. In the IT outsourcing, the IT service desk is an important function of incident management driven by alignment with the business objectives of the enterprise that requires IT support, balancing their operations and achieving desired service level targets.

By the case study of knowledge management systems applied to IT service desk outsourcing in the bank, it appears that the IT service desk outsourcing's role is not quite a single point of contact [3]. The bank takes ownership of the help desk agents called first level support (FLS) which acts as an interface for internal users and external customers. Thus, the

IT service desk as a second level support (SLS) will resolve the assigned incidents from the FLS by ensuring that the incident is in the outsourcing scope and still owned, tracked, and monitored throughout its life cycle. The service desk technology of computer telephony integration (CTI) has not been focusing and supporting automatic resolver group assignment. The assignment is still performed manually by IT service desk agents. The problem is there may be a mistake in assigning a resolver group to deal with the incident due to human errors. This problem of incorrect resolver group assignment will be resolved by means of the automatic assignment approach.

2. Related works

2.1 Decision support system

In the past decade, contributions of decision support systems for resource assignments have been proposed in several areas. In R&D project selection, Sun [5] presented a hybrid knowledge and model approach which integrated mathematical decision models for the assignment of external reviewers to R&D project proposals. The purpose of the model was to assign the most appropriate expert to relevant proposals. Before the research above, Fan [6] proposed a decision support system for proposal grouping, which is a hybrid approach for proposal grouping, in which knowledge rules were designed to deal with proposal identification and proposal classification, and a genetic algorithm was used to search for the expected groupings. Next was a decision support system for multi-attribute utility evaluation based on imprecise assignments was proposed by Jiménez [7]. The paper describes a decision support system based on an additive or multiplicative multi-attribute utility model for identifying the optimal strategy. Last but not least, in research for a rule-based system of automatic assignment of technicians to service faults, Lazarov and Shoval [8] presented a model and prototype system for the assignment of technicians to handle computer faults. Selection of the technician most suited to deal with the reported failure was based on the assignment rules which are correlations between the nature of the fault and the technicians' skills. The model was evaluated using simulation tests, comparing the results of the model assignment process against assignment carried out by experts. The results showed that the system's assignments were better than the experts'.

* Department of Information Technology, Faculty of Information Technology, KMUTNB

** Department of Teacher Training in Electrical Engineering, Faculty of Technical Education, KMUTNB

*** Department of Applied Statistics, Faculty of Applied Science, KMUTNB

For the technologies regarding service desk, many organizations have focused on computer telephony integration (CTI). The basis of CTI is to integrate computers and telephones so that they can work together seamlessly and intelligently [9]. The major hardware technologies are as follows: automatic call distributor (ACD), voice response unit (VRU), interactive voice response unit (IVR), predictive dialing, headsets, and reader bounds [10]. These technologies are used to make the existing process more efficient by focusing on minimizing the agent's idle time [11]. These technologies do not address the problem of resolving performance dropped due to incorrect assignments.

Incorrect assignment is still taking place because of human errors, because the assignment of resolver group to deal with the incident is performed manually by IT service desk agents. In fact, technologies for the service desk management do not focus on automatic assignment, although the ITIL framework guides the IT service desk outsourcing to resolve incidents by putting in place the best practice processes for IT service desk decision making regarding assignment and reassignment. In this paper, we propose a model for automatic resolver group assignment which is based on text mining discovery algorithms, and implementing the optimal algorithm in the model as well as validating the selected method of the model.

2.2 Methods

A decision tree is a simple structure where a tree in which each branch node represents a choice between a number of alternatives, and each leaf node represents a classification or decision. The ordinary tree consists of one root, branches, nodes (places where branches are divided), and leaves. In the same way, the decision tree consists of nodes, which stand for circles or cones, the branches stand for segments connecting the nodes [12].

The decision tree algorithms can be applied to solve the problem under discussion. The decision trees also represent a supervised approach to classification. In this case, we used several decision trees including ID3, J48, NBTree, Random Forest, Random Tree, and REPTree. The below are brief descriptions of various decision tree methods.

An ID3 [13] has been found to construct simple decision trees and can be described using the information gain criterion. It splits the data in two parts. The exact criterion is determined by examining the entropy of the two subsets. The split results in the largest information gain or decrease entropy. J48 [13], [14] classifier generates an unpruned or a pruned C4.5 decision tree with slightly modified C4.5. The decision is grown using depth-first strategy. The algorithm considers all the possible tests that can split the data set and selects a test that gives the best information gain. The naïve Bayesian tree learner, NBTree [15], combines naïve Bayesian classification and decision tree learning. In NBTree, a local naïve Bayes is deployed on each leaf of a traditional decision tree, and an instance is classified using the local naïve Bayes on the leaf into which it falls. A random forest [16] is an ensemble of unpruned classification or regression trees, induced from bootstrap samples of the training data, using random feature selection in the tree induction process. Prediction is done by aggregating (majority

vote for classification or averaging for regression) the predictions of the ensemble. A random tree is a tree drawn at random from a set of possible trees. The random means that each tree in the set of trees has an equal chance of being sampled. Another way of saying this is that the distribution of trees is uniform. Random trees can be generated efficiently and the combination of large sets of random trees leads to accurate models. REPTree [4] is a fast decision tree learner that builds a decision tree using information gain as the splitting criterion, and prunes it using reduced-error pruning. It only sorts values for numeric attributes once. Missing values are dealt with using the C4.5's method of using fractional instances.

2.3 Evaluation of classification trees

The evaluation of classification trees commonly uses 10-fold smooth out cross-validation [15] for estimation. The 10-fold cross-validation which is helpful in preventing overfitting. The cross-validation process is repeated 10 times, with 10 subsets of equal size, training on nine datasets and testing on one dataset and then used exactly one which mean is accuracy.

2.4 Text mining

Text mining is data mining applied to information extracted from text. It can be broadly defined as a knowledge-intensive process in which a user interacts with a document collection over time by using a suite of analysis tools [17]. A text mining handbook written by Feldman and Sanger [17] presents a comprehensive discussion of text mining and links detection algorithms and their operations.

3. The Proposed Framework

This section are to describe IT service desk outsourcing functions in terms of business understanding and technology usages, a sample of incident dataset and correlation of system type failures and resolver groups, and to illustrate the framework of automatic resolver group assignment.

3.1 IT service desk outsourcing

IT service desk is a crucial function of an IT outsourcing provider who takes over IT functions from the bank. However, the bank desires service level targets based on the service level agreement (SLA) to control the IT service desk operations [18]. The purpose of the IT service desk outsourcing is to support customer services on behalf of the bank's technology driven business goals. The role of the IT service desk is to ensure that IT incident tickets are owned, tracked, and monitored throughout their life cycle. In this case, we study the IT service desk outsourcing of a bank in Thailand.

There are three main agent levels for resolving incident end-to-end process. These are (1) First level support, called FLS, which is the Bank help desk agents; (2) Second level support called SLS is IT service desk outsourcing agents; and (3) Third level support called TLS is resolver groups. In this case, we focus on the IT service desk outsourcing, including SLS and TLS. The Tivoli CTI technology is used to interface among the three levels of agents in order to make them work simultaneously on the current ticket to be resolved by the target time. The internal users or external customers directly

contact the FLS agents with various incident reports. The incident reports are divided into two types depending upon the IT related that incident. One is Non-IT incident and another type is IT incident. Both are reported to FLS agents and then the agents review the reports in terms of incident types, initiate severity, complete necessary incident descriptions and then open the ticket one-by-one without recurring. The Non-IT incident tickets are resolved by bank's resolvers while IT incident tickets are assigned to the IT service desk outsourcing or SLS agents to resolve those incidents. Thus, the SLS agents review and validate the assigned IT incident ticket for adequacy and correctness based on outsourcing scope, incident types, and severity criteria. If the assignment is not correct both of FLS and SLS will be requested to solve the issue. The valid IT incident ticket may be resolved by the SLS agents using knowledge management system [3] or be assigned to the TLS to resolve the incident. TLS agents include five main resolver groups; (1) EOS (Enterprise Operation Support), (2) IE-AMS (Application Management Support), (3) NWS (Network Management Support), (4) OS-EC (Electrical Operating Support), and (5) VEN (Vendor). In this case, we improve IT service desk outsourcing's roles by proposing the model of automatic resolver group assignment. Figure 1 shows the framework of IT service desk outsourcing with automatic assignment.

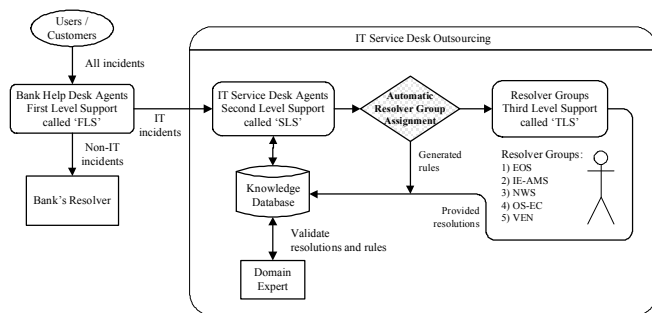


Figure 1. The model for IT service desk outsourcing with automatic resolver group assignment.

For the reason that the bank is already deploying strategies to improve the quality of IT services and reduce service delivery cost using some combination of outsourcing and internal process improvements as well as technology. Therefore, CTI technology and ITIL best practice frameworks are applied to the bank's and the outsourcing's functions. CTI technology such as Tivoli can help several agents working simultaneously and comfortably in tracking an incident through its life, the selection of the suitable resolver group to deal with that incident is still performed manually by IT service desk agents. However, the issue of incorrect assignment is still taking place. Another issue from the IT expert is that a one-to-one assignment may not help the ticket close completely, since one ticket may need more than one resolver.

3.2 Sample

Raw datasets are provided by the Tivoli system in a spreadsheet for 14,440 cases. They were collected for 4-months (April to July as shown in Appendix A, Figure A-1). Each column (or attributes) contains information about incident records. However, in this study, we focus on the information of four columns: incident descriptions, system-type failures, component failures, and the assigned resolver groups who are related to those system-type failures, since the objective of this paper is a text mining discovery methods to automatic assignment approach. Table 1 shows the number of incidents of various system types and resolver groups.

Table 1. The number of incidents of system-type failures and resolver

System-Type Failures	EOS	IE-MS	NWS	OS-EC	VEN
Hardware	0	0	5,605	1,841	294
Software	376	400	3,307	148	61
Network	0	0	308	593	1,120
Operation	0	6	6	6	18
Power Supply	0	0	0	357	0

3.3 Data preparation and method discovery

The raw dataset contains structured information about incident cases as previously described in Section 3.2. Figure 2 shows data preparation procedure for text mining discovery algorithms.

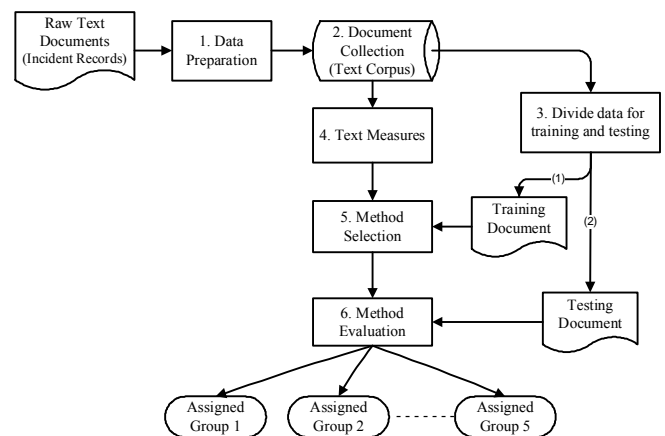


Figure 2. Data preparation procedure for text mining discovery algorithms.

For the model approach, we use the following six steps: 1) Data preparation with text documents of incident records; 2) Document collection or Text corpus; 3) Data divided for training documents and test documents; 4) Text measurement; 5) Method selection based on the training documents; and 6) Model validation based on the test documents.

3.3.1 Data preparation

Data preparation processes include data recognition, parsing, filtering, data cleansing [19], and transformation. In this case, we add data grouping by keywords. Hence, in this case, the data preparation processes are as follows:

(a) Data Recognition: identify the incident records collected from Tivoli CTI system as the sample of raw structured data in spreadsheet format.

(b) Data parsing: the purpose of data parsing is to resolve a sentence into its component parts of speech. We created another keyword dictionary and modify the program to execute both of a standard dictionary and the modified dictionary.

(c) Data filtering: involves selecting rows and columns of data for further document collection or text corpus. Consequently, the text corpus includes several columns, including system failure types, sub-system or component failures, incident descriptions, and assigned resolver group.

(d) Data cleaning: correct inconsistent data, checking to see the data conform across its columns and filling in missing values in particular for the component failures and assigned resolver groups.

(e) Data grouping: from the word extraction obtain a lot of words and then grouped them into the words of component and system-type failures.

(f) Data transformation: we transformed data prior to data analysis. Several steps need data transformation such as word extraction, text measurement, text mining via WEKA[4] and machine learning, which is applied to discover algorithms or methods, comparing several decision tree algorithms to find out the most suitable method for the nature of incident data.

3.3.2 Data separation

The sample dataset is divided into two document sets, (1) A training document consisting of 66% of the samples and (2) A test document set consisting of 34% of the cases.

3.3.3 Document collection

Document collection or so called “Text corpus” is the database containing text fields, which includes a sample of data. The data is a subset of the incident database. The textual fields are selected columns such as system type failures, component failures, incident descriptions, and assigned resolver group [20].

3.3.4 Text measures

The purpose of text measures is to find attributes that describe text in order to know how many keywords (KW_1 , KW_2 , ..., KW_n , where n is the number of words) related to the assigned groups are in the documents. We developed a program that provides text measures based upon word counts across the sample of the text documents. It displays the text measures.

3.3.5 Method selection

Method discovery is the core of text mining algorithms. Several decision tree methods; ID3, J48, NBTree, random forest, random tree, and REP Tree were implemented within the WEKA framework based upon the training dataset. The ID3 decision tree method was found to be the strongest method for the nature of that dataset.

3.3.6 Method evaluation

We propose an ID3-based model for the automatic resolver

group assignment. In order to validate the model, we implemented ID3 within the WEKA based on the test dataset.

4. Experimental Results

In this section, we divide the results into two parts, including: (1) the comparison results; and (2) method evaluation. The experimental results are as follows:

4.1 Comparison results

We conducted experiments to compare various decision tree algorithms within the WEKA framework. Based on the 66% of the sample dataset of 9,530 records, we used classified implementation of random tree, random forest, ID3, J48, NBTree, and REPTree by using 10-fold cross validation, which is to prevent overfitting. Table 2 shows the number of correct

Table 2. The number and percentage of correct incidents for various types of decision trees

Decision Tree classifiers	No. of Correct Instances	No. of Incorrect Instances	Accuracy of Classification (%)
ID3	8914	616	93.5362
Random tree	8914	616	93.5362
Random forest	8913	617	93.5257
J48	8896	634	93.3473
NBTree	8890	640	92.2844
REPTree	8866	664	92.0325

4.2 Method evaluation

To validate the Decision Tree-based model, the test data by default value 10-fold cross validation within WEKA platform were used. The test dataset is randomly selecting from 34% of the sample dataset for 4,910 cases. In addition, the IT experts who participate in the experiments also validated the result of validation. The results show the accuracy assignment was 93.06 % of the cases, which indicates the ID3 method is significantly suited for the model of decision support system for automatic resolution of group assignment.

4.3 Rule Generation results

A rule generation from the testing dataset based on ID3 decision tree method are shown in Figure 3 and Figure 4.

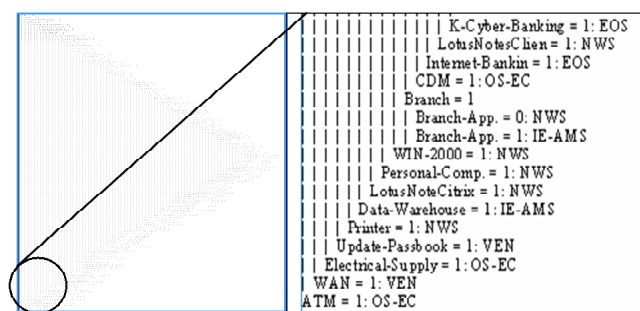


Figure 3. An Extended parts of the results of ID3

Attributes													Class
KW1	KW2	KW3	KW4	KW5	KW6	KW7	KW8	KW9	KW10	KW11	KW12	Assign Group	
ATM	WAN	E-Supply	Pushbook	Printer	D-Wardnet	Smartphone	P-Comput	Win2000	Branch	Branch-A	CDM		
0	0	0	0	0	0	0	0	0	0	0	0	OS-EC	
0	1	0	0	0	0	0	0	0	0	0	0	VEN	
0	0	1	0	0	0	0	0	0	0	0	0	OS-EC	
0	0	0	1	0	0	0	0	0	0	0	0	VEN	
0	0	0	0	1	0	0	0	0	0	0	0	NWS	
0	0	0	0	0	1	0	0	0	0	0	0	IE-AMS	
0	0	0	0	0	0	1	0	0	0	0	0	NWS	
0	0	0	0	0	0	0	1	0	0	0	0	NWS	
0	0	0	0	0	0	0	0	1	0	0	0	NWS	
0	0	0	0	0	0	0	0	0	1	1	0	IE-AMS	
0	0	0	0	0	0	0	0	0	1	0	0	NWS	
0	0	0	0	0	0	0	0	0	0	0	1	OS-EC	

The IF-THEN Rule generations from the rule table are as follows:

- IF keyword (KW) = 'ATM' THEN Assigned Group is OS-EC ELSE Go to 2,
- IF keyword (KW) = 'WAN' THEN Assigned Group is VEN ELSE Go to 3,
- IF keyword (KW) = 'E-Supply' THEN Assigned Group is OS-EC ELSE Go to 4,
- IF keyword (KW) = 'Pushbook' THEN Assigned Group is VEN ELSE Go to 5,
- IF keyword (KW) = 'Printer' THEN Assigned Group is NWS ELSE Go to 6,
- IF keyword (KW) = 'D-Wardnet' THEN Assigned Group is IE-AMS ELSE Go to 7,
- IF keyword (KW) = 'Smartphone' THEN Assigned Group is NWS ELSE Go to 8,
- IF keyword (KW) = 'P-Comput' THEN Assigned Group is NWS ELSE Go to 9,
- IF keyword (KW) = 'Win2000' THEN Assigned Group is IE-AMS ELSE Go to 10,
- IF keyword (KW) = 'Branch' THEN Assigned Group is NWS ELSE Go to 11,
- IF keyword (KW) = 'Branch-A' THEN Assigned Group is IE-AMS ELSE Go to 12,
- IF keyword (KW) = 'CDM' THEN Assigned Group is OS-EC ELSE Go to 13,

Figure 4. Rule Table and Rule Generation from ID3.

5. Conclusion

This article makes two contributions. Firstly, data preparation procedures proposed for text mining discovery algorithms. Secondly, the rule generation from data based on decision tree procedures proposed for knowledge acquisition. The comparison of several decision tree methods gave an ID3 decision tree is the strongest algorithm. It yielded correctly classified instance more than 93% of the cases. The proposed ID3-Based model for automatic resolver group assignment of IT service desk outsourcing in the bank. The method was validated based on the training dataset with 10-fold cross-validation and the accuracy of the results of the method was 93.54% of the cases. The experimental results indicate that the ID3 method is the optimal method to provide the model with automatic resolver group assignment that would significantly increasing productivity in terms of more assignments that are correct and thus decrease reassignment turnaround time. Furthermore, the results of the generated decision tree patterns by the methods that could also be kept in knowledge database in order to support and assist with future incident resolver assignments

For the future work, an ID3 decision tree method is suitable for automatic resolver group assignments based on dataset of IT outsourcing in the bank firm. The application of decision support system and automatic resolve group assignments should be developed based on the method.

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Appendix A

Figure A-1 shows a sample of incident dataset in spreadsheet.

No.	IncidentId	Open Date	Open Time	Resolve Date	Resolve Time	Problem Code	Assigned Group	Severity	System	Component	Incident Descriptions	Resolution Results
4036	TFB-00941903	21/6/2006	11:56:59	21/6/2006	11:57:27	CLOSED	IE_AMS	2	Software	CMAS	: 21/06/06 IBM K.จอม ชอให้เปิด Log ใหม่ สำหรับ สาขงกเคิดจาก DBA ทักการ start service ไม่	
3891	TFB-00925825	25/5/2006	9:29:44	25/5/2006	9:30:22	CLOSED	EOS	1	Software	K-Cyber Banking	: 25/05/06 K.Pornthep NMCC 4321 Inform K-Cy EOS_Unix K.songkran 4022 ได้ทำการ Ac	
2030	TFB-00932519	6/6/2006	9:12:31	6/6/2006	9:13:30	CLOSED	EOS	1	Software	Internet Bankin	: โทร. 02-470-1721 แจ้งปัญหาระบบ Internet Bank Activate Sorry Page" at 09:12"	
2558	TFB-00928258	30/5/2006	9:18:25	30/5/2006	9:20:00	RESOLVE	IE_AMS	3	Software	CMAS	: phl/SQไม่พบข้อมูลการสุจิจาล. PHA 11 กุมภาพันธ์ May 30th, 2006 10:05 This problem has s-	
2755	TFB-00940121	19/6/2006	15:17:46	19/6/2006	15:20:00	CLOSED	IE_AMS	0	Software	FX on web	: User แจ้งระบบ FX on web ใช้ระบบเข้ามา ปลงตาม 2006-06-19 14:40: Winat: Resolved by en.	
4359	TFB-00920896	17/5/2006	11:37:04	17/5/2006	11:40:00	CLOSED	EOS	1	Software	K-Cyber Banking	: 17/05/06 K.Nipon(NMCC) 4321 inform K-Cybe activate sorry page แล้วใช้งานได้ปกติครับ 1	
2919	TFB-00919138	15/5/2006	12:34:38	15/5/2006	12:37:35	CLOSED	IE_AMS	3	Software	Data Warehouse	: จากอุรุพันธ์ ติดต่อกับสิริธร 02-470-3397 เนื่องจาก user ไม่ได้ analyze table ที่เป็นขอ-	
3834	TFB-00929544	26/5/2006	9:37:40	26/5/2006	9:40:40	FINESD	FINES	1	Software	K-Cyber Banking	: คุณพรเทพ NMCC โทร.4721 K-Cyber Banking activate sorry page แล้วใช้งานได้ 9:30	
1201	TFB-00934034	9/6/2006	17:28:33	9/6/2006	17:30:00	CLOSED	EOS	3	Software	LotusNotesClien	: สาขงป๋ากจาก โทร.042-404280-3 ข้อมูล Drive EOS have checked and found that all files	
118	TFB-00897571	1/4/2006	10:09:25	1/4/2006	13:09:08	CLOSED	NWS	3	Hardware	Printer	: เครื่องพิมพ์ 4722 ส่วนประกอบ Cash Service ทำข้างจากได้เป็นต้นที่เริ่มให้ไฟฟ้ตอนนี้สามารถ	
199	TFB-00897633	2/4/2006	13:01:01	3/4/2006	9:54:21	CLOSED	NWS	3	Hardware	Printer	: Printer =>ไม่ Start ใช้งานไม่ได้ Type 9008 SM ซ้ำจนหมดได้เปลี่ยน Panel ให้ไฟฟ้ตอนนี้สามารถ	
1182	TFB-00898152	3/4/2006	14:05:57	3/4/2006	14:48:12	CLOSED	NWS	2	Software	App-NonPC	: เครื่อง Server Boot ปกติ แต่จาก Boot ค้าง DZZ IBM Deskside K. ปะทะไฟ กำลังดำเนินการแก้ไข	
3284	TFB-00897922	3/4/2006	10:33:06	3/4/2006	11:50:54	CLOSED	NWS	3	Network	HQ	: RAT 19 ติดต่อกับ ซัก้า โทรห 4702174 (user ะ 304/06 11:49 change ip \user ok\W ataph	
3966	TFB-00999125	3/4/2006	13:46:09	3/4/2006	15:06:39	CLOSED	NWS	3	Software	MS Office 2000	: ซัก้ากรายชื่อ ขึ้น 16 MS Excel เวลาเปิดโปรแกรม reinstall excel 2000\user ok	
2646	TFB-00966544	11/11/2006	8:22:41	11/11/2006	8:29:33	CLOSED	US_EC	2	Hardware	Server	: server PU 304 ไม่เข้า server	
1201	TFB-00952113	7/7/2006	9:03:37	7/7/2006	9:10:51	CLOSED	OS_EC	3	Network	CDM	: CDM05098 (IP) CDM ที่ขอมาหาผลลิตา (746): HAS BEEN DISCONNECTED	
3863	TFB-00928077	29/5/2006	18:26:20	29/5/2006	18:34:00	RESOLVE	VEN	3	Network	WAN	: S1B2552 (IP) โปรแกรม PS 2 ป้าของ อุศักดิ์ (ศูนย์ ping&SSMM atm up 18.34	
3638	TFB-00911167	28/4/2006	9:12:18	28/4/2006	9:20:00	RESOLVE	EOS	2	Software	KBANKNET	: โทร. 02-273-1332 User id=doaser1, doaser ปัญหาได้โดนบันทึกส่งให้ศูนย์ซ่อม OS_EC และ	
148	TFB-00935020	9/6/2006	7:41:56	9/6/2006	7:49:38	CLOSED	OS_EC	2	Hardware	Personal Comp.	: ไฟฟ้าเข้าจาก server / type 9331-4oe s/n 23nyg0	
2910	TFB-00919133	15/5/2006	12:32:04	15/5/2006	12:40:00	CLOSED	IE_AMS	3	Software	Data Warehouse	: จากอุรุพันธ์ ติดต่อกับสิริธร 02-470-3397 AMS เนื่องจาก user ส่ง SQL Statement ที่	
4222	TFB-00898155	3/4/2006	14:07:33	3/4/2006	15:28:27	CLOSED	NWS	3	Hardware	Printer	: Naming:ไม่มี MT 4722 S/N:41-FV512 สาขางนี้ เปลี่ยน Mechanic ให้ไฟฟ้ตอนนี้สามารถใช้งาน	
3125	TFB-00944097	26/6/2006	9:32:19	26/6/2006	9:40:28	CLOSED	IE_AMS	1	Software	CIPS	: ลม/SSไม่พบการแจ้งการพักพิมพ์ คุณ สิทธิ โทร. สาขงกเคิดจากจาก shutdown ที่ไม่ยอมยกเลิก D	
2633	TFB-00921386	17/5/2006	16:47:32	17/5/2006	16:56:01	CLOSED	OS_EC	2	Software	K-Cyber Banking	: โทร. 02-470-1774 แจ้งปัญหาระบบ K-Cyber Banking ถึง Back Office เข้าระบบไม่ได้ขึ้น The p	
4663	TFB-00933869	7/6/2006	14:40:57	7/6/2006	14:49:30	CLOSED	VEN	3	Network	WAN	: S1B3739 (IP) ที่อปส์ ฟูปเปอร์มาเก็ตข้างของ (สุ IT&T)คุณเอกพงษ์ เข้าใจที่ชุมสาย	
3993	TFB-00898193	3/4/2006	14:38:02	3/4/2006	16:17:52	CLOSED	NWS	3	Hardware	Printer	: ขอการบริการและทักถาม 3 พระยาของ คุณสมหวัง user k สมหวัง test ok	
3679	TFB-00927791	29/5/2006	13:51:18	29/5/2006	14:00:00	RESOLVE	FINES	2	Software	Internet Bankin	: ขึ้นสเ NMCC 4321 แจ้ง K-Cyber ซัก้า activate sorry page แล้วใช้งานได้ครบ 14:00	
3629	TFB-00928260	30/5/2006	9:21:05	30/5/2006	9:30:00	RESOLVE	EOS	2	Software	K-Cyber Banking	: คุณชนัน 4321 แจ้ง k cyber banking ซัก้าทักจาก K. Songkran activates Sorry Page" at 9:16	
3133	TFB-00897765	3/4/2006	8:54:59	3/4/2006	10:35:01	CLOSED	NWS	3	Hardware	Printer	: ***** หมายเลข ขอส่วนอื่น เนื่องจากเครื่องของ user k สัพพนี้ tes ok	
3973	TFB-00942599	22/6/2006	14:35:21	22/6/2006	14:44:32	CLOSED	VEN	3	Network	WAN	: user แจ้งปัญหา link true nodeบนสาขา คอนันใช้ชื่อ Contact True check line and let Branch us	
4480	TFB-00935850	11/6/2006	5:46:56	11/6/2006	5:56:23	CLOSED	VEN	3	Network	WAN	: S1A3295 ATM ทัก.ส่งไฟฟ้จุดสาขาทักถาม ประชาอุ True reset port atm up	
407	TFB-00897861	3/4/2006	9:38:32	3/4/2006	11:26:47	CLOSED	NWS	3	Hardware	Printer	: 14D4001A1083 // สาขางนบางนาทักถาม ณ. 4 ี ซัก้าสนัไม่ได้เปลี่ยน printhead ตอนนี้ใช้งานไม่	

Figure A-1. A sample of incident dataset.