An Application of Process Mining for Queueing System in Health Service

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***Abstract*—Health services are looking for ways to improve the processes and optimize the service time. Process Mining has been applied in the process discovery in variety of domain. The process mining is a promising method to discover the activity behaviors. However, early applications of process mining do not support the queue analysis. In this work, we introduce the method for applying process mining with queue system for health services. Process mining was used for the process discovery and the queueing theory was used to model the performance. The experiment shows that the process mining discovered the actual process model and provided the information to construct a queueing model. The method is suitable for analyzing control-flow and time performance in health service domain.**

Keywords; Process Mining, Workflow Analysis, Queue system

I. INTRODUCTION

Business process analysis in health service is very dynamic, complex and multi procedures [1]. Process Mining is an approach to understand those processes by using event log from information systems. The analysis of business process in health service is important to control and improve health service processes [2], for example, identify pathway behaviors and process variants. The performance indicators in quality of service such as waiting time, service time and queue analysis play the major role in health service [3]. Patients spend a lot of time waiting in the queue. Because there are sequence of services, when the patients arriving at a time, they were to wait in queue and transfer to multiple activities. Although, process mining can discover the activity flow but it does not present the information on performance.

This study introduces a method for the application of process mining to explore activity flows and apply queueing theory to analyze waiting time. Activity flows from process mining represent all activity behaviors, number of patients and average service time in each path. The usefulness of process mining mitigated the problem of collecting the data manually. This work includes the queueing model to analyze the queue length and the waiting time. The proposed method was applied to a real case from a public hospital with the data of 334 records.

II. PROCESS MINING

A. Overview of Process Mining

Process mining has been applied in many business domains [4]. Process mining can explore the behavior of activities, operation machines, and organization workflows. There are three types of process mining: discovery, conformance and enhancement.

- Discovery: The discovery technique inputs an event log and produces a process model. Many techniques have been developed to discover the control-flow perspective such as the inductive miner that uses event logs and produces a process model (a Petri nets) explaining the behavior recorded in the log.
- Conformance: The conformance technique is used to check if reality conforms to a model [5]. For example, the medical guideline protocols described the order for diagnosing stroke patients. The treatment activities are the brain scan, the lab test and the critical treatment that need to be done while in reality this may not happen. Conformance checking used to detect mistake from this workflow, to identify and descript these mistake.
- Enhancement: The enhancement is to extend or improve an existing process model using information about the actual process recorded in some event log. This technique assumes that there is an a-priori model.

In addition, process mining has various perspectives, e.g., the control-flow perspective, the organizational or the resource perspective, and the time perspective.

- *The control-flow perspective* focuses on the control-flow. For example, the order of activity behaviors. The objective of this perspective is to find all possible activity paths.
- *The organizational perspective* focuses on the information about the resources in the activity which the actors are used. For example in health services, the doctors, nurses or beds.

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- *The time perspective* focuses on the timing and the frequency of events. The events with timestamps can be used to discover the bottlenecks, to measure the service levels, to monitor the utilization of resources, and to predict the remaining processing time.

This work focuses on the *discovery* task and the *control-flow* perspective to discover outpatient activity behaviors. The control-flow in process mining represents all the activity behaviors, the number of patients and the average service time in each path. Then, this information is used to model the queue system.

B. *Event Logs*

The starting point in process mining is the event log [6]. Process mining approaches the data with a mental model that maps the data to a process view. The minimum requirements for an event log are three elements: Case ID, Activity, and Timestamp.

TABLE I. EXAMPLE OF EVENT LOG

Case ID	*Activity*	*Time Stamp*
5645773	OPD	19/8/2014 6:30
5645773	Lab	19/8/2014 7:05
5645773	Drug	19/8/2014 9:12
5645773	Billing	19/8/2014 9:28

From the sample data in Table 1, the simple activity processes related to the analysis, such as the frequency of processes, or the time between activities. For example, the event log from Table 1, one process instance (case 5645773) starts with the status OPD on 19/8/2014 6:30, moves on to LAB at 7:05, moves on to Drug at 9:12 and moves on to Billing at 9:28. So, the best complete event log must have the start time and the end time. The processing time and waiting time can be calculated. It will not be possible if the complete timestamp is missing

C. *Produce process model*

In this section, the process mining is used to produce a process model. To discover any process it is important to understand activities in workflow. The goal of creating a process model is to explore which the activities need to be executed and in what sequence.

1) *Transition System*

A transition system consists of states and transitions, TS = {S,A,T} where S is the set of states, A is the set of activities, and T is the set of transitions. The sets S^{start} and S^{end} are defined from the first state and the end state implicitly.

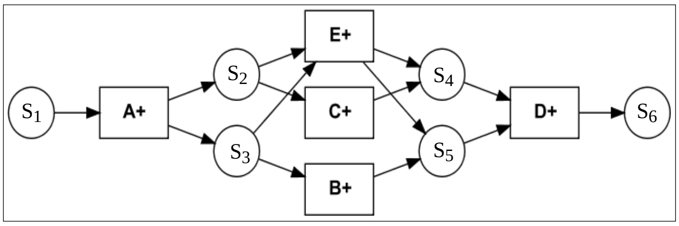

Figure 1. A transition system having one initial state and one final state.

The transition system in Figure 1 can be defined as follows: S = {s_1, s_2, s_3, s_4, s_5, s_6}, S^{start} = {s_1}, S^{end} = {s_6}, A = {A, B, C, E, D}, and T = {(s_1, A, s_2), (s_1, A, s_3), (s_2, E, s_4), (s_2, C, s_4), (s_4, D, s_6), (s_3, E, s_5), (s_3, B, s_5), (s_5, D, s_6)} The transition system in one path shows about its behavior. Any path in the graph starting in such a state corresponds to a possible execution sequence.

2) *Petri Nets:*

Transition systems are simple but they are not suitable to model concurrency. For example, there are n parallel activities, therefore there are n! possible execution sequences. The transition system requires 2^n states and $n \times 2^{n-1}$ transitions. Petri nets needs only 10 transitions and 10 places to model the 10 parallel activities. The network structure is static, but, governed by the firing rules, tokens can flow through the network. The state of a Petri nets is determined by the distribution of tokens over places and is referred to as its marking.

3) *Inductive visual miner:*

It is a discovery approach to construct a Process Tree from a given log. Many available process exploration tools do not produce models having executable semantics definition of Process Trees [7]. Inductive visual Miner (IvM) supports process exploration and improves on evaluation by a new notation and the addition of animation (Fig. 2) and quick node selection filtering.

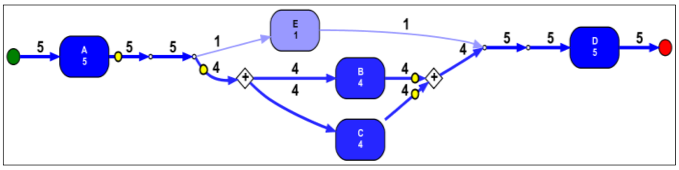

Figure 2. Process discover with inductive visual miner

Process discovery has many techniques and tools. This work used inductive visual miner which avilable in ProM (www.processmining.org). This technique built the process model that represents the control-flow, the number of frequent activities (the number of patients) and the average service time. This model does not represent the time performance in queue length and the waiting time. Therefore, this work combines this information with the queue system and build a queueing model for analizing patients waiting time.

III. QUEUE SYSTEM

Predicting the queue length and the waiting time has been a popular research in queueing theory. In queuing mining [8] the delay time was predicted using mathematical functions. However, the graph model shows activity behaviors and all possible paths for analyzing the time performance.

The problem of hospital's waiting time is based on the number of patients [5]. There are multiple procedures and patients move between these procedures. When the number of outpatients arriving, they were to wait in queue. The long waiting time effected to service performance in health service. For example, the outpatient behaviors (in Table 1 and expanded in Fig. 3) are registered in OPD, Lab test, X-ray, Drug, and Billing. However, not all patient activities were ordered in the same sequence. The quality index of queueing system such as the average of the queue length, the waiting queue length, duration of stay and waiting time were used to analyze the time performance.

The queueing models in standard single server are [9]:

λ = Average Arrival Rate (person per hour)

μ = Average Service Rate (person per hour)

L = the number of patients

$$L = \frac{\lambda}{\mu - \lambda} \tag{1}$$

Lq = the number of patients in queue

$$Lq = \frac{\lambda^2}{\mu(\mu - \lambda)} \tag{2}$$

W = waiting time in system

$$W = \frac{1}{\mu - \lambda} \tag{3}$$

Wq = waiting time in queue

$$Wq = \frac{\lambda}{\mu(\mu - \lambda)} \tag{4}$$

Hospital queueing system consists of many stations. Generally, the order of patient activities are OPD, or LAB, or Drug, Billing and End. All nodes are parallel service stations. The most common service rule is FCFS (first come first serve). This work followed this rule.

IV. Methodology

The proposed method comprised of (1) the preparation of event logs (2) build the process model (3) combine with a queue system (4) improve the process (5) report the experimental results

A. *Preparation of event logs*

The main purpose of this step is to build the event log from health information system. The propose method used the real case from a public hospital with 334 outpatient records in a general department. The event logs are collected from one day at the peak of the month and they met minimum requirement for process mining. The attributes included the case-id (the visit number), the activity (the name of department), and the timestamp. The process mining tool accepted the .csv file. Then, the tool transforms the data to the XES file that is used for modeling.

B. *Process Mining built process model*

The graph model generated many traces which are called activity behavior pathways (Fig. 3). The variant of activity behavior pathways is based on patient activities. The first circle on the left is start. The other circle on the right is the end. Each pathway weight represented the number of patients. The nodes of graph represented the activity name and the average service time. For example trace:

Start -> OPD -> LAB -> X-ray -> Drug -> End

From OPD -> LAB shows 89 patients and average service time 1.03 hour.

From LAB -> X-ray shows 20 patients and average service time 1.30 hour.

From X-ray -> Drug shows 11 patients and average service time 1.15 hour

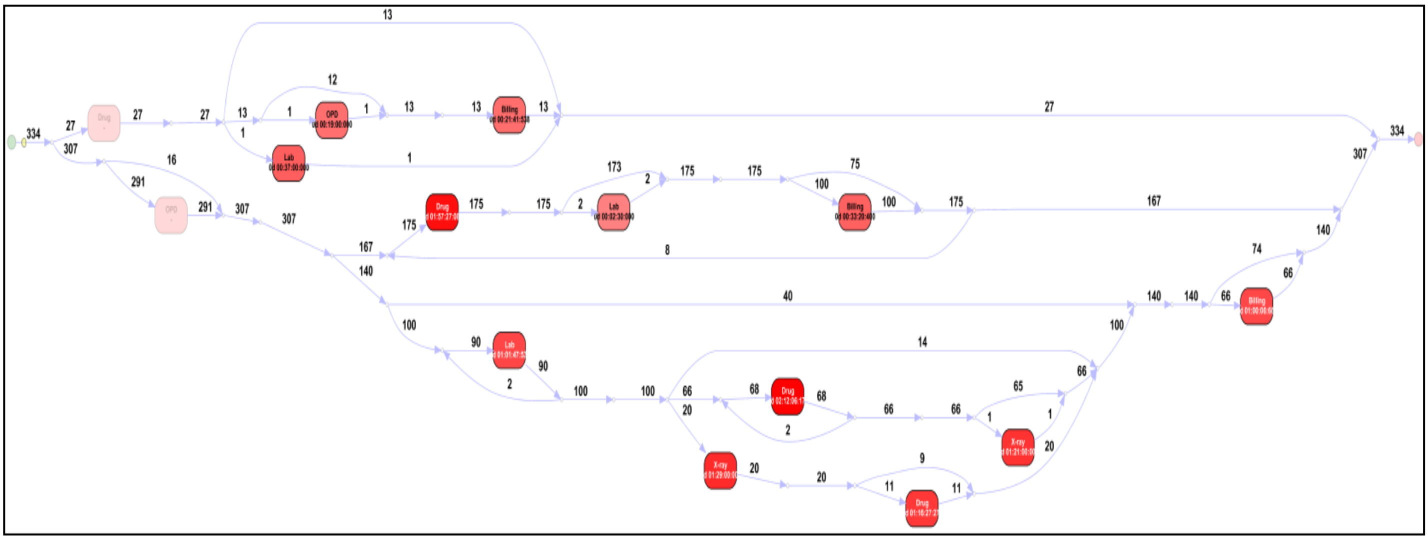

Figure 3. Process model built by inductive visual miner

It was found that there are 10 distinct pathways. From the start, the percentage of regular activity behaviors is 87% (291 patients), and 13% (27 patients) of infrequent activity behaviors. The nodes from different order are independent to processing. Each node has the number of patients and the average waiting time.

The inductive visual miner achieved the process discovery. To analyze the queue performance such as the queue length and the waiting time, it is necessary to use a queueing model. It is explained in the next section.

C. *Process mining included queue system*

The process mining requires minimum event log with a complete timestamp that contains the start-time and the end-time of activities. If the event logs are incomplete (for example, have just one timestamp), it will not be possible to analyze the processing time and the waiting time. A queue system is used to solve this problem. In the traces of graph model, there are some information (the number of patient and the average service time) that can be used for timing calculation. The queue system quality index can be used to predict other relevant results. The service time can be calculated from the number of patient divide by the average service time.

The process model shows average service time and the number of patients.

From queue quality index:

μ = Average Service Rate (person per hour)

L = the number of patients per hour

$$L = \frac{\lambda}{\mu - \lambda} \qquad (1)$$

From the equation, we can find λ . Then, if we knew λ we can calculate W, Wq and Lq (from equations (2), (3), (4)). The process model shows many traces that can be used to calculate the average value. For example, the prediction of λ in OPD node can be computed. OPD nodes have three directions.

OPD-Drug, the average service time = 2 hours, the number of patients = 166

μ = 166/2 = 83.5 person per hour

$$166 = \frac{\lambda}{83.5 - \lambda}$$

λ ~ 83 person per hour

OPD-LAB, the average service time = 1 hour, the number of patients = 89, μ = 89, λ = 86

OPD-Billing, the average service time = 0.21 hour, the number of patients = 1 μ = 45, λ = 40.5

The average of μ = 71.83

The average of λ = 69.83

Then, if we knew λ we will calculate W, Wq and Lq (from equation (2), (3), (4)).

$$Lq = \frac{\lambda^2}{\mu(\mu - \lambda)}$$

Lq ~ 47 persons

$$W = \frac{1}{\mu - \lambda}$$

W = 0.8 hour or ~ 49 minutes

$$Wq = \frac{\lambda}{\mu(\mu - \lambda)}$$

Wq = 0.82 hour or ~ 48 minutes

We applied this method with all of traces in process model.

TABLE II. WAITING TIME RESULTS

Activity	***Avg. service time (Hour)***	***L***	***Lq Person per hour***	***W minutes per person***	***Wq minutes per person***
OPD	3.21	256	47	49	48
LAB	3.30	84	31	88	86
X-ray	1.15	12	10	75	68
Drug	2	118	87	30	29
Billing	1.30	179	60	30	29

All nodes and paths were used in calculating the number of patients (L), the queue length (Lq), the waiting time in queue (Wq) and the waiting time in system (W) (Table 2).

The results in table 2 are based on the fixed resources. All of activities start at 6.00 am and end at 16.00 pm. The cost (C:H) is based on average income (baht) per hour.

TABLE III. RESOURCES AND COST

Activity	***Doctor***		***Nurse***		***Pharmacist***		***Staff***	
	qty	***C:H***	***qty***	***C:H***	***qty***	***C:H***	***qty***	***C:H***
OPD	3	900	5	1000	-	-	5	250
LAB	-	-	2	400	-	-	2	100
X-ray	1	300	-	-	-	-	5	250
Drug	-	-	-	-	5	500	5	250
Billing	-	-	-	-	-	-	5	250

The total cost per hour in OPD is 2,150 baht, LAB is 500 baht, X-ray is 550 baht, Drug is 1,050 baht and Billing is 100 baht per hour. Drug and Billing had the high queue length and had the low cost per hour. We suggest some scenarios for reducing the queue length and the waiting time. Our scenarios are:

- Scenario one: add one staff in drug process. This process used the average service time (μ = 77.4) 77.4 persons per hour and used the resource 13 staffs. The service time per staff is 6 patients. We added the staff from 13 to 14. The new μ is 14 × 6 = 84 persons per hour.
- Scenario two: add two staffs in billing station. This process used the average service time (μ = 124) 124

person per hour and used the resource 5 staffs. The service time per staff is 24 patients. We added the staff from 5 to 6. The new μ is $6 \times 24 = 144$ persons per hour.

TABLE IV. RESOURCE IMPROVEMENT

Activity	Improved rate			Cost: hour
	Lq	W	Wq	
Scenario 1	90%	80%	82%	100
Scenario 2	83%	90%	93%	50

This work focused only average income cost per staff. Costs such as office equipment are disinterested.

V. EXPERIMENTAL RESULT OF PROCESS MINING WITH QUEUEING SYSTEM

A. Process Mining Result

The process mining built the model from the actual activity behaviors. Health service requires flexibility and dynamic decision making. The process mining can be used to discover the behavior of these processes. Then it is possible to improve the process and the performance of their services. This work used the process mining to discover the activity behavior pathways. The model was built by inductive visual miner tools. The results are reported in two perspectives: the control-flow perspective, and the time perspective.

1) Control-flow perspective: This work used 334 patient event logs from the health information system database in a general outpatient department. The graph model generated the actual activity behavior pathways. The service must be started from OPD before transfer the patient to the another department. But, the model shown in Figure 3 had some path that starts from Drug (27 patients). The chief of the information system confirmed that path can happen with the patients who filled the chronic disease medicine or requested the service more than one department. However, the staff in OPD must record the history of this case previously. Control-flow perspective monitors the real process from actual event logs and help to discover what activities are important and how to improve some process.

2) Time perspective and performance: Event log properties were minimum requirements (Case ID, Activity, and Timestamp). The weights of graph model represent the frequency of patients who execute this activity and the average service time. In Table 2, the highest frequency was the billing process. Clearly, most patients finished in the billing process. The highest average service time was LAB process because some specimen has been processed many times for the result. In addition, the other performance such as the queue length and the waiting time are the key performance which are computed by combining the graph model with the queueing model.

B. Queuing Model Result

The information from process mining (activity behavior pathways, the number of patients, and average waiting time) were provided to the queue system. This work applied the queue system to predict the queue length, the waiting time in queue, and the waiting time in system. The queue quality index equations were used to calculate the time performance by using the data from process mining. The two processes that had the high queue length were Drug and Billing. Two processes that had the high waiting time were Lab and X-ray. This was consistent with the graph model from process mining. In addition, this work presented the resources that used in the processes. To improve the process, the low cost per hour of processes were chosen. In Table 4, we suggested two scenarios. Scenario 1, the queue length was reduced 90%, the waiting time in queue was reduced 80%, and the waiting time in system was reduced 82%. The cost was increased 100 baht per hour. Scenario 2, the queue length was reduced 83%, the waiting time in queue was reduced 90%, and the waiting time in system was reduced 93%. The cost was increased 50 baht per hour.

VI. CONCLUSION

This work proposed an application of process mining for a queueing system in health service. The process model was built from patient data and it was analyzed to get the time performance in the services. Process mining is used to discover the model and provides relevant information for making decision. The model is based on the real data from event logs. This work combines process mining with queue system and it is applied to analyze control-flow and time performance. It is also offer suggestions to the hospital administrator on how to improve their processes.

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