베이지안 규칙을 사용한 비즈니스 프로세스 관리 시스템에서의 인적 자원 배정

Bayesian Selection Rule for Human-Resource Selection in Business Process Management Systems

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초 록

본 연구에서는 비즈니스 프로세스 관리(Business Process Management, BPM) 환경에서 자원의 성능에 영향을 미치게 되는 여러 요소를 고려하여 인적자원을 선택하는 방법론을 개발한다. 스케줄링에 있어서 자원의 선택 문제는 작업 수행도에 직접적인 영향을 미치기 때문에 중요한 문제로 인식되어져 왔다. 비록 많은 문제에 있어서 전통적인 자원선택 방법론이 의미를 가져왔으나, 인적자원을 다루는데 있어서는 가장 좋은 방법론이라고 볼 수 없다. 인적자원은 작업부하, 작업소요시간, 작업간 시간 등의 다양한 요소에 의해서 영향을 받는 특이한 요소이며 본 연구는 이러한 다양한 요소를 고려하여 작업자를 선택하는 방법론을 제시한다. 이를 위해서 베이지안 네트워크를 사용하며, 앞서 기술한 여러 요소들을 한꺼번에 고려하기 위한 베이지안 선택규칙(Bayesian Selection Rule, BSR)을 도입하였다. 또한, 시뮬레이션을 통해서 본 연구에서 개발된 방법론이 대기시간, 작업수행시간과 사이클 타임을 줄일 수 있음을 보였다.

ABSTRACT

This study developed a method for selection of available human resources for incoming-job allocation that considers factors affecting resource performance in the business process management (BPM) environment. For many years, resource selection has been treated as a very important issue in scheduling due to its direct influence on the speed and quality of task accomplishment. Even though traditional resource selection can work well in many situations, it might not be the best choice when dealing with human resources. Human-resource performance is easily affected by several factors such as workload, queue, working hours, inter-arrival time, and others. The resource-selection rule developed in the present study considers factors that affect human resource performance. We used a Bayesian Network (BN) to incorporate those factors into a single model, which we have called the Bayesian Selection Rule (BSR). Our simulation results show that the BSR can reduce waiting time, completion time and cycle time.

키워드 : 베이지안 네트워크, 자원 선택 규칙, 비즈니스 프로세스 스케줄링
Bayesian Networks, Resource Selection Rule, Business Process Scheduling

This work was supported by a two-year Pusan National University Research Grant.

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2011년 12월 02일 접수, 2011년 12월 28일 심사완료 후 2012년 02월 06일 게재확정.

1. Introduction

In the modern business environment, customer satisfaction is essential to a company's success and indeed its very survival. A crucial factor in this regard is timely provision of products and services. Most customers are unwilling to wait, and dissatisfied customers typically switch their orders to other companies. Resource selection for timely service provision, therefore, is crucial. Assignment of a job to the appropriate (correct) resource, either human or automated, ensures faster job processing.

Human resources are prevalent in financial services and public sectors. People are assigned to check files, review documents and come to conclusions on them. Companies rely on humans for such tasks because humans can make qualitative assessments that cannot easily be quantified by automated systems. Another issue is that of executive authority : Automated systems, for example, machines cannot perform the heuristics necessary when erroneous decisions have been made; only humans can.

Human resources, however, are more difficult to manage because they entail less constant processing time than automated resources. Several factors such as workload, hours of work, and human capacity can combine to determine human performance, and cannot be separately blamed when human resource performance decreases. Hancock and Desmond [1] established that workload, manifesting as fatigue, can affect human resource performance. The higher the workload, the more fatigued a human will become, leading to diminished performance.

Companies employ selection rules to assign specific human resources to incoming jobs. One of the common selection rules is LIDDLE (see <Table 1>), according to which an incoming job is assigned to the longest-idle human resource. Operation of this rule is easily seen in the process of teller selection at banks. Another selection rule is ORDER (<Table 1>), by which an incoming job is assigned to human resources in a certain preferred order. An example is a procurement request made to a department of finance. The finance head will determine whether to act on the request or not. Otherwise, the vice-head will do so.

The problem with such selection rules is that they typically are not ideal for human resources, especially when long working hours are involved. Here, complex factors determining a resource's speed are at play, and these include workload, queue, daytime, inter-arrival time, and, not least, human ability. Such factors can diminish system performance by lowering resource utilization, lengthening queues and slowing job completion.

Bayesian Network (BN) is a probabilistic causal model initially built by knowledge workers and later improved by evidence data. It has drawn considerable attention over the last few decades from scientists and engineers representing a number of different fields [2]. For example, numerous research studies have utilized BN to model knowledge in computational biology and bioinformatics (specifically with regard to gene regulatory networks, protein structures, gene expression analysis [3], medical document classification, information retrieval [4], image processing, data fusion, and decision support systems [5]).

The aim of our present study is to establish a new selection rule by assessing factors affecting human resource performance using BN : the Bayesian Selection Rule (BSR). The main feature of BSR is its incorporation of several factors affecting human resource performance into a single BN model for selection of the best resources for incoming jobs. BSR accomplishes this on the basis of an hypothesis that completion time will decrease. We demonstrate our method using a case study of a Driver's License Obtainment Process at the Police Department in Surabaya, Indonesia. The contribution of our paper is its application to BPM of a resource-selection mechanism that considers factors affecting human resource performance. To our best knowledge, this is the first study to do so.

This paper is organized as follows : Section 2 provides a brief overview of the most pertinent related work. Section 3 offers a detailed explanation of BN's selection rule. We show how this BN can be used to assign human resources based on their respective performance rates. Further, we simulate a Business Process (BP) to compare the performance of the BSR to those of other selection rules. Section 4 discusses an experiment demonstrating the proposed method's implementation and its results. Section 5 draws conclusions and looks ahead to future challenges.

2. Related Work

2.1 Bayesian Network (BN)

A BN is useful for prediction of the occurrence of certain events. A BN is a probability-based knowledge representation method appropriate for modeling of causal processes involving uncertainty [6]. A BN is a Directed Acyclic Graph (DAG), its nodes (also called BN variables) representing random variables and its links defining the probabilistic dependences of those variables [7]. These relationships are quantified by associating a conditional probability table with each BN variable, given any possible configuration of values for its parents.

There are several definitions that can be assigned to a BN. For all definitions, let $G = (V, E)$ be a DAG with a node set V and an arc set E, and let $X = (X_v)_{v \in V}$ be a set of random variables indexed by v. The joint probability density function of a BN G with X as its random variables is

$$prob(x)=\prod_{v\in V} prob(x_v|x_{pa(v)}) \quad (1)$$

where $pa(v)$ is the set of parents of v. For any set of random variables, we compute the joint distribution probability as

$$prob(X_1=x_1,\cdots,X_n=x_n) \quad (2)$$
$$=\prod_{v=1}^{n} prob(X_v=x_v|X_{v+1}=x_{v+1},\cdots,X_n=x_n)$$

2.2 Traditional Selection Rules for Resource Allocation

Selection rules determine the resource(s) that is (are) to be allocated to an incoming job. Initially, selection rules were widely applied only in the manufacturing industry and within factory settings, but now, they are indispensible in various domains, includeing transportation, operating systems, business processes, and others. The several well-known selection rules defined in previous research are listed in <Table 1>.

〈Table 1〉 Established Selection Rules [8]

Code	Description
ORDER	Select from free resources in a preferred order
CYCLIC	Select resources in a cyclic manner, that is, select the next free resource starting from the last resource selected
LBUSY	Select the resource that has the highest usage (busy time) to date
SBUSY	Select the resource that has the lowest usage (busy time) to date
LIDDLE	Select the resource that has been idle for the longest period of time
SIDDLE	Select the resource that has been idle for the shortest period of time
RANDOM	Select randomly from among free resources according to pre-assigned probabilities

2.3 Bayesian Network, BPM, and Human-Resource Selection

BPM has specific resource-selection characteristics, which can be understood from two perspectives, the resource view and the control-flow view. With regard to resource view, their changing behavior (e.g., speed, availability) should be considered during resource selection. Failure to allocate a job to the correct resource can result in longer process execution or even bottleneck. With regard to control flow, the path of a job is determined in real-time execution. There can be a lack of or even no previous information on how a job will proceed in a business process. The ability to cope with this issue can speed up job accomplishment.

Traditional algorithms such as linear programming, tabu search and the genetic algorithm have been implemented for resource selection. Unfortunately, they fail to provide adequately appropriate solutions [9]. Other approaches, for example dynamic programming and reinforcement learning, can be applied to allocation problems such as job scheduling, grid computing, activity network and others, most of which, being domain-specific, cannot be directly mapped to business process resource selection [9].

BN is a promising method for BPM scheduling that has not been explored in any considerable depth. BN, significantly, can articulate factors in such a way as to model resource behavior in a causal-effect diagram, and can reinforce learning as business process execution is carried out. BN includes a strong statistical concept that ensures a model's reliability. Moreover, BN's representational aspect, its causal-effect diagram, aids the reader's understanding. This feature surely can help non-statistician workers to verify the BN model, thus increasing the success rate of BN prediction.

3. Bayesian Selection Rule (BSR)

3.1 Work Factors

The BSR is formulated by means of the BN model, which incorporates the factors determining human-resource performance. We identified nine work factors affecting human resource performance (see <Table 2>) based on the previous study in human management domain.

Workload is perceived as a very important factor affecting system performance [14]. Workload is defined as the number of tasks waiting to be processed by the system [14]. There are strong relations among stress, workload and fatigue [1]. A high workload

〈Table 2〉 Work Factors Affecting Human-Resource Performance

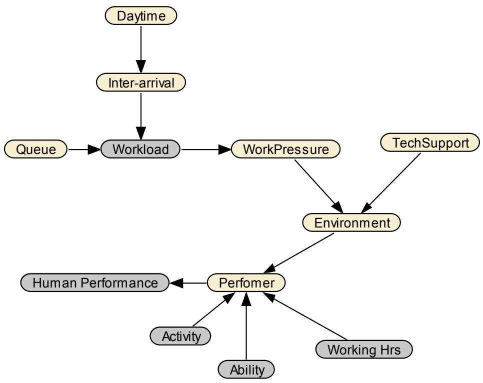
#	Factor	Possible States	Notes	Ref.
1	Workload	low, medium, high	Human resource's activity workload	Hancock and Desmond [1]
2	Queue	low, medium, high	Queue at human resource's activity	-
3	Inter-arrival	short, medium, long	Mean of inter-arrival time/hrs calculated from systems	-
4	Daytime	morning, afternoon, evening		Hines [10]
5	Working Hrs	first(09:00~13:00), second(13:00~16:00), third(16:00~)	Human resource's working hours	White and Beswick [11]
6	Ability	low, medium, high	Human resource's skills and ability	Murphy [12]
7	Work Pressure	low, medium, high	Human resource's work pressure	Hancock and Desmond [1]
8	Technology Support	low, medium, high	Technology used by organization	Woo and Postolache [13]
9	Environment	low, medium, high		

can increase stress and can result in fatigue, both of which can hinder performance. There are two factors influencing workload : arrival and completion of jobs in the system. Here, arrival can be represented by inter-arrival time. However, workload itself is a factor that increases work pressure in a working environment. As Hancock and Desmond stated in their book, a high workload increases work pressure for humans by creating an excess of stress [1].

Daytime also has a relation to human resource performance. Hines [10] found that some people prefer to work in the morning and some others in the evening. White and Beswick [11] reported that the longer human work, the more their performance decreases.

Human skill is strongly correlated with the speed of job accomplishment [12]. The more skillful the human resource, the faster a job will be completed. We denote skill as the humanresource's job-related cognitive ability. We interviewed human resources so as to understand how long they have been in their current assignment. The resultant data will be the basis for determining the skill of each human resource in our model. Woo explored the relation between working environment and human resource mood [13]. He found that a good working environment could maintain a human resource's positive mood. If a good mood can be maintained furthermore, so too will work quality be maintained. Both technology support and work pressure can influence a working environment. Good technology support can help workers complete their jobs in a timely manner and with a good result. An appropriate level of work pressure can enhance workers' efficiency and effectiveness; however, an excess of work pressure can produce stress, thereby diminishing performance.

Based on <Table 2>, the Bayesian Network model illustrated in <Figure 1> can be generated. The BN model in <Figure 1> is partially established by those in <Table 2>. Additional nodes such as human performance, performer, and activity are added to accommodate real world condition. These nodes have specific states, which are highly depending on the business process real-world operation. Activity is a node to indicate the name of activity, and a performer is a node to indicate the name of human resources in the process. All possible activity names are captured in the activity states while all possible human resource names are captured in the performer states. Hence, different business process will introduce different activity states and performer states. Human performance is a node to sum up the human resource performance. We indicate that human resource influences human resource performance. Here, we perceive that performance is merely on the ability of human resource to accomplish a job in a shorter period of time. Each human resource has three possible levels of performance : high, medium, and low. High means the ability of human resource to finish a job in very short period of time, while medium and low means that human resource will finish the job longer.



〈Figure 1〉 Bayesian Network for Human Resource Selection

The human resource, a Performer, is influenced by several factors such as activity, working hours, ability, and environment. Environment is a node that summarizes work pressure and tech support in a company. It also represents a working environment where human resources are carrying out their job responsibilities. Working pressure is how much stress human resources will get, which can summarize the workload rate at the company, and technical support is the level of technology used by human resources when they perform their work. The more sufficient technology used by the human resource, the better performance a human resource can have. Technology support also perceives the continuity of the technology while human resource is performing jobs. For example, when either electricity or network is often down, it means that the technology support is low. All aforementioned nodes are given as causal relationships, which are established by experts. Except the activity node and performer node, all nodes have general characteristics. Hence, it can be applied to various applications in scheduling as long as they involve human as the main performer.

Workload is the average utilization of a specific resource. We can see that workload is affected by queue and inter-arrival. In addition, inter-arrival is itself influenced by daytime. In Indonesia, customers tend to come in the morning and after lunch. The time before, between and after those two times are relatively quiet.

3.2 Simulation Evidence and Human-Resource Selection

To ensure the prediction's quality, it is necessary to periodically update BN knowledge by incorporating observed (the evidence) BN variables. We update the BN once a job is accomplished in one activity. The BN variables (working factors) that we update are listed in <Table 3>. <Table 3> lists the BN nodes that will be used as evidences of Bayesian Network (BN) model in predicting human performance since not all the nodes will be used as evidences. <Table 3> is derived

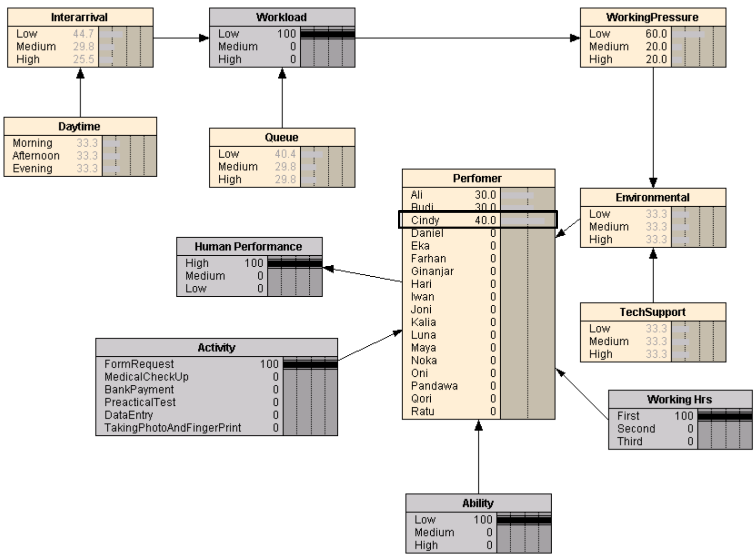
〈Table 3〉 Updated Simulation Evidence

#	Factor	Possible States	Notes	Ref.
1	Workload	low, medium, high	Human resource's activity workload	Hancock and Desmond [1]
2	Queue	low, medium, high	Queue at human resource's activity	-
3	Inter-arrival	short, medium, long	Mean of inter-arrival time/hrs calculated from systems	-
4	Daytime	morning, afternoon, evening		Hines [10]
5	Working Hrs	first(09 : 00~13 : 00), second(13 : 00~16 : 00), third(16 : 00~)	Human resource's working hours	White and Beswick [11]
6	Ability	low, medium, high	Human resource's skills and ability	Murphy [12]
7	Performer	{name of the human resource}		-
8	Activity	{name of the activity}		-

based on <Figure 1> which depicts the BN model for human resource selection.

Human-resource selection is done when a job comes to an activity. The system will select an appropriate human resource based on a prediction of high performance. We input some evidence, regarding current workload, queue, inter-arrival, and daytime at the time the job comes to the activity.

<Figure 2> shows the human-resource



〈Figure 2〉 Human-Resource Selection at time t=n selection at time $t = n$. Consider that we have to select the best human resource to carry out an incoming job in activity "form request" when the workload is "low", the working hours are "first", and the human-resource ability is "low." However, we want to maintain human resource performance as "high". Thus we input all of the evidence (activity = "form request", workload = "low", working hours = "first", ability = "low", human performance = "high") and we determine that Cindy, at 40%, is the best human resource. The system should select Cindy to carry out the job; however, if Cindy is busy, the next-best human resource should be Ali and Budi, which have the same probability at 30%.

3.3 BSR Algorithm

3.3.1 Definition 1 Business Process (BP)

A BP comprises multiple activities each of which connects to each of the others, thereby forming a chain. This chain is the path on which a work process travels among activities. By means of BPMS, a BP can be modeled, executed, monitored, and evaluated. In this paper, we use BP defined by Bae et al. [15] as follows.

- $A = \{a_i | i = 1, 2, \cdots, N\}$ is the set of activities, where a_i is the i-th activity and N is the total number of activities in the process structure Ps.
- $L = \{l_{ij} = (a_i, a_j) \mid a_i, a_j \in A \text{ and } i \neq j\}$ is the link among activities where an element (a_i, a_j) represents that ai immediately precedes a_j.
- For a split activity a_i, such that $|SA_i| > 1$, where $SA_i = \{a_j | (a_i, a_i) \in L\}$, $f(a_i)$ = 'AND' if all a_i's should be executed; otherwise, $f(a_i)$ = 'XOR'.
- For a merger activity a_i, such that $|MA_i| > 1$, where $MA_i = \{a_j | (a_i, a_i) \in L\}$, $f(a_i)$ = 'AND' if all a_i's should be executed; otherwise, $f(a_i)$ = 'XOR'.

3.3.2 Definition 2 BSR

We denote $BSR(t, a_i)$ as the use of the BN model to allocate resources considering factors that affect human resource performance in a_i at time t. BSR (t, a_i) has several parameters :

- $R_a = \{r_n | n = 1, \cdots, N\}$ is the set of resources where r_n is the n-th resource and N is the total number of resources in a_i.
- $Q_a(t)$ is the queue in front of a_i at time t
- BN represents the Bayesian Network model
- $D_a(t)$ = {morning, evening, afternoon} is daytime at time t
- $I(t)$ = {low, medium, high} is the inter-arrival rate at time t
- $W_a(t)$ = {low, medium, high} is the workload in a_i at time t
- $Ab(r_n)$ = {low, medium, high} is the

ability of r_n

- $Wo(r_n)$ = {first, second, third} is the working hours of r_n

<Figure 3> shows the BSR algorithm. This algorithm is used to select resources from among all that are available. We define an object, namely RESOURCE (see line 5), which represents each individual human resource. We define function *do_inference* ($Q_a(t)$, R_a, BN, $D_a(t)$, $I(t)$, $W_a(t)$, $Ab(r_n)$, $Wo(r_n)$) as a probabilistic function using *BN*. The BN inference used in the BSR relies on the NETICA [16] which uses Junction Tree algorithm. Here, *High Performance, Activity, Queue, Human resource, Daytime, Inter-arrival, Workload, Ability, Working_hrs* are the names of the nodes in *BN*. The *do_inference* function is defined as follows :

$$P(\mathit{High\_Performance} = \text{"High"} \mid \mathit{Activity} = a_i,\ \mathit{Queue} = Q_a(t),\ \mathit{Human\ resource} = r_n,\ \mathit{Daytime} = D_a(t),\ \mathit{Inter\text{-}arrival} = I(t),\ \mathit{Workload} = W_a(t),\ \mathit{Ability} = Ab(r_n),\ \mathit{Working\_hrs} = Wo(r_n)).$$

The general idea is to pick the highest probability value among resources in one activity. We use bubble sort to accomplish that. Consider that a set of resources in a_i, which consists of three resources : r_1, r_2, r_3. We define *temp* as DOUBLE to store temporary value and RESOURCE *res* as a temporary resource. The initial value of *temp* is -999 (line 5). We then establish which re-

```
1   FUNCTION SELECT_RESOURCE (a_i, Q_a(t), R_a, BN, D_a(t), I(t), W_a(t), Ab(r_n), Wo(r_n)
2   BEGIN
3       BOOLEAN loop := TRUE;
4       RESOURCE res;
5       DOUBLE temp := -999;
6
7       WHILE (loop = TRUE)
8       {
9           FOR (INT index := 0;index<Ra_i.size(); index++)
10          {
11             value := do_inference (a_i, Q_a(t), R_a, BN, D_a(t), I(t), W_a(t), Ab(r_n), Wo(r_n));
12             IF (temp<value &&r_index IS IDLE) THEN
13                temp := value;
14                // r_index is the resource in the R_a with index = index
15                res := r_index;
16             END IF
17          }
18          IF (res! = NULL) THEN
19              loop := FALSE;
20          END IF
21      }
22      RETURN res;
23  END
```

〈Figure 3〉 BSR Algorithm

source introduces the highest inference *value* (line 7~21). First, we check r_1 and get 0.566. Since this is higher than temp, we change the value of *temp* to the r_1 value and set $res = r_1$. Second, we check r_2 and get 0.455. Since this value is lower than *temp*, we iterate the same procedure. Third, wecheck r_3 and get 0.4. Since the value is lower than *temp*, we reiterate the same procedure. After this step, the iteration procedure is completed, since the index is larger than the resources set size.

Here, the BSR will always find a feasible solution. BSR will assign a human resource once at least one job finishes its accomplishment. Otherwise, BSR will let all the jobs waiting in the queue. Thus, the loop to find the best human resource will always find its end. BSR also assumes that at least one human resource is performing in the activity, and there is no human resource move in and move out in the business process. Therefore, all human resources will perform, and there will be no deadlock due to a lack of performers.

The skill, pressure, technology support and environment are obtained through direct observation, and thus, very subjective. The skill is according to the police rank. A police officer who obtains a higher rank is assumed to have a better skill because he/she is likely to deal with the job longer. Pressure is according to the working environment captured by the observer. Working pressure is subjectively measured by seeing how the police officers work. When they look like stressful, it means that the working pressure for them is quite high. However, this condition is varying from one person to another, because some persons do not look very stressful, even though they have to cope up with high workload.

The technology support is about the technology used by the human resources while they are working. Sufficient technology support will lead to a faster job accomplishment; otherwise, the speed will be much reduced. Technology support can be computer devices or camera. Environment is an additional node to summarize working pressure and technology support. The additional node is introduced to reduce the computational time when doing inference. The environment describes how working pressure and technology support affect human performance.

It is necessary to add those subjectivities to increase the prediction quality. There are some situations that by incorporating subjectivity, we can improve prediction. The example is tossing a coin. Suppose there are two possible outcomes : Head and Tail. If we know that the coin is not balanced, we can set the probability of the outcome. For example, we set 30% for Head and 70% for Tail.

3.4 Case Study

We demonstrate our approach by way of a real case study on a Driver's License (Indonesian : SIM) Obtainment Process in

Surabaya City, Indonesia. In Surabaya, a citizen can apply for a driver's license at either of two places : Satpas Colombo or SIM Corner. Every day, around 300 people extend their driver's license and about 200 people obtain a new driver's license [16].

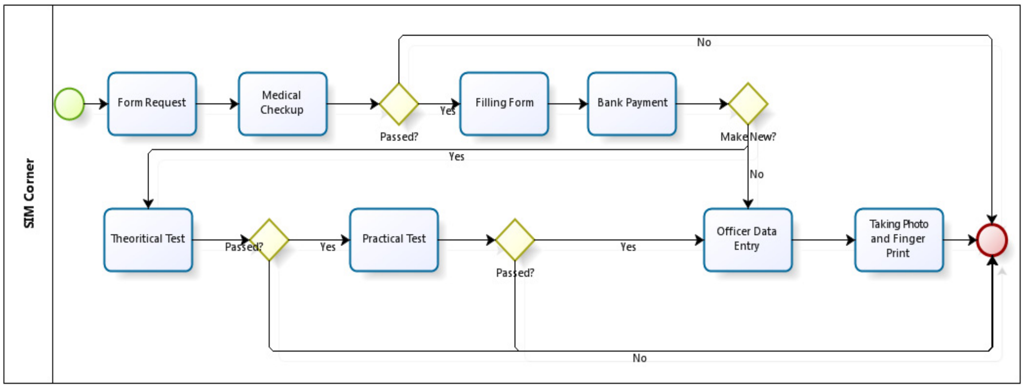
According to the latest observations, a long queue and high lead-time is common at SIM Corner, due to an imbalance between arrival rate and accomplishment speed. <Figure 4> shows the process of Driver's License Obtainment.

When customers come to get their driver's license, first they have to request a registration form and undergo a medical checkup. If they pass the checkup, they can then take and complete the form. In order to process their application, they have to pay driver's license obtainment fee. The fee amount is determined according to whether they are obtaining a new driver's license or an extended one.

There are two types of driver's license : a new license and an extended license. For those desiring to obtain a new driver's license, two tests have to be taken. The first is a theoretical test related to traffic regulations, safety regulations, and others. The minimum score is 60 out of 100. In cases of failure, the test must be retaken after two weeks. Where examinees pass, the second test can be administered.

The second test is a practical test of driver skill. The driver-examinee drives his vehicle on several types of route such as narrow road, 8-shape road, and others. If this second test is successfully passed, the customer's application data will be entered. As a final step, the customer provides identification, that is, a photo and finger prints. The procedure for extending a driver's license is similar, but without any tests.

The process of obtaining a driver's license is semi-automatic; it is highly dependent on human resources. The human resources have to start work at 10:00 AM in the morning and continue until 9:00 PM at night. It is nat-



〈Figure 4〉 Driver's License Obtainment Process ural that over this long time period performance fluctuates between good and poor. This affects service quality. It is important to maintain a good level of service quality by considering factors affecting performance. Traditional BPM does not consider these factors : when a customer arrives as a job, the system simply generates a schedule by which a job is assigned to the most appropriate resource.

4. Experiment and Results

We conducted an experiment to demonstrate how our proposed method can be implemented. We also qualitatively compared of our method with traditional selection rules.

4.1 Experiment Design

We conducted an experiment using AnyLogic and Netica. AnyLogic is simulation software released by XjTec, and Netica is BN software released by Norsys. The reason for using both is the shared platform : Java.

We obtain the data during four busiest days namely : Monday and Wednesday in the two subsequently weeks. We obtain at least 30 points in each human resource. The data observation is conducted from 9 AM to 3 PM. From the six hour data, we divide into three times : Morning, Afternoon and Evening. In the each time, a human resource has different processing time distribution. Here morning is identified is from 9AM to 11AM, afternoon is from 11AM to 1 PM and evening is from 1 PM to 3 PM For each time we obtain at least also 30 data, so that the total data we obtain for each human resource is at least 3×30 = 90 data. <Table 4> and <Table 5> show the distribution used in our simulation.

The objective of this experiment was to measure the effectiveness of the Bayesian Selection Rule compared with traditional selection rules. We chose four traditional selection rules : RANDOM, ORDER, SIDLE, and LIDLE. For the ORDER selection rule, we assigned a higher priority to a human resource with smaller index.

We measured the effectiveness of the selection rule in several ways, such as by completion time, by average waiting time, and by cycle time.

The running time of the simulation was set into 13 hours, from 8 : 00 AM to 9 : 00 PM. We divide the time into three : Morning (8 AM~12 AM), Afternoon (12 AM~4 PM) and Evening (4 PM~9 PM). When the time is morning, a human resource will follow morning processing time distribution, etc. For every selection rule, the average number of instances was 1500, and the number of replication was 10.

4.2 Input Parameter

Input parameter is a set of inputs obta-

〈Table 4〉 Distribution for Each Activity (1)

No	Activity	#Performer	Time	Performer
1	Form Request	Form Officer 1	Morning	normal (0.5468, 0.2173589)
			Afternoon	normal (0.58526, 0.28254)
			Evening	normal (1.104, 0.708141804)
		Form Officer 2	Morning	normal (1.03186, 0.716902)
			Afternoon	normal (0.888, 0.562754285)
			Evening	normal (1.03186, 0.716902)
		Form Officer 3	Morning	normal (1.24274, 0.9558)
			Afternoon	normal (1.287, 0.964985464)
			Evening	normal (1.2436, 1.030563068)
2	Medical Checkup	Doctor 1	Morning	normal (0.7714, 0.5810)
			Afternoon	normal (1.09048,0.6492059)
			Evening	normal (0.77083, 0.351725)
		Doctor 2	Morning	normal (1.80303, 1.521188)
			Afternoon	normal (1.602, 0.731334708)
			Evening	normal (1.74319, 0.613607)
		Doctor 3	Morning	normal (1.1543, 1.028704115)
			Afternoon	normal (1.2194, 1.263424238)
			Evening	normal (1.6818, 1.211255833)
3	Filling Form manually	Customer	-	normal (7.17, 1.779146797)
4	Bank Payment	Accountant 1	Morning	normal (0.6817, 0.48384073)
			Afternoon	normal (1.1742, 1.0784599)
			Evening	normal (0.84118, 0.64474)
		Accountant 2	Morning	normal (0.783, 0.73560255)
			Afternoon	normal (0.7, 0.208832735)
			Evening	normal (0.583, 0.153115788)
		Accountant 3	Morning	normal (1.780, 1.206233587)
			Afternoon	normal (1.17121, 0.5388353)
			Evening	normal (1.19085, 0.890812)
5	Theory Test	Customer	-	normal (15.2, 10)
6	Practice Exam	Officer 1	Morning	normal (7.22, 1.488252081)
			Afternoon	normal (6.27, 1.486007769)
			Evening	normal (7.12, 1.411014552)
		Officer 2	Morning	normal (6.65, 1.115855739)
			Afternoon	normal (7.03, 1.43422125)
			Evening	normal (6.38, 1.717206752)
		Officer 3	Morning	normal (6.68, 1.873760692)
			Afternoon	normal (7.10, 1.877697954)
			Evening	normal (6.37, 1.231971365)
7	Data Entry	Off Data Entry 1	Morning	normal (0.9478, 0.325860684)
			Afternoon	normal (1.78, 0.777808956)
			Evening	normal (2.0755, 3.21980696)
		Off Data Entry 2	Morning	normal (0.893, 0.513925138)
			Afternoon	normal (1.4471, 0.972597383)
			Evening	normal (1.7049, 1.138388919)

〈Table 5〉 Distribution for Each Activity (2)

No	Activity	#Performer	Time	Performer (Minutes)
		Off Data Entry 3	Morning	normal (2.04123, 1.205660601)
			Afternoon	normal (1.54305, 0.963965774)
			Evening	normal (1.49773, 1.080515158)
8	Taking Photo and Finger Print	Photographer 1	Morning	normal (2, 1.183744)
			Afternoon	normal (1.82, 1.82)
			Evening	normal (1.68125, 1.159463)
		Photographer 2	Morning	normal (1.26733, 0.603126)
			Afternoon	normal (1.32467, 0.69943959) (1.324666667, 0.69943959)
			Evening	normal (1.289, 0.919622275)
		Photographer 3	Morning	normal (1.589, 1.327077235)
			Afternoon	normal (2.110, 1.467686656)
			Evening	normal (25.6, 17.5)
9	Inter arrival	-	Morning	exponential (1) [as arrival rate]
			Afternoon	exponential (1) [as arrival rate]
			Evening	exponential (1) [as arrival rate]

ined by BSR during simulation run time. Input parameter is the current simulation environment update where the BSR is employed. The input parameters are useful to predict the best human resource to perform a job. There are several input parameters BSR uses : Workload, Inter arrival, Queue, Daytime, Ability, and Working Hour (see <Figure 3>). BSR will attach the input parameter in the BN as set of evidences. For example, at a period of time, the input parameters are equal to {Workload = "High", Queue = "High", Daytime = "Morning", Inter arrival = "High", Ability = "Good", Working_hrs = "First"}.

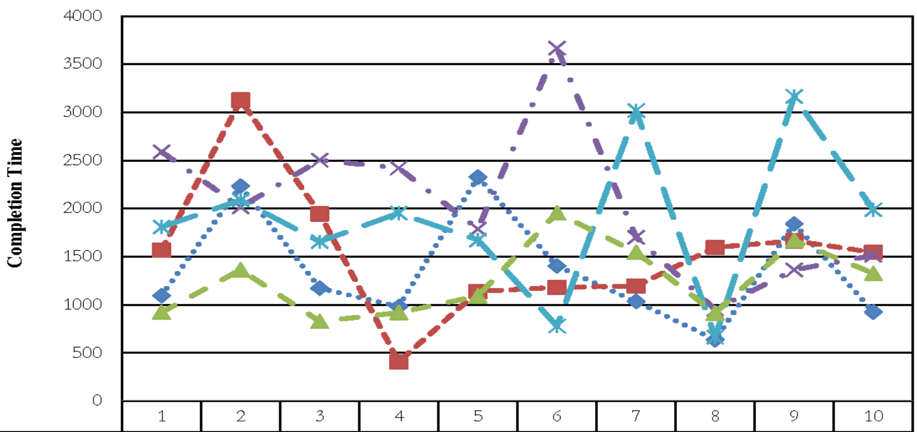
4.3 Experiment Results

<Table 6> lists the completion-time results for the five selection rules. We can see that BSR offers the shortest completion time and the lowest standard deviation. The second-shortest completion time is RANDOM, with a mean of 1365.669. The most interesting thing is that the standard deviation of the BSR is 33% lower than RANDOM and 53% lower than LIDDLE, which has the highest standard deviation. This result can be interpreted as indicting that BN prediction is quite accurate and that job completion, thereby, can be sped up.

<Figure 5> shows the completion times for 10 experiments. All of the selection rules experienced fluctuation, and the trends were quite difficult to capture. ORDER, in experiment #4, once had the shortest completion time, but also, once, the second-longest completion time. The BSR experienced less fluctuation than the other selection rules. The BSR never had the shortest completion time,

〈Table 6〉 Completion Time (in Minutes)

Replication #	RANDOM	ORDER	SIDDLE	LIDDLE	BSR
1	1096.167	1567.904	2590.262	1808.748	922.6673
2	2232.817	3127.327	2016.082	2088.21	1364.995
3	1171.825	1945.549	2502.724	1656.001	828.006
4	983.3494	407.1013	2421.051	1953.586	919.0942
5	2327.259	1139.865	1789.55	1674.413	1092.204
6	1403.965	1181.13	3668.057	779.2716	1954.795
7	1034.707	1195.526	1702.11	3018.147	1547.087
8	638.2284	1597.009	952.9931	664.4587	912.9886
9	1842.827	1664.555	1363.279	3165.451	1670.024
10	925.5398	1544.924	1514.428	1987.32	1326.165
Mean	1365.669	1537.089	2052.054	1879.561	1253.803
Standard Deviation	576.8249	698.775	774.9154	802.4066	382.0263



	1	2	3	4	5	6	7	8	9	10
RANDOM	1096.16	2232.81	1171.82	983.349	2327.25	1403.96	1034.70	638.228	1842.82	925.539
ORDER	1567.90	3127.32	1945.54	407.101	1139.86	1181.13	1195.52	1597.00	1664.55	1544.92
SIDDLE	2590.26	2016.08	2502.72	2421.05	1789.55	3668.05	1702.11	952.993	1363.27	1514.42
LIDDLE	1808.74	2088.21	1656.00	1953.58	1674.41	779.271	3018.14	664.458	3165.45	1987.32
BSR	922.667	1364.99	828.006	919.094	1092.20	1954.79	1547.08	912.988	1670.02	1326.16

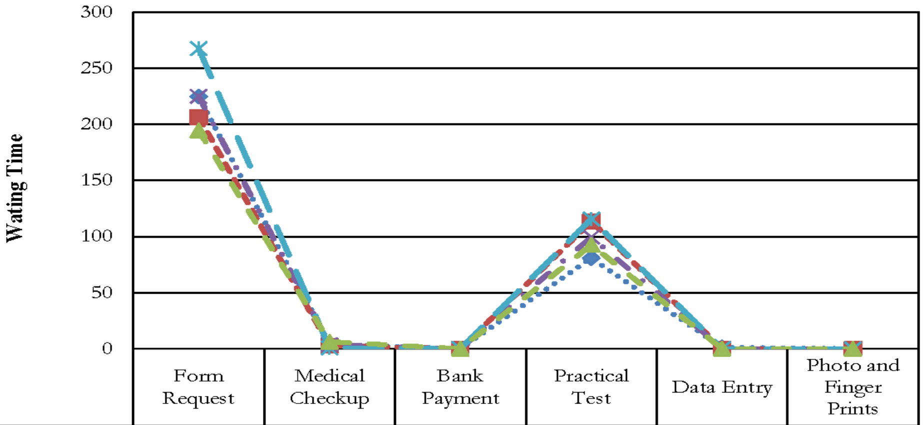
〈Figure 5〉 Completion Time (in Minutes)

but it did have the third-shortest completion time in experiment #3.

<Table 7> lists the average waiting times. The BSR again shows the shortest average waiting time, 48.92631, which is 5% shorter than the second-shortest, RANDOM. The BSR was 31% better than the worst selection rule, LIDLE. The standard deviation results also were promising. The BSR was the shortest among all of the selection rules, at 80.20511

〈Table 7〉 Average Waiting Time (in Minutes)

Activity	RANDOM	ORDER	SIDDLE	LIDDLE	BSR
Form Request	224.7818	206.5963	225.0322	267.7362	194.7239
Medical Checkup	4.014034	2.831565	3.663344	0.758919	6.215309
Bank Payment	0.006002	0.004097	0.020814	0.039402	0.000671
Practical Test	80.82907	113.5231	99.56056	115.6766	92.57955
Data Entry	1.226816	0.090305	0.083761	0.111389	0.031523
Taking Photo and Finger Prints	0.027605	0.004505	0.149922	0.010129	0.006911
Mean	51.81422	53.84165	54.75177	64.05544	48.92631
Standard Deviation	90.5202	87.3888	92.28078	109.9507	80.20511



	Form Request	Medical Checkup	Bank Payment	Practical Test	Data Entry	Photo and Finger Prints
RANDOM	224.7818	4.014034	0.006002	80.82907	1.226816	0.027605
ORDER	206.5963	2.831565	0.004097	113.5231	0.090305	0.004505
SIDDLE	225.0322	3.663344	0.020814	99.56056	0.083761	0.149922
LIDDLE	267.7362	0.758919	0.039402	115.6766	0.111389	0.010129
BSR	194.7239	6.215309	0.000671	92.57955	0.031523	0.006911

〈Figure 6〉 Average Waiting Time (in Minutes)

(RANDOM : 90.5202; ORDER : 87.3888).

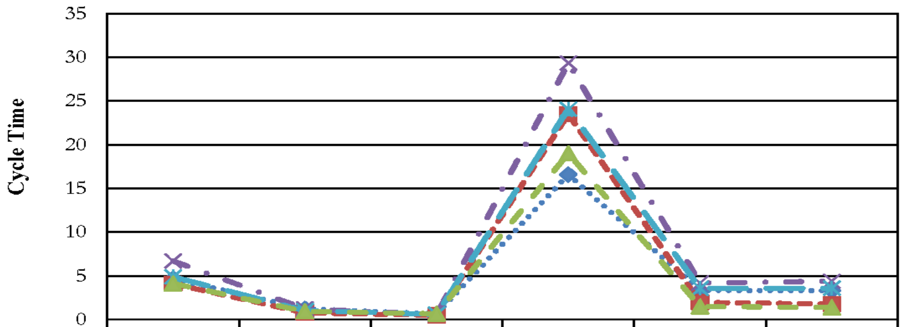
<Figure 6> plots the average waiting times. It is apparent that the differences among the selection rules were not wide. Only in Practical Test and Form Request showed thedifferences relatively. The main reason for this was the fact that the processing time standard deviation was higher.

The cycle time is the difference between the time at which a job enters an activity and that at which it exits the activity. In cycle time, we do not measure the waiting time. <Table 8> plots the average cycle times in each activity. The BSR showed the shortest cycle time, 4.598393, the second-longest being RANDOM (4.966121), and the worst, SIDDLE (7.740794).

<Figure 7> plots the cycle times for the

〈Table 8〉 Cycle Time (in Minutes)

Activity	RANDOM	ORDER	SIDLE	LIDLE	BSR
Form Request	4.664486	4.094495	6.700794	4.893714	4.124972
Medical Check Up	1.243807	0.768388	1.236227	1.027269	0.923016
Bank Payment	0.656858	0.482826	0.574739	0.60807	0.666056
Practical Test	16.58146	23.48475	29.3501	24.07019	19.00394
Data Entry	3.343396	1.974114	4.183457	3.585939	1.487211
Taking Photo and Finger Prints	3.306715	1.786776	4.399449	3.581873	1.385165
Mean	4.966121	5.431891	7.740794	6.29451	4.598393
Standard Deviation	5.879105	8.935086	10.8215	8.862408	7.165469



	Form Request	Medical Check Up	Bank Payment	Practical Test	Data Entry	Taking Photo and Finger Prints
RANDOM	4.664485914	1.24380684	0.656857969	16.58146141	3.343396245	3.306715036
ORDER	4.094495454	0.768388208	0.482825638	23.48474558	1.974114222	1.786775662
SIDDLE	6.700794048	1.236226717	0.574738711	29.35009597	4.18345673	4.399449442
LIDDLE	4.893713945	1.027268676	0.608070346	24.07019453	3.585938662	3.581872752
BSR	4.124972417	0.923016204	0.666055973	19.00393507	1.48721094	1.385164555

〈Figure 7〉 Cycle Time (in Minutes)

five selection rules. For the same activity, there were no significant differences among the rules. The selection rules showed slight differences for Practical Test, because there, the processing time was longer than in the other activities. The cycle time of Practical Test accorded with customer ability. The better the customer's ability was given, the faster the cycle time was shown.

Our result shows that the BSR yields better results than other selection rules in terms of completion time, cycle time and waiting time. ORDER and CYCLIC might be suitable to in-crease resource utilization by distributing workload to human resources. They hamper one human resource to dominate performing jobs. Although they may well reduce the cost of utilization, both selection rules can have a higher completion time because of the human resources with the shortest completion time has a smaller chance to do a job because of the uniform distribution of the workload. RANDOM is a means to distribute workload as well as reaching a fair completion time by arbitrarily select human resource from human resource sets. The problem with RANDOM in terms of completion time is on its reliability. At a period of time, RANDOM can introduce a short completion time, but in another time it cannot. The real performance of RANDOM compare to BSR can be obtained by employing more human resources in the same activity (not just only three).

5. Conclusions and Future Challenges

The unique point about BPM compared with the manufacturing domain is its resources. In BPM, human resources dominate over other resource types such as automation. However, it is in the nature of human resource performance to fluctuate. Sometimes it is good, but at other times, it is poor. This kind of unevenness or inconsistency can affect an organization's quality of service.

The present study used a Bayesian Network (BN) to derive an alternative method for assigning human resources to jobs : the Bayesian Selection Rule (BSR).

We defined the BSR based on the factors that affect human resource performance. The study limits performance only in terms of completion time. High performance is perceived as the ability of a human resource to finish a job in a very short period of time. We identified nine such factors, including workload, working environment, skill, ability, and others. By means of these factors, we can predict human resource performance, select the human resource with the best performance, and assign that resource to a given job. Traditional selection rules, for example RANDOM, ORDER, and LBUSY, notably do not consider human resources' fluctuating performance.

Our result shows that the BSR yields better results compare other selection rules in terms of completion time, cycle time and waiting time.

Even though our BSR was developed to deal with human resources, other researchers can apply a similar approach to deal with automated resources, simply by omitting nodes such as *environmental working pressure*, *ability*, and *working_hrs*. Future research will strive to accommodate many resource patterns, such as those identified in [17]. Resource selection might also involve workflow security issues (e.g. separation of duty). Future research works can pertain in how to select the best resource once a resource shift an ongoing job to another resource. Further, a dynamic BSR could be developed to deal with workflows involving high-turnover resources.

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