A User Activity Recognition Framework for Supporting Electricity Planning in Campus Library

Suwit Somsuphaprungyos*, Salin Boonbrahm*, and Marut Buranarach**

Abstract

To assist on campus library management on electricity usage, activity recognition is applied to detect students' actions in library environment. An RFID was selected as a tool to identify and detect users' action. A supervised data-driven method approach is invented to generate an activity rule set in activity recognition. The activity data were used in an automatic process to manage rooms specified by activity based on two main factors, i.e. past activity data and room capacity. From experiment, the results of accuracy indicated that the proposed method got the satisfied results for 0.993 precision and 0.988 recall score in overall. The room management plan using the obtained acidity data yielded the plan to lower the weekly electricity usage for approximately 4,089 units from original setting of 5,962 units which are equivalent to 31.53 percent reduction of electricity.

Keywords: Activity Eecognition, Electricity Saving, Library Usage, RFID, Sensor Data Pattern.

1. Introduction

A library in a university is a building facility providing information archives in both physical and digital form including books and materials for students to borrow and study. A campus library is generally operated in official time for people to access. To operate a library, electronic devices are employed to facilitate users including lighting system, air-conditioning system [1], [2] and digital content providing tool. Apparently, there are cases that electricity has been wasted from no visitor or visitors with unrelated library activities. This leads to the losing of unnecessary electricity resource which is regarded as the failure of resource management [3], [4], [5] and against power-saving policy.

To prevent the unnecessary loss of electricity, the demand to recognize amount of library visitors and their activity has been raised. The statistical data of visitors and their activities in a library are crucial for effective management. The statistical data can be analyzed and learnt to understand the probability of the future case. In this work, the crucial information is the amount of visitors based on activities in time and day.

To recognize human activity [6], [7], it is required to observe one's actions in a combination. With the invented sensors, detecting one's actions can be done without offensively monitoring by person. However, a sensor [8], [9] and [10] may detect the actions and store the data into database, but it cannot directly use to either identify person who acts or imply activity directly from actions. It requires a decision model [11], [12] to indicate activities from a combination of actions and an identifying method for activity in open-accessed area.

In this work, the data of activities from library users are used to represent actual usage phenomena. The sensor data are collected for actions of users and integrated [13] to a combination of several actions as a pattern from identifiable users. The patterns are used to generate rules to furnish action data into activities. We expect that activity data is more useful in management than the direct use of sensor data. With activities, a management plan can automatically be

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recommended to manage library resources based on actual data aiming to reduce resource usage for less electricity usage as much as possible.

This work proposes on applying activity recognition for electricity saving in a campus library. Moreover, the proposed method exploits real data for supervised learning to create inference rules. This work is expected to assist on campus management in terms of optimizing resource usage.

2. Related Work

There are several publications mentioning about recognizing activity in a certain area. These work projects applied different technology to accomplish their goal. Most of them used sensor data to imply human action or movement while some exploited knowledge representation such as ontology to assist in determination or represent data schema. However, their objective mostly is to recognize human activity. The summary of related works is given in Table 1.

From the review of related works, the recognitions were conducted with two approaches as logical reasoning based (such as [19], [20] and machine learning-based (such as [21], [22], [23]). The benefit of first is that obtained rules are more flexible and fit to situation, but are a burden for creators to thoughtfully analyze and design. The second has the benefit of automatic method. It does not require much manual-analysis for generation for learning, but a large amount of data to determine difference in attributes. Furthermore, the review indicates the difference on used sensors and environment. It can be concluded as follows.

• Closed environment with a single target: many types of sensors since the settings do not concern in identification but action detection.

• Closed environment with a group of participants: RFID or wireless signal since identification is needed, and movement and headcount are mainly used to understand actions of several targets at once.

• Opened environment: wearable or signal from hand-held items since the environment is wide and unlimited. Though, it requires a permission to access such data.

Table 1. *Comparison of Related Projects.*

Publication	Data Input	Technology	Targeted Environment	Objective
An ontology based framework of modeling movement on a smart campus [14]	- Enrollment Database	- Ontology	Campus	Analyzing and visualizing human movement
Building A Smart University using RFID Technology [15]	- RFID reader	- RFID	Building	Development of Smart University model
The smart University experience : A NFC-based ubiquitous environment [16]	-NFC : (near field commu-nication) sensor	-Wireless proximity commu-nication -Mobile phone	Campus	Development of Smart University model
Activity recognition using context-aware infrastructure ontology in smart home domain [17]	- Home sensor Network - Body sensor Network - Wireless sensor - RFID reader	- Ontology	Home	Recognition of activity in home
Inferring Students' Activity Using RFID and Ontology [18]	- RFID sensor - Enrollment Database	- Ontology	Campus	Recognition of activity in campus

Thus, this work selects RFID sensors [24], [25] for their ability to identify student. The supervised data-driven approach is chosen to reflect actual circumstance of actions in a library. The resulted activity is to be used for managing plan to reduce electricity used in vacant time in a library.

3. Methodology

This work aims to acquire data of activities in library to use for managing electricity usage. The system is separated into 3 parts as shown in Figure 1.

3.1 Data Preparation

The targeted location in this study is a campus library, and the targeted population is students who attend a campus library. To realize information of 'who', 'when' and 'where', several RFID readers are deployed in a library for students to activate. This will inform us of a user's identification, place and time. The first and foremost RFID readers are to attach to the library entrance for both entry and exit. The rest of the RFID readers are to place at where library-based activity could occur. This research focuses on 5 main activities in a

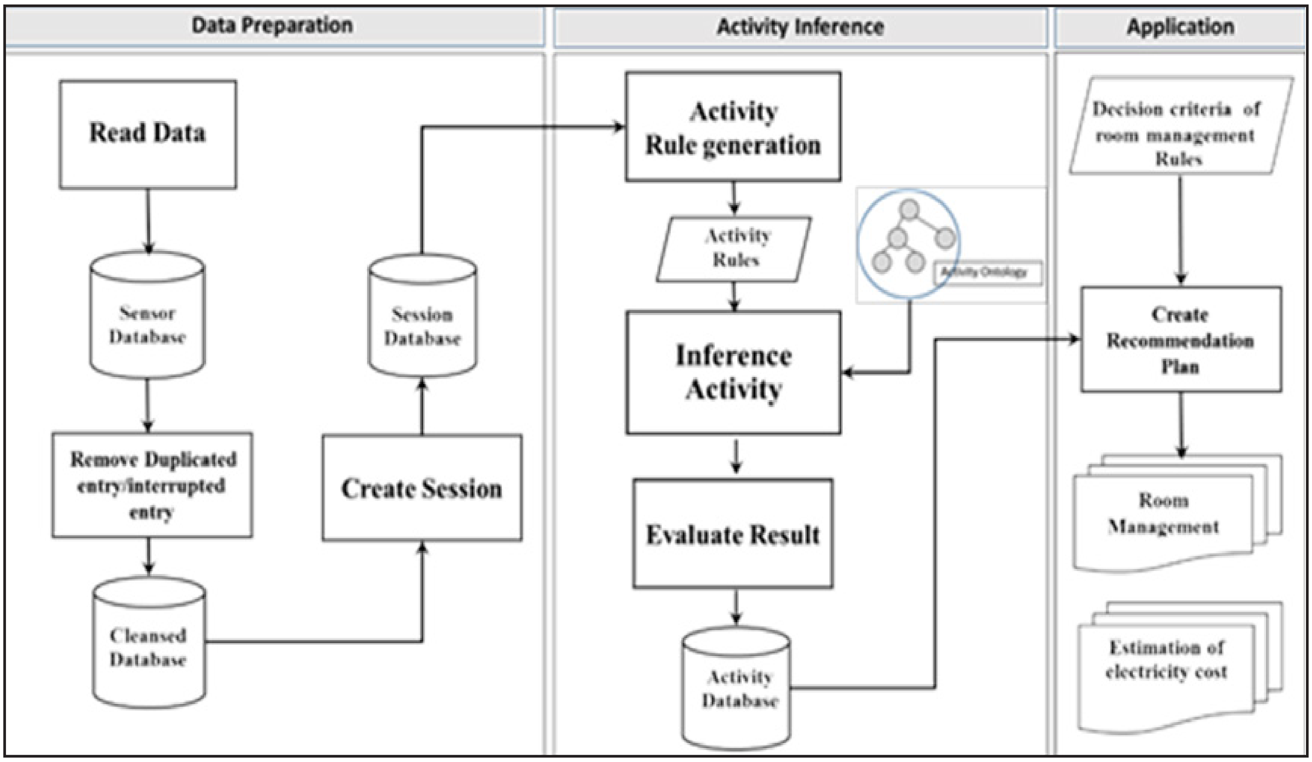

Figure 1. *Conceptual research frameworks.*

library as reading, self-studying, using-computer, borrowing book and returning book. Thus, the RFID readers are to attach to activity related objects, namely reading table, bookshelf, facilitated computer, self-study boot and counter for book service. These readers are to be activated by touching the own student ID card with the located reader if user has interaction to the object.

For example according to the RFID reader setting, an example blueprint of a library with specified RFID spots can be drawn as shown in Figure 2. For details, the blueprint composes of 7 compartments. The space at the entrance (front) contains a front counter which is for providing book services (borrowing-returning a book). There are 2 reading rooms, 2 self-study rooms, 1 computer room, and a room for book collection. The example blueprint also shows a location of RFID readers regarding the setting explained earlier (shown as small circular icon with the ID). At best, the RFID readers should be attached to all the objects; however, they can be placed for sharing if the same type of objects is nearby each other for preserving equipment cost.

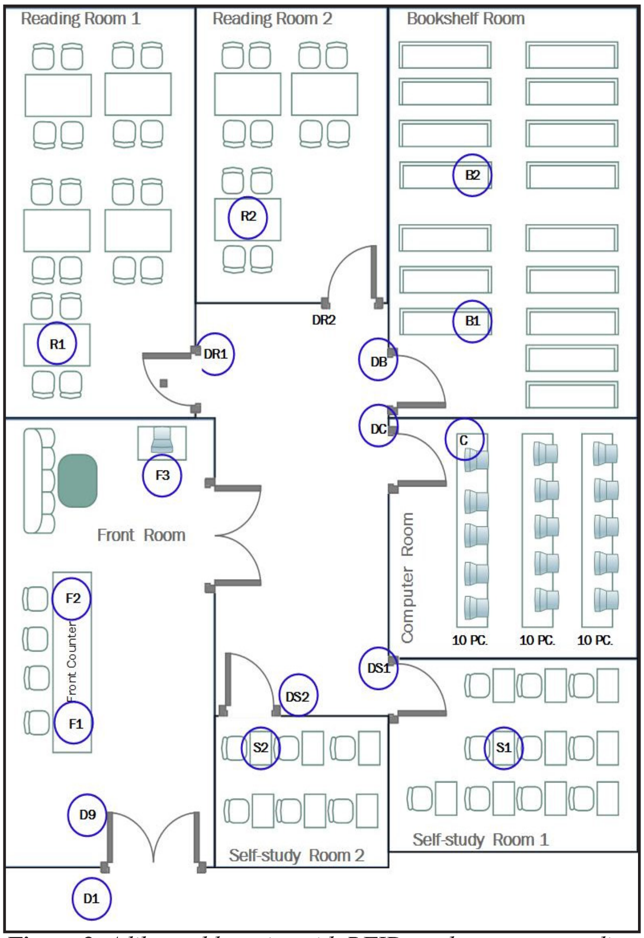

Figure 2. *A library blueprint with RFID reader spots according to settings.*

For data collection, students are asked to activate RFID readers with their student ID card. A condition for activation of each spot is differed as shown in Table 2 since each action involves different items.

Table 2. *A condition to activate major RFID readers.*

RFID Reader Spot	Reader ID	Activation Condition
An entrance of a library	D1	When a student enters a library
An exit of a library	D9	When a student exits a library
An entrance of a chamber	D*	When a student enters a certain chamber
A table for reading in Reading chamber	R*	When a student reads a book(s) in a provided facility
A self-study booth	S*	When a student uses a self- study machine
A bookshelf	B*	When a student takes a book(s) from a book shelf
A counter for borrow a book	F1	Officer activates it once a student borrow a book
A counter for returns a book	F2	Officer activates it once a student returns a book
A search system for searching a	F3	When a student performs a search for a book
A computer desk	C1	When a student uses a facilitated computer

3.2 Activity Inference

With the obtained data of sensor activation, they are used to create activity inference rules. The rules are generated from the pre-existed data. The rules are generated in a favor of explicit patterns of sensor activation sequence and their frequency. The input data are a pattern of sequential sensor activations based on a session. Frequency of patterns is used to determine a reliability of the generated rules.

a. Pattern Detection

Sessions are an input for this method. The session consists of a sequence of sensor activations of an individual and a resulted activity. The sequence of activations is transformed into a diagram to represent a pattern of actions in library. A diagram composes of activations as states connected to other activations with a link representing a sequence, and a sequence is separated based on the result activity.

The diagram is a representation of all possible patterns regardless of date and time. An activation of the same action is grouped together to reduce variation, such as B1 and B2 in which both refers to action with the bookshelves and R1 and R2 are also grouped as R to stand for using reading tables in a library. The ending state of a diagram is assigned with the resulted activity to differentiate the same pattern with a different result. Each pattern is counted for a frequency given in collected data. The frequency is used to demonstrate how common the pattern is, and the low number of frequency can indicate a possible error in data or insignificant occurrence.

A method to generate diagram from input session is drawn in a flowchart given in Figure 3 and explanation in stepwise is as follows.

1) Actions in a session are read from top to bottom. The answer of activity from user is inserted at the bottom. The initial node is the root node, and nodes are connected with a one-direction path. Every session starts at root node.

2) If the path from the current node leads to a node that matches to the current action, then the current action is removed and follows the path to the next node. Else, a new path is created with the current action as the next node, and the current action is removed and follows the path to the next node.

3) Iteration of step 2 until there is no action left. Frequency is added towards the last node.

4) Going back to step 1 for next session until no session left.

The example of action pattern diagram is illustrated in Figure 4.

b. Pattern to Rule Generation

With the supervised activities, patterns are recognizable for different result. Patterns are grouped regarding the result activity. According to the ontology, the list of proper activities in a library in general includes ‘Reading’, ‘Borrowing_Book’ and ‘Returning_Book’. However, the library as testing site of this research provides extra services including computer room for students to use a facilitated desktop computer and self-study booth for students to privately listen and watch to recorded lessons. Hence, this research includes those activities,

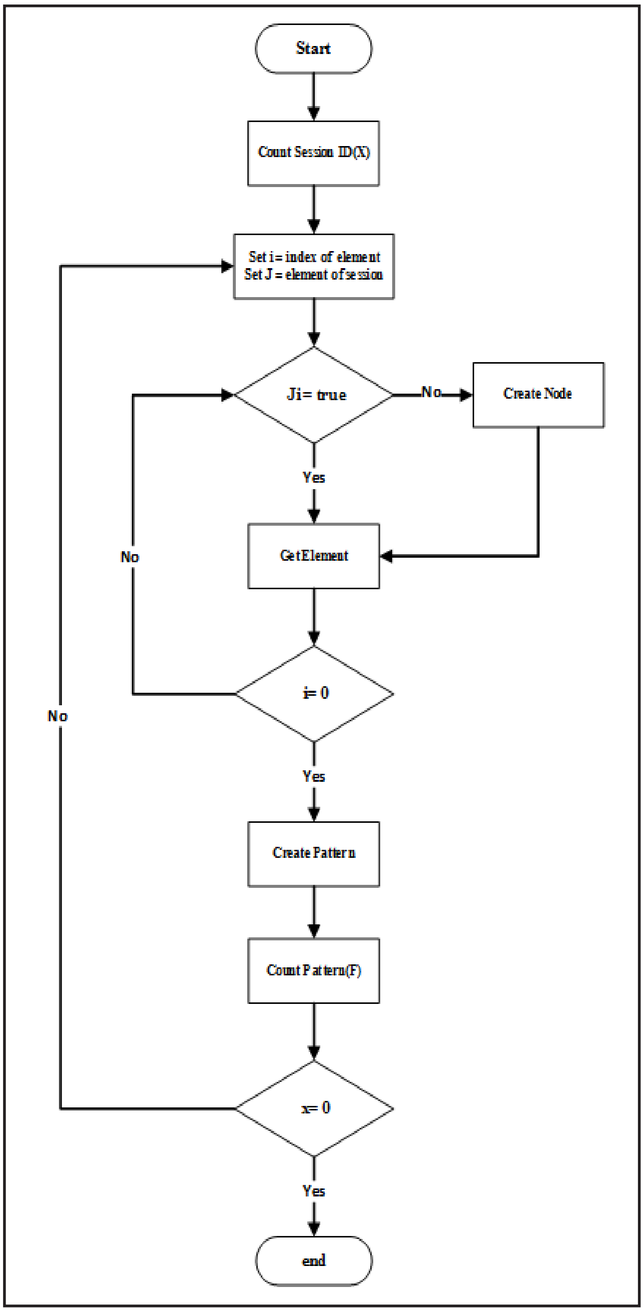

Figure 3. *A flowchart of a method for to generation diagram of pattern.*

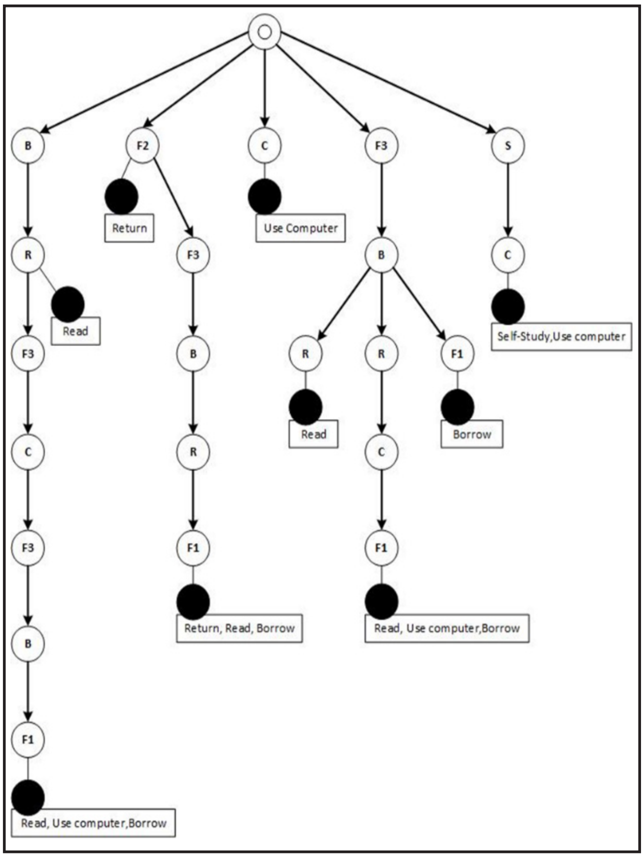

Figure 4. *An example of generated diagram of sensor-data pattern.*

i.e. 'Using_Computer' and 'Using_Self-study_Boot'. 'Other' activity is added as a mandatory output to define the rest of sequence actions unmatched to given condition and non-library related tagged activity. Hence, in this work, there are 6 possible activities as result of the rule, i.e. 'Reading', 'Borrowing_Book', 'Returning_Book', 'Using_Computer', Using_Self-Studying Boot' and 'Other'.

To generate rules, firstly the list of single-activity patterns is exploited. The patterns of each activity are processed

Activity	Found patterns with frequency	
	• F3>B>R	(340 [59.75%])
	• B>R	(65 [11.42%])
	• F3>B>F3>B>R	(57 [10.01%])
	• F3>B>R>B	(30 [5.27%])
	• R	(29 [5.09%])
	• B>R>B>R	(24 [4.21%])
	• B>F3>B>R	(19 [3.33%])
	• F3>B>S	(3 [0.52%])
	• B>S	(2 [0.35%])
Using Computer	• C	(189 [35.84%])
	• B>C	(5 [2.55%])
	• B>F3>C	(1 [0.51%])
	• F3>B>C	(1 [0.51%])
Other Activity	• R	(38 [35.84%])
	• B	(21 [19.81%])
	• F3	(21 [19.81%])
	• F3>B>F3	(13 [12.26%])
	• F3>B	(9 [8.49%])
	• C	(4 [3.77%])

Figure 5. *Examples of found patterns of activity for single-activity.*

separately. The patterns are sorted based on frequency for the higher frequent pattern as a top respectively. To exclude an irregular pattern from error, a threshold is set to prune out obviously low frequent patterns. The threshold value is assigned in a percentage of frequency to normalize the difference in activity amount. Though the threshold value is adjustable to fit the actual situation, the default threshold value in this research is set to 5% since 5% gave the best result in preliminary testing.

For better understanding, a scenario is set to assist in explanation. Please consider the examples of detected patterns given in Figure 5. This part only concerns about single-activity patterns; hence, the found patterns are less complex and straight-forward.

From the example, there are 9 detected patterns for 'Reading' activity. The total occurrence of this activity is 558. The majority of patterns is 'F3>B>R' and 'B>R' for 60.93% and 11.64%, respectively. If the threshold value is set to 5%, only the top five patterns pass the criterion. From the top five, pattern 'R' (the 5th pattern) is ambiguous as it is the same pattern to the 1st pattern for 'Other' activity. In comparison with the frequency (not the percentage frequency by activity type), the amount of pattern 'R' is divided into 'Other' for 67% and Reading for 33%. Since the proportion of 'Unknown' is higher than 'Reading', this pattern is discarded as a rule for 'Reading'. For the rest top four after discarding, they all are treated as rule candidates. For each candidate, a repeated element within condition part is checked from left to right. The repeated elements are removed if the element is found on their left side. For instance, the 3rd pattern of Reading, 'F3>B>F3>B>R', contains the repeated elements including F3 and B. Hence, the F3 in third position and B in forth position are both removed and resulted to 'F3>B> R'. After removing repeated element(s), if the removed pattern is exactly the same to the existing pattern, they will be merged and left as one single pattern with combined frequency. From all the examples in Figure 5, rule candidates are generated as given in Table 3.

Table 3. *Examples of generated rule candidates based on detected patterns given in Figure 5.*

Rule Candidates for Activity	Rule Conditions
Reading	1. F3>B>R 2. B>R
Using Computer	3. C
Other Activity	4. R 5. B 6. F3 7. F3>B

c. Rule Format and Specification

In this work, a production rule is formed for inferring activity as shown in Figure 6. Rules are designed for two specifications, forward chaining and able to multiple matching.

Forward-chaining rule is a rule designed in consequence to represent conditions in distinguish antecedent parts (If part). An inference using forward chaining finds rules until the antecedent is satisfied, namely all conditions are matched. When such a rule is found, the engine can activate its consequent part (Then part), resulting in new information to add to its data. The new information can be used to match another antecedent part of another rule until no rule is matched and considered as a finalized result.

Multiple Matching is that information can be repeatedly used to match an antecedent part of rules though it is already used in another rule. It leads to be able to generate several results as long as an antecedent part of rule is matched.

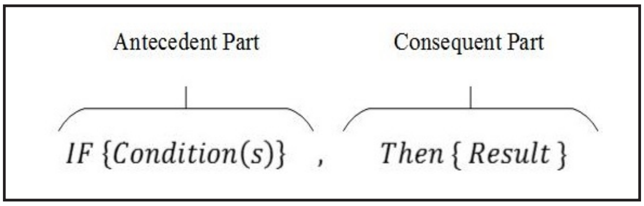

Figure 6. *Description of rule parts and example.*

In this research, inference system is developed specifically for the task. To accommodate with forward-chaining and multiple matching, the sequence of elements is separated to one element per a rule referring to a state in a diagram. For each state, if there are following states, the indexed label is created as intermediate layer for referring between paths.

According to rule candidates in Table 3, we obtain the following rules:

- 1# IF ‘F3’ is found, THEN result = ‘I1’;
- 2# IF ‘I1’ has ‘B’ followed, THEN result = ‘I2’;
- 3# IF ‘B’ is found, THEN result = ‘I2’;
- 4# IF ‘I2’ has ‘F3’ followed, THEN result = ‘activity(Borrowing_Book)’;
- 5# IF ‘I2’ has ‘R’ followed, THEN result = ‘activity(Reading)’;
- 6# IF ‘C’ is found, THEN result = ‘activity(Using_Computer)’;

With the design, an amount of rules is controllable with reusable rules. Moreover, the less condition to match as one single element contains less complexity and better manageability. With a specification for multi-matching, a session instance as ‘F3>B>R>F1’ can yield two activities as ‘Borrowing_Book’ and ‘Reading’ from the uses of rule chaining of 1# → 2# → 4# and 5#. Last, the activity result of rules those finalized to a proper activity (indicated as result = activity) are yielded as an activity result. Otherwise, ‘Other’ activity is answered including for unfinished chaining result (result without activity) and ‘other’ activity.

3.3 Applications of Obtained Information

Since the goal of this work is to effectively prevent losing unnecessary electricity in a library without interrupting users’ lifestyle, statistic of the inferred activity of library users in the past is essential for library management. Results of previous processes yield an actual statistic of student usage in library based on activity and time. In this research, the activity information is to automatically generate [26] a plan regarding a cost of electricity consumption. It considers the amount of activity conducted by students in each library part, and it decides to plan on open-close the parts that tentatively should be vacant in order to prevent wasting energy.

With the information of library activity from previous method as an empirical evidence of the past usage, a statistic can be used to determine which part to be closed. In this section, an automatic generation of plan to manage open-hours of unused parts in library is designed. The method to decide plan considers inputs composing of statistic data and decision rules to activate when criteria are met. The statistic data for consideration are average of activity in specific time of a day. Decision criteria are amount of activity in average, maximal capacity of the place, and in-used policy. The decision criteria are illustrated in Figure 7.

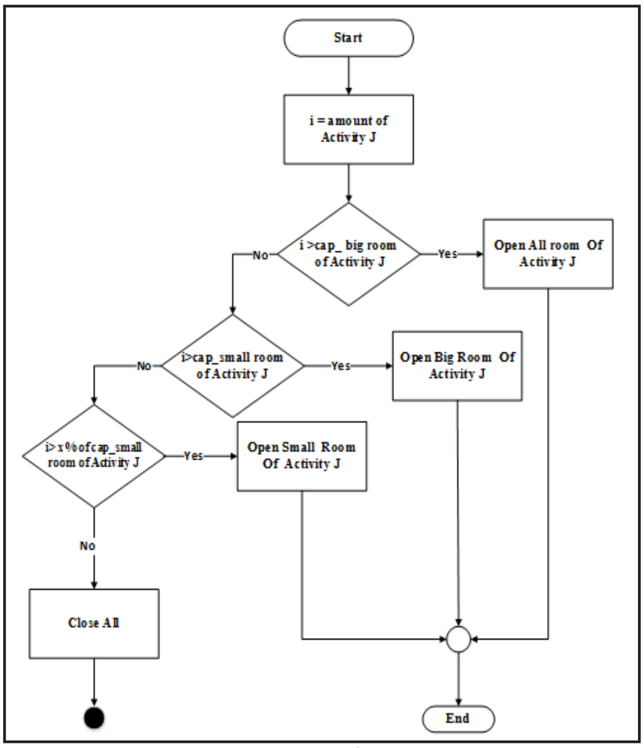

Figure 7. *Decision criteria for room management.*

X% given in decision criteria refers to an adjustable value in percentage. This value is set depending on current policy of the library or faculty. In this research, a default value is 20; hence, it means 20% of room capacity is a criterion for decision-making. After applying decision criteria for room management, a room for specific activity that may be vacant from past data will be planned to temporary closed. Hence, a summation of electricity consumption should be relatively decreased.

4. Experiment and Discussion

4.1 Experiment Setting

The testing site was a library located in a second floor in a 2-story building. The library information is given in Table 4.

Table 4. *Details of testing library site.*

Room	Max Capacity/Person	Estimated Electricity Unit Used Per Hour
Bookshelf	N/A	51.89 watt
Front	N/A	13.77 watt
Reading 1	20	26.74 watt
Reading 2	12	9.63 watt
Self-Study 1	10	2.33 watt
Self-Study 2	6	1.37 watt
Computer	30	26.74 watt

There were 120 students participated in the experiment. All participants were instructed to activate their student ID card to a reader if they were to interact with the library item.

4.2 Accuracy Result

For accuracy testing, collected data are split into two sets, training set and testing set. The training set composes of session data with an answer collected from 13th November 2017 to 2nd February 2018. The data however were from the official date without weekend and official holiday, and a total number of days were 39 days. The testing set is a collection of 10 official days from 5th to 16th February 2018. For statistics, there are 1,187 sessions for learning and 298 sessions for testing. The measurement [27] is precision, recall and f-measure. The accuracy results of the proposed method are given in Table 5.

Table 5. *Details of testing library site.*

	Precision	Recall	F-measure
Overall	0.993	0.988	0.988
1 activity	0.996	1.0	0.997
2 activities	0.992	0.982	0.983
3 activities	0.991	0.976	0.980
>3activities	0.980	0.966	0.970

4.3 Usage Results

This section is to apply room management plan to the activity results from previous section. For comparison, data with activity and data of headcount (pure sensor data without activity inference) are applied to see the difference of room management. The applied statistic data from both inferred activity and headcount changed amount of open hour for some rooms; thus, the amount of open hour of a room is reduced and affected to lowers spent electricity unit. The comparison in spent electricity unit are provided in Figure 8.

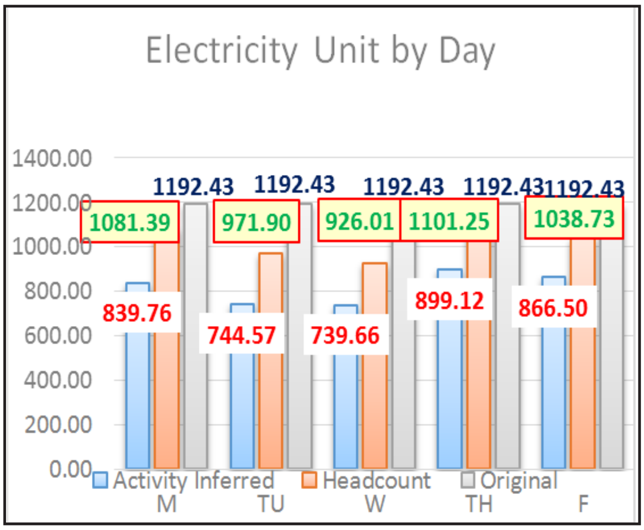

Figure 8. *Comparison of electricity unit of original setting (baseline), the plan generated from Headcount data and the plan from activity-inferred data [28].*

The difference in spent unit and cost is noticeable [29]. The baseline was much higher comparing to both of managed hours. The statistic from inferred activity showed slightly lower than the headcount for every day. In average, the statistic from inferred activity led to lower spent unit from baseline for 39.68% and from headcount for 27.93%.

The significant reduction in electricity unit from a library can prove that the plan generated from activity-inferred data is useful in management. Moreover, the management plan is generated from past data collected from the actual site so it should conversely not affect user's usage behavior.

5. Conclusion

This research proposes a method to recognize library users' activity using supervised data. The method applies action pattern and their frequency to develop an activity model for recognition. The obtained activity data are then used to assist in management plan for electricity saving. From the experiment on rule generation, the results showed that the generated rules were usable as they gained more than 99% accuracy. Furthermore, the result of applying activity data in room management towards electricity saving showed that around 35% of open time was suggested to close. With spent electricity unit estimation, the suggested plan lowered the weekly electricity unit for approximately 1,880 electricity units which is 31.53% of electricity saving per wee.

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