

FSI DRIVENERGY: MITIGATING SMARTPHONE ENERGY CONSUMPTION USING FUZZY INFERENCE

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DOI: <https://doi.org/10.22452/mjcs.vol33no3.2>

ABSTRACT

Smartphones today help people accomplish daily activities, from simple tasks such as taking a reminder, to more complicated processes such as predicting road traffic while driving. However, performing complicated processes on smartphones cost the device's energy to drain much faster. As an effect, the phone's main purpose which is to enable communication whenever it is needed is degraded in terms of performance. In relation to this problem, researchers have tried to mitigate smartphone's energy usage. An area that has yet to be further explored, is on examining smartphone's context while the user is travelling. This paper presents a method to mitigate smartphone's energy usage by gathering its context and to analyze it using Fuzzy Inference technique whilst the user is driving and using navigational application at the same time. Our finding shows that using this method can improve smartphone's battery lifespan at an average rate, ranging between 1.6% to 3.1% for every hour with up to 19% of energy saving. These results proved that analyzing smartphone using context-awareness and Fuzzy Inference can reduce smartphone's energy usage whilst the user is travelling, which in turn improves the overall energy efficiency in smartphone.

Keywords: *Energy Efficiency, Context-Awareness, Smartphone, Fuzzy Inference*

1.0 INTRODUCTION

Smartphones today are doing much more complex activities rather than just a communication device that makes call, manage contacts and sending SMS. With over 3.5 million apps available on Google Play store and 2.2 million apps on the Apple App Store as in December 2017, the list of activities that can be done with smartphone are endless[1][2]. Even though communication still stand as user's main activity, it only covers 50% of smartphone's usage and the the rest of the activities goes to productivity, browsing, maps, media and games[3]. Despite performing these activities on a smartphone helps people accomplish their tasks faster, it actually jeopardizes the main purpose of a phone by draining the battery power.

Smartphone power consumptions are based on user activities or requests which rely on embedded components such as GPS sensor and accelerometers on the smartphone. GPRS, Wi-Fi radios, graphic processors and CPU are some of the components noted to significantly contribute to battery drainage in Android-based phone, even though the process only perform common tasks[4]. Without a doubt, constant usage of multiple sensors at the same time also drains significant amount of battery power, particularly processes that involve GPS sensor or location service[5][6]. For instance, a crowdsourcing app like Waze collecting data of road traffic from time to time using HTTP and GPS protocol. According to a profiling research using genetic algorithm, both protocols consumed the highest power (watt) in mobile component[7]. Making the matter worse, battery technology for mobile device has not grown as much as other components' technologies[8]. This situation shows that this problem has clearly becomes a critical issue and various methods need to be introduced to solve the problem[9][10].

Researchers are trying to explore alternative ways to solve this problem and one of it is by implementing context-awareness method on smartphone energy issues. Context-awareness is long known for its capabilities to help solving computing problem in multiple domain, and smartphone/mobile device[11]. For example, a study in 2015 had tried to balance smartphone battery usage over user experiences using context-awareness[12]. However, the proposed scheme need to predefine user experience value first because there is no absolute way to scale user's experience acceptance to each power configuration applied. As a result, implementing this concept to save the energy may return inconsistent experience results to user's acceptance. On the other hand, M. Moghimi in 2012 proposed an interesting concept to implement context-awareness in power management using fuzzy inference as a high-level description context. Unfortunately, the research only test the method on two kind of smartphone activities, and both tasks did not involve GPS sensor or location based services.

This paper experiments a method to mitigate smartphone energy consumption using fuzzy inference, focus particularly on activity involving location based service by analyzing context gathered from the smartphone. The objective of this paper is to see possibility of fuzzy inference to leverage energy saving when involving services that consuming high energy usage in smartphone. Furthermore, this study combine this technique with context-awareness method to maximize the possibility.

For validation, we do simulation of smartphone user whom travels by driving and using navigational application to arrive at the destination. We setup two identical smartphones, one that works in default settings while the other configured to run with FSI Drivenenergy, an app that analyze the smartphone context and mitigate the smartphone energy using fuzzy inference technique. Both smartphones are then run concurrently while driving and battery usage on both devices are monitored and recorded periodically. Our method finds that implementing fuzzy inference involving location based service using context-awareness can reserve up to 19% on fully charged smartphone battery.

2.0 RELATED WORKS

In this section, studies related to mitigating energy usage in mobile platform are discussed. In 2012, a study has implement context-aware in power management using fuzzy inference as a high-level description context, and use it as a middleware application in mobile devices[13]. The study aims to mitigate energy power consumption in mobile devices through extensible framework that handle power-related context variable. The experiment is done on two different kind of tasks. First task represents running background activity that require periodically download such as email checking and RSS feeding. On the other hand, second task will involve running streaming application to stream audio from the internet. Rather than using absolutes value, the model uses the advantages of degrees confident in fuzzy inference to establish crisp thresholds context[14]. The power manager will derive context information either from direct input of sensors or via a central context manager detection block known as CDB. CDB by routine will registers every context updates requested by other application. So as to handle the input value, set of rules using fuzzy logic is designed to translate binary digit context. The outputs of it will then be use to provide a low-level data in a high-level abstraction. Reaching the end, power manager will tune the system to provide energy saving by following defined fuzzy rules accordingly. In order to estimate power consumption along the test, the study turn to PowerTutor application as the application has demonstrated to have below 2.5% long-term error[15]. The proposed power model successfully proved that when comparing to similar method, energy usage can be saved up to 50% in both periodic download and streaming tasks. Likewise, when comparing over traditional decision-tree models the method showed up to 18% power consumption improvement as a result. As for future work, it was said that by adding more context variable to the power manager or by upgrading it with self-learning technique for higher-level context can improve the proposed model. Overall, the study proved that by using partial truth concept in fuzzy logic on mobile power management, significant improvement can be achieved in mobile's battery usage. However, the experiment lack in experimenting task that involve GPS sensor, which is known for consuming highest energy in a smartphone.

Besides fuzzy logic, a battery management system using Bayesian network also had been proposed to save mobile phone battery for Android OS[17]. This context-aware system gathers user's environment to controls embedded sensors' functions by assessing the context and minimizing probability calculation using probabilistic models as in Figure 1. Component's function such as Wi-Fi, Bluetooth and screen backlight are some of the element that are managed by the proposed system. The system comprises of four components, specifically: sensor data collection, pre-processing, Bayesian network based inference, and energy management. Sensors data

collection is the place where raw phone components data is being collected using Android's API. Some of the important data gathered includes CPU and RAM utilization, battery usage and other component's state like accelerometer and proximity sensors. Using decision tree algorithm, these data are then converted into discrete values in pre-processing phase before it can be passed to Bayesian probabilistic model in inference phase. The study has collected three-day training data first to be used to learn the classifier and tune the parameter on the system in order to test the proposed system. Using LG Optimus 2X phone, actual test data is gathered for another two days and were left to operate for about 40 hours before the analysis and comparison are made. The outcome result shows that the time need to loss 1% of battery level has increased to 128% compared to default method. The research though does not include GPS sensors in the test. There are few things that can be learned from the study. First, the practice of managing smartphone functions from surrounding context are proved not only to be working fine but also return positive results. Second, the measurement picked to be use for energy consumption by monitoring battery level make sense as it indicates practicality in real world environment. Last but not least, as mentioned in the study too, GPS sensors control must be studied in the future as it is an important module to mitigate energy consumption.

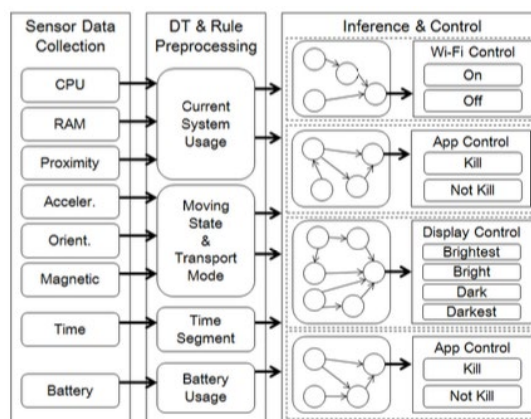


Fig. 1. Overview of proposed energy management system using Bayesian Network[17].

Research by Hiram Galeana-Zapié in 2014 proposed a location based context-awareness architecture that intended to expand battery lifetime without needed to sacrifice GPS data accuracy on mobile phone[18]. The architecture which act as a middleware application, tracks user's location spatio-temporal evolution to adjust the GPS sampling rate driven by the user surrounding context. In simple words, the GPS location updates interval changes only whenever it needed, based on user's context (such as moving state) and thus saves the device energy. The process of requesting location updates will starts with a service request for current device position within some interval time, and switch it off after some elapsed time and removing all callbac'ks to OS's location manager. Once it is done, the request intervals are now schedule dynamically depending on the gathered context as shown in Figure 2. In general, the framework was able to achieve its objective to improve battery lifetime, thanks to the fusion of batch transmissions and context-aware reading intervals. Depending on the sensing intervals sets and transmission size, results of battery improvement can perform up to 37% and can save battery lifetime up to 7 hours on simple GPS packet transmission test. However, using this method will face conflict if the same context needed by other simultaneous running application like a navigational application. Moreover, controlling GPS data interval technique also is not suitable for navigational application use because this kind of app need accurate location data in every second. By sharing such accurate information to the server is very dangerous too and will involve critical security issues with privacy matters.

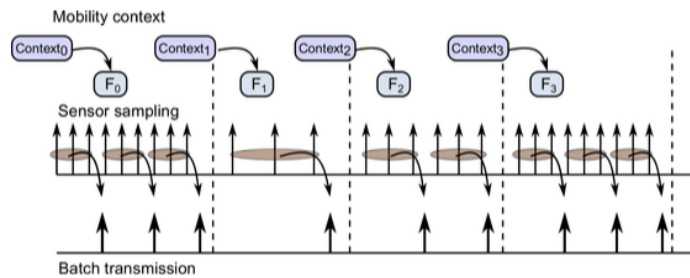


Fig. 2. Dynamic adaptation of sensing parameters and batch transmission concept[18].

Later study in 2017 try to achieve energy efficiency for video streaming by using video adaptation and backlight control on smartphone[16]. In the study, two schemes are proposed to accomplish energy saving in smartphone. The first scheme suggested video's streaming quality are administer by analyzing signal quality on client device using received signal strength indicator (RSSI). Considering smartphone's mobility nature, the scheme also includes prediction method to expect network quality changes while on the move. Second scheme on the other hand focuses on the screen's energy consumption and manage the energy by dimming backlight level of the screen based on client's surrounding. But since changing backlight level would decrease image contrast, the scheme incorporated together with histogram equalization method based on brightness reduction ratio (BRR). By applying both schemes to the experiment, the research successfully achieved energy saving in smartphone. This result shows that by adapting smartphone's settings based on current needs and current resources such network environment or backlight level, smartphone's energy can be affected in positive way.

In other research, a sensing interval management named AAGPS has been introduced, aims to achieve energy efficiency in smartphone using GPS sensing. By detecting user's state either in travel or stationary mode, the study believed that by minimizing GPS sensing interval, rely of the sensors will be minimized too thus save the energy[19]. The architecture proposed accelerometer sensors implementation to achieve the goal. Accelerometer are using less power than GPS sensors and it can determine user's mobility context in order to control the GPS sensing interval. For instance, sitting and watching television are considered as in 'stationary' state. Sitting on a train to work on the other hand is considered as 'in-motion' state. By referring to user's Cell-ID details, mobility changes can be detected over time to reset the sensing interval. In their test case scenario based on daily commuter trail of a delivery driver, AAGPS successfully shows better battery consumption usage compared to default sensing method. The difference of battery utilization is almost 28% saving in AAGPS. But during worst case scenario when user continuously in travel state, the method almost did not imply at all and the power usage result shows same energy utilization as predicted. Using Cell-ID details to detect user's mobility state changes is one of the weakness in this method. In urban areas, this method will be doing just fine but in remote area, it is doubt to return proper result as the cell size rang could go up to 35km before any changes can be detected[20]. The experiment done in the study also are not feasible to cover all user's daily activities and involving more activities are some of future works proposed in the paper.

In a research to compare battery outage over user experience, the study found out that increasing user's experience in mobile devices will giving up excessive amount of phone's battery. Since user experience in computing is essential because it is correlate to human behaviour and feeling, a context-aware global power management scheme named *Boe* was proposed[12][21]. *Boe* offers a scheme that will balance mobile device's battery outage and user experiences by analyzing users' activities and built up pattern to maximize user experience while minimizing battery usage. From the learned pattern, system will then adjust device's global power management policy as suggested by the scheme. *Boe* uses Markov Decision Process (MDP) to dynamically assign power level to each smartphone component, thus maximizing user experience within targeted defined battery lifetime. In the proposed model, each component is assigned with different weightage value so that user experience can be controlled by the system. For evaluation, performance of *Boe* was evaluated using three different metrics; User Experience, Outage Count and Outage Time. After evaluated using smartphone for over 2 months from 10 users, *Boe* proved that user experience is improve 20% for light users, maintains the same user experience for moderate users but degrades 23% for heavy users. The proposed scheme however has some weaknesses. First, the scheme uses predefined user experience value. It's understandable because there is no absolute way to scale user's experience acceptance to each power configuration applied. In addition, alternative method to scale user experience should be presented too to support the result. Secondly,

trained data uses in the scheme for the experiment is based on consistent user behaviour. Therefore, it is unknown if the proposed scheme can return consistent result when users act differently especially when affected by emotion.

3.0 RESEARCH METHOD

In this paper, we implement context-aware method to examine surrounding state of the user before we mitigate smartphone's energy consumption using fuzzy inference. In pursuance of assessing tasks that involve location based activity, we chose to simulate the use of navigational application while user is driving a car. Apart of using the location service, navigational application also chosen because it uses top three most power hunger API in Android OS, that are GUI & Image manipulation, database and task that involve context activities[17]. In the simulation, parallel method is used to monitor and examine energy usage between normal energy management and the one with location based context-awareness power manager.

Parallel in this context means two-identical smartphone with different energy management approach will be running together simultaneously while driving. The first phone, Phone A will be used with energy efficiency application or power manager called FSI Drivenenergy with 'Save Energy Mode' activated. Phone B on the other hand will run FSI Drivenenergy only to log battery usage without interfering OS's default power management technique. These settings which are illustrated in Figure 3 required both smartphones' battery to be fully charged for every driving session to have fair min, max and mean of battery usage records.

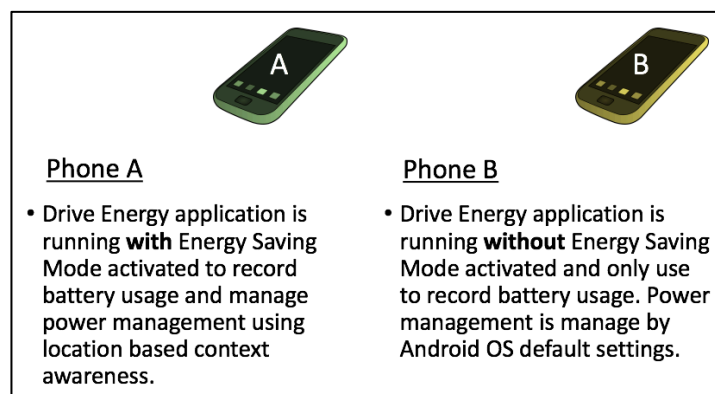


Fig. 3. Two smartphones are tested concurrently for the experiment.

3.1 Context-Awareness

Context-awareness uses surround information to improve service delivery by proactively adapting resources and information behavior[22]. This context information can be categorized into four categories; *identity*, *location*, *activity* and *time*[23], in which will answer to the question of what, who, where and when. Once the context has been identified, it can then be used to handle energy usage on smartphone by adapting user's environment and needs.

Identity context of the user can be identified by look into current user's system preferences. User's preferences work as baseline settings for any changes wants to be applied or when the settings need to be revert back to original state. For *location*, context can be gathered from GPS sensors via OS API. Information for this context is not just on user's coordinate but also speed and velocity of the user's himself, in this case the car speed and velocity while driving. This context plays main role in the experiment. Given that the test will involve navigational application, all the information need has already been collected by the app, and context can be request from OS without having to re-interfere the sensors. Meanwhile, *time* context can be collected from timestamp of the device. This context later will be defined further in fuzzy logic.

Under *Activity*, two user’s contexts have been identified from the beginning. First context is *driving* while the other one is *using navigational application*. Other activities that might be possible are listening to music using music application, active Bluetooth connectivity that paired with vehicle’s radio system and connected to the internet via Wi-Fi. Meanwhile, activities such as text messaging, web browsing and playing games might not be happening as the user is driving. Effectively identify as much as many context information will leads to best configuration that will fulfill user’s need without having to sacrifice battery lifetime.

3.2 Processing Context Using Fuzzy Logic

Once information gathered, a technique is required to interpret the collected context to produce the right results. According to J. Mañtyja`rvia, fuzzy logic can handle information from context-awareness naturally because the information are often underlying approximate rather than exact value, just like fuzzy logic[14][24]. Fuzzy logic treats real world complexity and uncertainties into logical computing, similarly like people’s expression of “big”, “morning” or “fast”. Unlike in computer’s binary digits, everything in real world cannot have absolute value[25].

For instance, high-level abstraction of speed input while driving by GPS sensors can be defined as $Speed = \{Slow, Normal, Fast, Very Fast\}$. In order to form the fuzzy logic context, member function for *Speed* are composed as in Figure 4. For the experiment, values for *Slow, Normal, Fast, Very Fast* are determined statically.

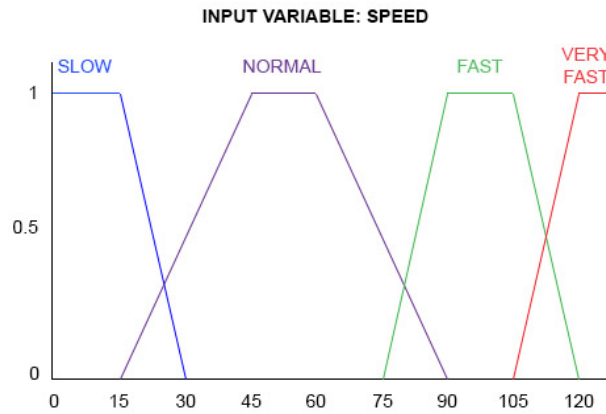


Fig. 4. Fuzzy membership function for *Speed*.

Fast in above example is defined when speed is detected with absolute confidence ($90 \leq x \leq 105$) as well as in gradual threshold start from ($75 < x < 90$) and ends at ($105 < x < 120$). Instead of trying to find absolute value, building boundary for *Fast* context is more suitable for the with the real-world definition. By implementing such gradual transition as proposed in fuzzy logic, application can have more flexible control over system or device behavior.

$$\text{Fast} = \begin{cases} 1, & 90 \leq x \leq 105 \\ 1 - \frac{(x - 105)}{15}, & 105 < x < 120 \\ \frac{(x - 75)}{15}, & 75 < x < 90 \\ 0, & x \leq 75 \cup x \geq 120 \end{cases} \tag{11}$$

Afterwards, a context like *Speed* can be paired with output action such as *ScreenBrightness* to develop a rule. Having adequate sets of rules like this can helps the power manager to control devices sensors more efficiently. In development, this correlation can be defined in “IF context THEN output_action” format such as:

IF *Speed* == “fast”, **THEN** *ScreenBrightness* = “Low”

Supposedly while driving, user will focus on the drive and not using the smartphone, either to use application or change devices' settings like screen brightness or Bluetooth state. It's a waste of energy to perform the phone as on active usage and this is the rule that we have to define to mitigate the energy consumption.

There are few rules that can be listed on what user cannot do or do not need to do the phone while driving. For instance, user is not supposed to hold the phone to use an app while on the road. Meaning, a very bright screen is not necessary during this time. On top of that, screen brightness values should be depending on the time of driving too. It is pointless to waste battery usage on bright screen whenever device in dark ambient environment. In different example, speed and velocity of the car can play roles too. Case in point, chances of the driver to look at the phone are smaller when the car is speeding because the driver need to look straight on the road and his drive. Thus, dimmer screen can help to save the energy.

In such many possibilities to save the energy, we believe that fuzzy inference is very suitable to handle the situation as it can balance and optimize the correlation between the smartphone usage and energy in use.

3.3 FSI Drivenergy Application

FSI Drivenergy application is a power manager that is designed to perform two important functions. First function, called 'Save Energy Mode' is engaged to implement battery usage management using location based context-awareness and process the data using fuzzy inference technique as discussed. These processes which start with retrieving smartphone's sensors information to accomplish energy saving are illustrated as in Figure 5.

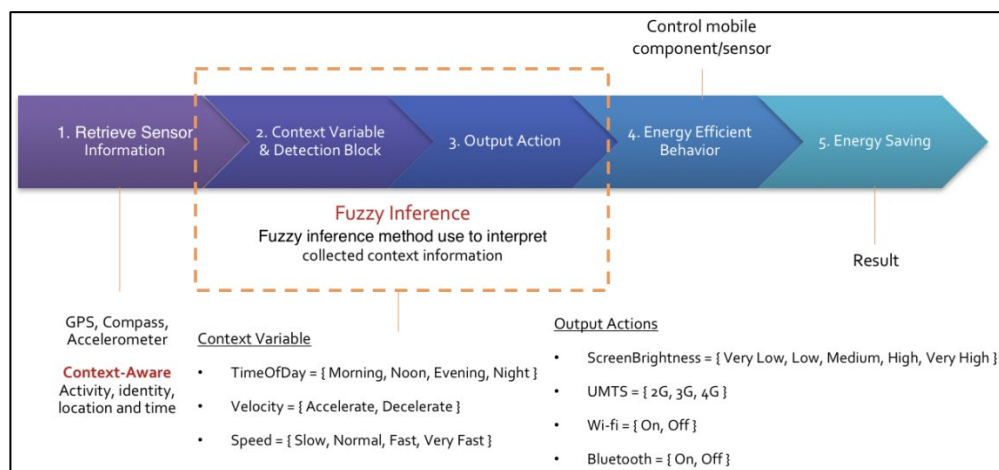


Fig. 5. FSI Drivenergy energy saving model.

The second FSI Drivenergy application's function is to monitor and log battery usage of the phone. Both function can be enable or disable to fulfill experiment's needs. In order to optimize the application's codes and reduce any possible burden to battery usage, FSI Drivenergy is coded using Android Studio, a native development tools for Android using java as recommended by Google. Therefore, code in the application can communicate directly to OS's API without any interference from other middleware application.

4.0 VALIDATION

Two types of routes had been designed to validate the method proposed. First route called Routine Drive Route (RDR). This route is designed for worst-case scenarios in driving, to imitate Kuala Lumpur drivers' routine whom staying at outskirts city (suburban area) and driving in traffics to Kuala Lumpur almost every day. Second route, the Long Drive Route (LDR), will act as additional supporting data. This route will cover normal long drives between cities in Malaysia and travel mostly along federal intercity road with town traffic. In order to avoid any undesirable variables caused by different driver's driving styles, all drives are only driven by the same person whom is a Malaysian, as they are well aware with local regulation and roads safety.

4.1 Routine Drive Route (RDR) Plan

Routine Drive Route (RDR) covered drive from Kuala Lumpur International Airport (KLIA) to Petronas Twin Tower (KLCC) and return back. This route is designed to imitate Kuala Lumpur/Lembah Klang drivers whom stay at suburban area and drives to work at Kuala Lumpur almost every day. The landmark KLCC and KLIA are chosen as destinations because KLCC is known as the heart of Kuala Lumpur; while the Malaysia International Airport KLIA, is the farthest landmark from KLCC in Greater KL initiative declared by the government[26]. On top of that, this route consists a fair of 50% highway driving and 50% of federal road driving as shown in Figure 6. This route as map view in Figure 7 has total length of 106KM back and forth.



Fig. 6. RDR Driving route from KLIA to KLCC, and return.

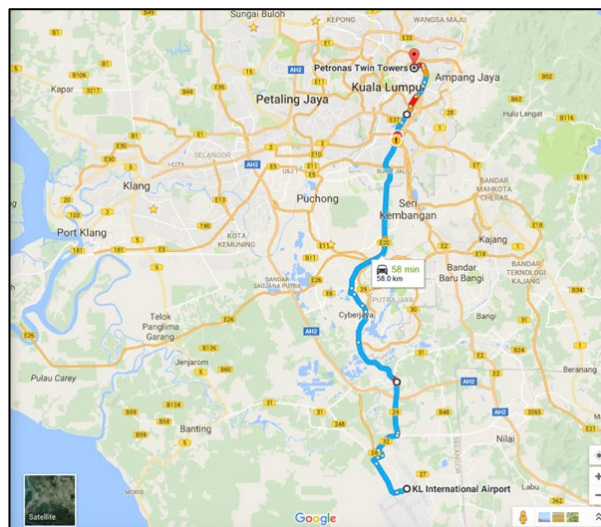


Fig. 7. RDR Driving Map.

4.2 Long Drive Route (LDR) Plan

Long Drive Route (LDR) is designed to support RDR data, in which to confirm if RDR results is valid. It is also designed to validate that different driving style and road condition will not affect the energy saving result. Therefore, different approach is taken for LDR. If RDR is planned to be run continuously on the same route with similar city traffic condition, LDR needs to cover normal long driving condition between cities in Malaysia, from fully charged battery until the phone battery drained. The route will mostly be on federal intercity road with town traffics. Therefore, driving route which fulfil the need between Kuala Lumpur and Kelantan as in Figure 8 is designed.

Driving in LDR will only be done in two sessions. The first session starts from Gombak (Kuala Lumpur) to Kota Bharu (Kelantan), and the second session is driving back from Kota Bharu (Kelantan) to Gombak (Kuala Lumpur). Each session involves 424KM of travelling distance and will takes approximately between 360-480 minutes of driving, depending on traffic and driving condition. This route consists of 21% of highway and 79% of federal road driving. It is expected that the drives will cover various real driving conditions such as small town traffic, meddling with road junctions and traffic light, intercity double line road, railing behind heavy and slow transportation and driving in various weather conditions (based on weather forecast). In order to guarantee the drive gets involve in town traffic, this driving is done during daytime and weekdays only. Figure 9 display the drive route in map view.



Fig. 8. LDR Driving route from Gombak to Kota Bharu, and return.

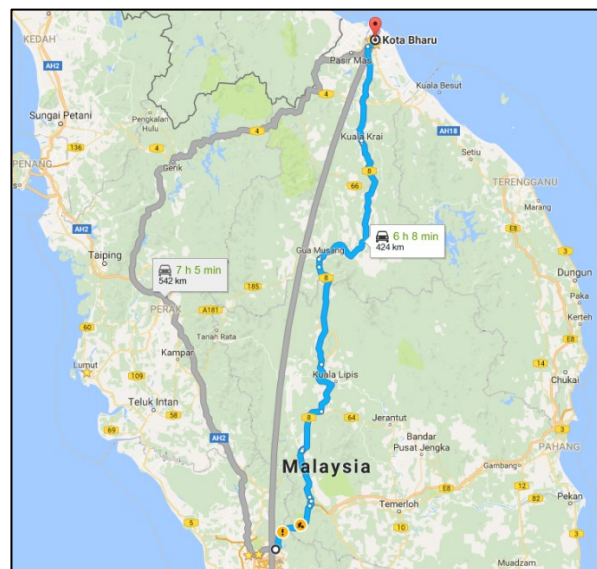


Fig. 9. LDR Driving Map.

5.0 RESULTS

In this section, results of the experiments are discussed accordingly to each categorized route.

5.1 Routine Drive Route (RDR)

Routine Drive Route (RDR) has taken over 56 hours of driving time and record 3,504 raw data to be analyze. As the records generated by two devices, the records are then combined and cleaned based on time, which left to 1,738 data to be processed. Most cleaned invalid data in the records are happen due to pre-mature recording time. All drive sessions are using Waze as navigational application. Conclusion of the driving are presented in Table 1 below:

Table 1. Driving Summary for RDR

Total Recorded Driving Hours	56 hours 48 minutes
Total KM of Driving	3,248 KM
Total Driving Session	28 sessions
Total Data Recorded	3,504 records
Total Data to be Analyzed	1,738 records

The drive has been through different kind of driving situation. It has been through bumpy roads, straight highway and traffic jam due to weather, accidents or unexpected event. But overall it is safe to say that this experiment is able to replicate multiple driving situation of Kuala Lumpur. For each driving session, we find both min and max for each driving session and calculate the mean of driving speed and energy differences before and after drive of each smartphone. The results are summarized by daily in Table 2 and by session in Table 3.

Table 2. Travelling summary by day

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Average Speed (KM)	63.77	57.39	60.93	63.42	32.18	64.64	66.19
Average Time (Minutes)	110.01	118.50	123.01	110.00	124.49	95.51	104.50
Energy Saving (%)	3.0	4.25	4.5	4.5	5.75	3.5	3.25

Table 3. Travelling summary by session

	Morning	Noon	Afternoon	Evening
Average Speed (KM)	Weekdays: 49.08 Weekends: 74.77	Weekdays: 58.08 Weekends: 55.16	Weekdays: 50.30 Weekends: 64.98	Weekdays: 64.69 Weekends: 66.75
Average Time (Minutes)	Weekdays: 132.02 Weekends: 91.99	Weekdays: 111.60 Weekends: 98.0	Weekdays: 133.60 Weekends: 105.01	Weekdays: 91.59 Weekends: 105.03
Energy Saving (%)	4.0	3.71	4.14	4.57

To calculate min and max energy saving per/hour (S), the min or max value of energy saved needs be divide by average minutes of daily driving. Then, to get the results, it needs to be multiply by 60 as 60 minutes per hour.

Minimum Energy Saving per hour

$$vS = \frac{\nu \text{Daily Energy Save}}{\mu \text{Daily Driving Time}} \times 60 \tag{2}$$

Maximum Energy Saving per hour

$$\Delta S = \frac{\Delta \text{Daily Energy Save}}{\mu \text{Daily Driving Time}} \times 60$$

Calculative result for RDR shows that implementing this method successfully save smartphone energy between 1.6% to 3.1% for every hour. Considering that operating GPS module in smartphone will sacrifice huge amount of energy, every unit of saved is indispensable. For example, four hours of daily driving back and to work can save up to 12% of battery power, and that amount of energy is very important when you are in emergency cases.

Besides having the desired results, we also managed to extract additional information from the collected data. For instance, travelling to Kuala Lumpur for occasional traveller in working hours by driving is best done on Thursday noon, or in the evening if working time is not in concern. If it is on weekend, Saturday noon should probably the best time to do it. If possible, driver should try to avoid Monday or Wednesday morning, and especially on Friday afternoon as it is the worst traffic time recorded in our experiment.

5.2 Long Drive Route (LDR)

Long Drive Route as mentioned before will act as supporting data, see if it compliments with result found in RDR. Two sessions were recorded, one to Kota Bharu and the other is returning journey back to Gombak, Kuala Lumpur. Additionally, to check if there is any possibility having different result by using different navigational application, driving to Kota Bharu is done using Google Maps application while the other session is using Waze application. Both sessions record battery usage until both devices are running out of battery.

On the first session to Kota Bharu, *Phone B*'s battery runs out an hour earlier *Phone A* at Machang (Kelantan) after 5 hours 40 minutes of driving time. At the moment, *Phone A* still have 18% battery energy left before it runs out at 6 hours and 52 minutes. Average driving speed for this session is 67.04KM/hour, and average of energy saving per hour is 3.17% which match with RDR results.

On second session driving back to Kuala Lumpur, *Phone B* battery reach 0% at Bentong (Pahang) before entering Lebuhraya Karak. It happened after 5 hours and 55 minutes of driving from Kota Bharu. At the moment, *phone A* still have 19% battery energy left before it runs out at hour 6 and 56 minutes. It shows consistent result with the first session where *Phone B*'s battery runs out an hour earlier. Average energy saving is 3.2% per hour, a bit higher than result achieved in RDR experiment. Possible reason for increase in average energy saving is longer driving route interfere with lesser traffic jam. Average driving speed for this session is 71.99KM/hour.

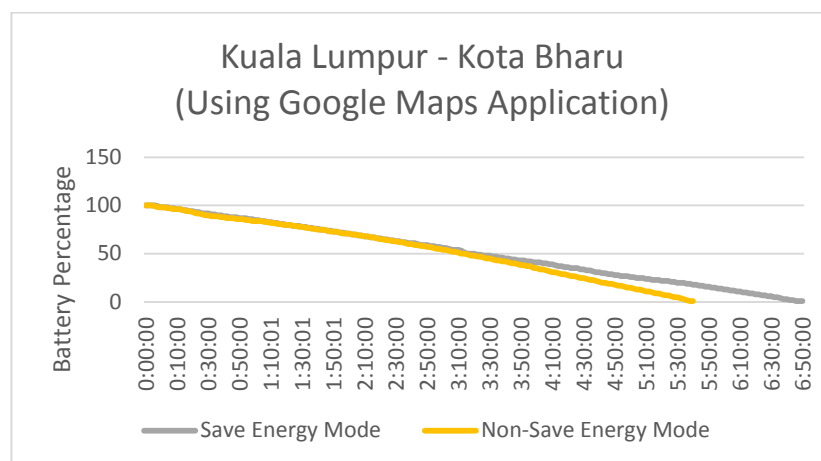


Fig. 10. Battery usage travelling from Kuala Lumpur to Kota Bharu

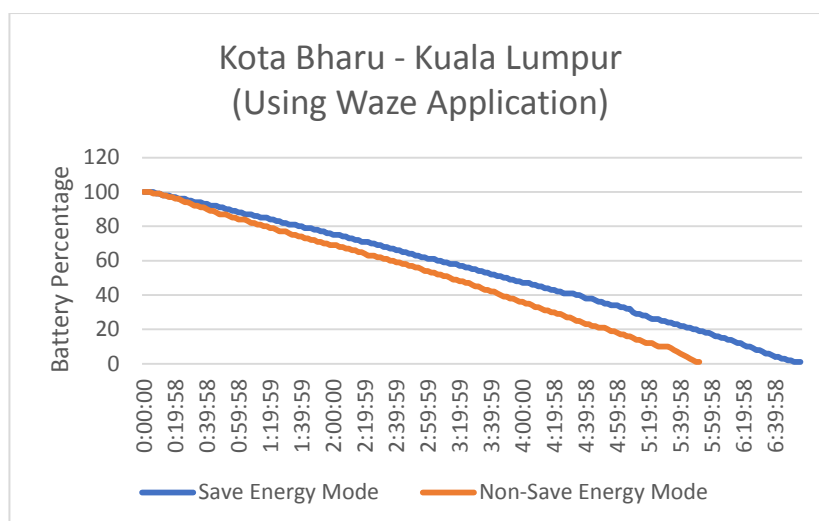


Fig. 11 Battery usage travelling from Kota Bharu to Kuala Lumpur

Comparing both travel sessions, session back to Kuala Lumpur which is use together with Waze application as navigational application seems to drain energy much faster at the beginning of driving. However, as time passed both sessions return almost the same final result regardless what navigational application used. This is probably caused by same consistent usage amount of GPS sensor all the time. Moreover, during this test Waze application was set to display 2D maps only which given possible reason why the result between both application have not much different. And since there are many areas along the way that did not have internet connection, traffic and other information report along the route might not able to be gathered, thus returning identical result despite knowing Waze gathered much more traffic information than Google Maps.

5.3 Comparison with Other Study

In Table 4 below, we try to compare effectiveness of fuzzy inference in mitigating energy consumption with multiple smartphone activities from other study. Overall, each activity proven significant energy improvement whenever fuzzy inference technique is applied.

Table 4. Energy improvement over smartphone activities using fuzzy inference

	Sensor/Component	Energy Improvement
Periodically Download	GSM/GPRS/Wi-Fi	Up to 49%
Music Streaming	GSM/GPRS/Wi-Fi, Accelerometer, microphone	Up to 29.9%
Navigational App	GSM/GPRS, GPS, LCD Screen	Up to 19%

If we look at the table, periodical download is the only activity that uses a single phone component to process at a time. The activity is either uses GSM/GPRS sensors, or the Wi-Fi component to connect to the internet. That explains the result why it can achieve most significant energy improvement, compared to other activities. Furthermore, this activity only running as background services and it did not affect any changes in GUI or screen interface. Music streaming activity uses the GSM/GPRS or Wi-Fi to connect to the internet too. But in addition, the researcher also included extra features which implement accelerometer and microphone in the experiment. While the streaming activity running continuously almost all the time, fuzzy inference implementation is still able to push the energy improvement up to almost 30%.

Compared to both two other activities explain above, our experiment uses navigational app and it operates among top highest energy usage components in smartphone. GSM/GPRS, GPS sensors and LCD screen are the components' name to be precise. While other activity can use Wi-Fi connection as an alternative to be online, this is not the cases as user is always on the move and fairly need to rely on GSM/GPRS connectivity. With all

the disadvantages to the battery life, the result is in agreement with our hypothesis that the proposed approach is able to increase the duration of the battery life. Energy usage for this activity can be reached up to 19% improvement, thanks to fuzzy inference application in the experiment.

6.0 CONCLUSION

The aim of this study is to examine possibility of mitigating smartphone energy consumption using fuzzy inference technique while travelling. Context-awareness which gathered user's environment contexts such as time and speed contribute critical information to power manager to decide on how the smartphone should act to save the energy. While there are few possible techniques to handle this context, fuzzy inference is proven to be naturally processing this information to get the desired results. We had travel over 4,000KM and our experiments proved that using this method can increase battery lifespan with average rate between 1.6% to 3.1% for every hour, even though a result on LDR driving exceed that range. On LDR results, phone with energy saving mode can survive an additional hour before the battery runs out. On top of that, we also manage to gather additional information of recommendation driving timing into or out of Kuala Lumpur from suburbs. We had proved that this method is possible to be implemented in real usage condition, and the results achieved can lead to more interesting future works in smartphone energy saving.

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