CLOUD BASED POWER CONSUMPTION ESTIMATION FOR ELECTRIC VEHICLES

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Abstract- Inaccurate range estimation is a major problem which comes with Electric Vehicles. Because of this many people face issues when planning long trips and short trips with limited battery capacity. To overcome this issue, it is necessary to have a better power consumption prediction algorithm which uses vehicle data and other dynamic environmental conditions. This paper is based on cloud based power consumption estimation system which uses linear regression in machine learning to obtain a better estimation based on above mentioned areas.

Keywords- Electric Vehicle, Range, Power Consumption, Estimation

I. INTRODUCTION

Electric Vehicles are now a trending vehicle type in Sri Lanka because of its environmental friendly approach, cost effective fuel consumption, comfortable interior design and cutting edge technology. According to the PUSL report related to electric vehicles (Public Utilities Commission of Sri Lanka, n.d.), from 2012 to 2017 there have happened more than 4000 EV registrations. Considering the size of Sri Lanka 4000 is a great number. But most of the people interested in EVs are not willing to buy an EV and the second hand market of EVs is rapidly decreasing. Industry research has uncovered that this is caused due to "anxiety felt by many drivers about the remaining driving range their vehicle can run before the next charge". This anxiety is mainly because of the current range and power consumption estimation algorithms do not accurately estimate the remaining driving range and required power to complete a journey. Range estimation technologies use limited data to calculate the estimated range such as battery health, state of charge, acceleration information, fixed auxiliary device power consumption and aggregated trip data. And current technologies do not use external environmental data such as traffic condition, speed limits, altitude and weather information to predict range. To overcome this anxiety, it is necessary to have an accurate power consumption prediction mechanism integrated into EVs.

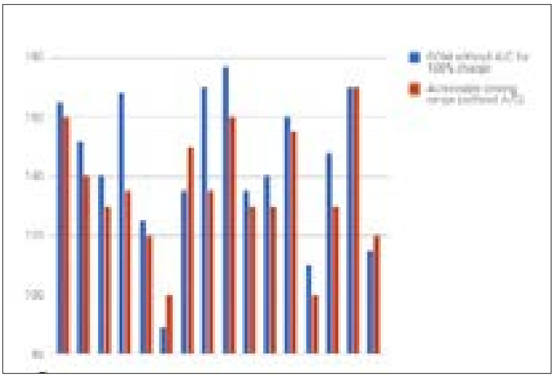

Figure 1. Difference between Estimated Range vs Achievable Range (km)

According to the survey based on Nissan Leaf 24kWh owners in Sri Lanka, Figure 1 shows that there's a considerable deviation on predicted range by inbuilt default prediction model in the vehicle with the achievable range for a full charge.

In order to predict accurate required power consumption to achieve a journey in an electric vehicle, it's necessary to have a prediction model which analyses battery consumption against achieved driving distance including various dynamic facts.

In this paper we propose a power consumption estimation framework which uses machine learning to identify the relationship in between various dynamic facts collected through OBD interface and GPS.

The rest of this paper is organized as follows: section II reviews the existing power consumption models; section III describes the range estimation architecture; section IV describes the methodology; section V describes about converting power consumption to battery percentage; section VI describes about switching between estimation models; section VII explains about the prototype and results; and section VIII concludes the paper and explains the future work.

II. LITERATURE REVIEW

The rest of this section is organized as follows: Prediction Model I; reviews the range prediction model proposed in the paper “Big-Data Framework for Electric Vehicle Range” by Habiballah Rahimi-Eichi and Mo-Yuen Chow. Prediction Model II; reviews the hybrid range prediction model proposed in the paper “Energy Consumption Prediction for Electric Vehicles Based on Real-World Data” by Cedric De Cauwer, Joeri Van Mierlo and Thierry Coosemans. Prediction Model III; reviews the macro range prediction model proposed in the paper “Energy Consumption Prediction for Electric Vehicles Based on Real-World Data” by Cedric De Cauwer, Joeri Van Mierlo and Thierry Coosemans. Prediction Model IV; reviews the range prediction model proposed in the paper “Range prediction of electric vehicles” by Viktor Schreiber, Axel Wodtke and Klaus. Prediction Model V; reviews the range prediction model proposed in the paper “Remaining Driving Range Estimation of Electric Vehicle” by Yuhe Zhang, Wenjia Wang, Yuichi and Keisuke Shirai.

A. Prediction Model I

This prediction model (Habiballah Rahimi-Eichi, n.d.) is a big data framework based on analysing real time data, previous driving patterns (Tseng, et al., 2012) and energy consumption of the vehicle. This model contains 5 sub models in order to identify Route and Terrain Information, Weather Information, Driving Behaviour Information, Vehicle Information and Battery Information.

By incorporating the results gathered from each sub module with a set of equations, authors have tested range estimation on simulated environment which was named SimBattery.

B. Prediction Model II

This model (Cedric De Cauwer, 2015) is based on the underlying physical principles of vehicle dynamics and kinematics. The total required mechanical energy at the wheels as a function of the kinematic parameters describing vehicle movement been expressed as a vehicle dynamics equation. And the equation includes five terms, each describing a contribution to the energy consumption. These terms describe, the rolling resistance, potential energy, aerodynamic losses, kinetic energy, and energy for the acceleration of rotational parts. According to the given equation by authors, the aerodynamic losses and rolling resistances are pure energy losses. And the potential and acceleration (kinetic) energy can partly be recovered by regenerative braking.

Battery consumption of the auxiliary devices is also used to predict the range of EV, and as described on the paper the consumption of auxiliary devices is based on the ambient temperature because of heating and air conditioning systems.

This model uses aggregated trip data to estimate range, bbut it does not use weather and traffic information which impacts the battery consumption. But since the estimation based on collected real-world data, authors have mentioned that weather and traffic information is inherently included in the calculation. Still two obvious factors which influence energy consumption, acceleration and weight information are absent in this prediction algorithm because the mentioned information cannot be extracted from the vehicle directly.

C. Prediction Model III

This model (Cedric De Cauwer, 2015) is an extended version of model II which was developed by same authors. The main idea of this model is to provide accurate range based on micro trips. This model has the potential to be more accurate than Model II as it does not apply averaging and so more information resides in the values of parameters. However, making prediction with this model is impossible dueto lack of available data, and to make this model applicable to range prediction of new trips, an additional correlation has to be done

between characteristic values of these kinematic and physical parameters and external factors. However unlike Prediction Model I, accuracy of this model is tested on a real environment using data collected from Nissan Leaf 2012 24 kWh using OBD Port.

D. Prediction Model IV

This range estimation model (Viktor Schreiber, 2014) is based on preliminary studies and experiments of the energy flow and statistic method Design-Of-Experiments (DOE). According to the paper description, authors have divided driving cycles into 3 categories, such as motor ways, city and suburban area in order to analyse vehicle energy consumption through CAN signals. As a general model this contains 2 main sections as Energy Storage Model and Energy Consumption Model. Energy storage model analyse SOC (Stage of Charge) behaviour of the vehicle and Energy consumption model analyses energy consumption based on consumer and powertrain.

In consumer model, it provides the sum of all aggregated currents. Because usually consumers are periodically switching on/off, and they are running it permanently or they are not very dynamic.

Powertrain model analyse aerodynamic force, hill climbing force, rolling resistance, acceleration force and rotary inertia of powertrain to produce total power consumption of vehicle.

Apart from that this model uses GPS data to forecast route and prioritize routes. To forecast routes, it is required to obtain the destination from user. Based on the forecasted route other predictions like speed profile prediction, altitude prediction and driving time are made in order to improve the accuracy of range prediction. Overall the above mentioned areas are used in powertrain model to analyse energy consumption.

E. Prediction Model V

This range estimation model (Yuhe Zhang, n.d.) is developed considering 9 factors such as vehicle current location, remaining battery energy, road network topology, road grade, road link travel speed, acceleration and deceleration, wind speed, status of on-board electric devices and driver’s driving style. This range estimation method is classified into 2 sections, such as rough range estimation and precise range estimation. Since processing part of this estimation model is done on a cloud server, all of the aggregated vehicle data are stored inside the server. It requires some processing power and time to calculate precise range, in order to reduce this situation, the authors have introduced rough range estimation model which takes less time to produce estimated range. From 100% to predefined level of battery percentage, rough range estimation model is used since drivers less cared about range when battery percentage is at satisfied level. But when battery percentage is at low level, drivers have anxiety about the achievable range from remaining battery percentage. In that scenario precise battery estimation model is used to predict range for remaining battery level.

III. RANGE ESTIMATION ARCHITECTURE

Like all other range estimation systems, this architecture also required to have all the standard data such as historical data, real time vehicle data including GPS locations (J. G. Hayes, et al., 2011), traffic data, weather information, battery information in order to predict range. Therefore, first we develop a framework to collect data from various resources and simplify collected data in order to apply machine learning. The range estimation system consists of 2 major prediction models; prediction based on previous matching data and machine learning prediction which uses a model trained by Google tensor flow applying linear regression. Figure 2 shows the diagram of data collection framework with major data collection nodes including vehicle information, weather information, traffic and route information.

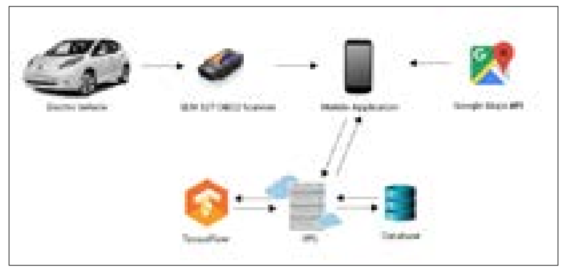

Figure 2. Data Collection Framework

A. Vehicle Information

Major task of the vehicle information node is to collect real-time and static vehicle data such as battery capacity, state of charge, state of health, power usage under different driving patterns (H. He, et al., 2012), (Tseng, et al., 2012), average power consumption for each user, power consumption of auxiliary devices including Air Conditioner etc. In order to collect the necessary information, we use ELM 327 (elmelectronics.com, n.d.) device which uses OBD interface to communicate with vehicle and retrieve CAR CAN Bus and EV CAN data stream. To retrieve data from OBD interface its necessary pass AT commands to the vehicle. Table 1 shows AT commands sequence which require to obtain data from Nissan Leaf Electric Vehicle.

Table 1. AT Commands Sequence to fetch Data (Tseng, et al., n.d.)

Leaf Setup	Decription
ATZ	reset all
ATLO	line feed off
ATSP6	set protocol to mode 6 (ISO-15765-CAN)
ATH1	set headers on
ATSO	set space off
ATCAFO	set auto formatting off
ATSH797	set header to 797
ATFCSH797	set flow control and header to 797
ATFCSD300014	set flow control and date to 300014
ATFCSM1	set flow control to mode 1
ATSH79B	set header to 79B
ATFCSH79B	set flow control and header to 79B

Likewise, through OBD interface it's possible to collect various meaningful information such as SOC (State of Charge), SOH (State of Health), Speed, Odometer, Motor Power Usage etc. Table 2 shows all the table of all the available data which can fetch over OBD interface of an Electric Vehicle.

Table 2. Available data over OBD Interface

Available data over OBD Interface			
Date / Time	Gps	Elevation	Speed
CP Min	Avg	Cell Pack	
Voltage	Volt	Temperature	Odometer
SOC	Ahr	Pack Volts	Pack Amps
Gids	SOH	CP Max Volt	Torque
Ambient Temperature	Motor Power	Anx Power	AC Power

CP – Cell Pack , Avg – Average

B. Weather Information

Although it's possible to fetch outside temperature from Car CAN Bus data stream, weather information node is used to fetch the temperature and other necessary information along the given route till reach the destination for given distance splits. In order to fetch weather information, we use openweathermap (OpenWeather, 2018) which is an open web based API. Through openweathermap it is possible to fetch temperature, pressure, humidity, wind speed with direction as degree in respect to north.

C. Traffic and route information

Route information such as distance to stop point, average speed, elevation, speed limits are the most important information set which requires to predict the power consumption of the electric vehicle. Using Google Maps' Directions API, it is possible to get all the mentioned information as an encoded string which is named as polyline. Through an available polyline decoder, it is possible to get GPS coordinates of the route and elevation. Since the prediction process happens inside the server we use PHP polyline decoder which is an PHP library under MIT and GPLv2 Licenses.

IV. METHODOLOGY

Major output of the system is a predicted numerical value which represents the average power consumptions of the given route. For an example if there are two locations namely A & B with a given distance in km, System will output the average required power in kWh in order to travel the distance from A to B. To predict this value, we propose 2 estimation methods which are

1) Find Previous Matching Data
2) Machine Learning (ANN) Based Prediction

Since the proposed system is a community based cloud application all the process happens inside the server and the historical data of the users are stored inside server. Since we can conclude that the dataset strength will be strengthened daily and the accuracy of the prediction models will get increased. But in order to protect privacy of the users, system will not store users' data specifically, but some portion of data will be used to analyse each driver's driving patterns specifically.

1) Find Previous Matching Data

This prediction model is based on finding nearest power consumption data which matches the current environmental condition based on the routes' GPS points. In order to apply this model, it is necessary to have previous power consumption records of the given route or similar set of data which can mimic the road condition of selected route.

It is necessary to fetch environmental changes including temperature, elevation and traffic status of the route and average driving speed of the route for given distance splits (default value is set to 200m). So if the total distance is 1km, system will collect traffic and environmental condition for each 200m, and finally it will have total of 5 records. Once the system collects data it will search for best matching records which mimic the required situation and get the power consumption value.

```
$records = [
    [
        'elevation_difference' => [illegible],
        'acceleration' => [illegible],
        'temprature' => [illegible],
        'speed' => [illegible],
    ]
    ...
];

$total_consumption = 0;

foreach($records as $record){
    $total_consumption += DataSet::avg('power_consumption')
                ->whereBetween('elevation_difference',
                        array($record['elevation_difference']+2,
                        $record['elevation_difference']-2))
                ->whereBetween('acceleration',
                        array($record['acceleration']+2,
                        $record['acceleration']-2))
                ->whereBetween('temprature',
                        array($record['temprature']+2,
                        $record['temprature']-2))
                ->whereBetween('speed',
                        array($record['speed']+2,
                        $record['speed']-2))
                ->get();
}
```

Figure 3. Sample code to find total power consumption

Figure 3 shows a sample code written in PHP laravel framework which can identify estimated power consumption for a given route by finding nearest possible behaviour patterns. In here the power consumption of auxiliary devices such as Air Condition and Audio System is not included and they will be added into final prediction by multiplying average required travel time since the required power for those devices remain constant most of the time if outside temperature remains unchanged. As shown in the figure 3, each feature has a threshold value of +/- 2 to maximize the availability of previous data records which mimic the current situation. In here we assumed that the weight of electric vehicle as a constant value in order to test the model, But it is a required feature in production release. This simple power consumption model provides accurate results for routes which have less elevation and temperature changes and for city areas.

2) Machine Learning (ANN) based prediction

Machine learning based power consumption estimation is also similar to the above mentioned prediction model. But instead of finding related previous data from the data set; this prediction model uses trained Artificial neural network model to predict data. Like model 1, this model uses various data as features additionally including wind direction, battery temperature and State of Health. This prediction model uses linear regression to train the neural network. Since there are many features provided as inputs, it is required to have a large amount of data records to improve the accuracy of the model. Figure 4 shows the expected vs predicted values of the ANN model which has been trained using a limited set of data. Since the weight of the dataset is low there is noise in the prediction. But overall the prediction is at a satisfactory level.

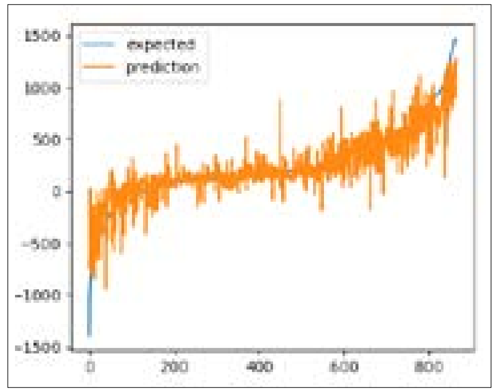

Figure 4. Expected vs Predicted Values of ANN Model

PROCEEDINGS

V. POWER CONSUMPTION TO BATTERY PERCENTAGE

SOH and SOC play a major role when converting prediction power consumption to battery percentage which is a human understandable value. SOC means the available battery capacity as a percentage value and SOH means the maximum capacity which can be held in battery as a percentage respect to the original battery capacity, or simply SOH represents the battery degradation of the electric car.

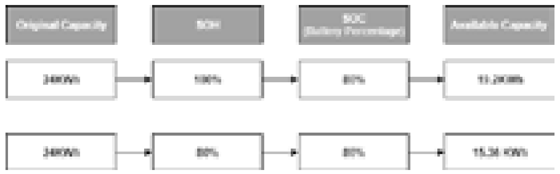

Figure 5. Find available capacity

By default, most of the electric cars cannot use advertised battery capacity. There is a threshold value. In a Nissan leaf AZEO 24kWh electric car, there is a 5% of threshold value, which means 95% of the capacity is usable (roughly 22.8 kWh).

Calculate remaining capacity of a Nissan Leaf 24kWh,

24*0.95*SOH*SOC

24*0.95*100%*100% = 22.8 kWh

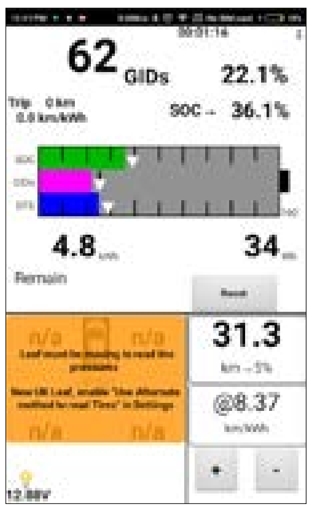

Figure 6. OBD Reading of a Nissan Leaf 24kWh

Figure 6 is an OBD reading of a Nissan Leaf 2014 24kWh taken from Leaf Spy mobile application which has 28% usable SOC (36.1% Total SOC) and 75.43% of SOH.

According to the above numbers the remaining capacity should be,

22.8*28%*75.43% = **4.81 kWh**
which is already displayed in the figure 6.

Calculating predicted required & remaining battery percentage,

R = Predicted required Power (kWh)
C = Current Battery Percentage (%)
B = Total usable capacity of a 100% SOH Battery (kWh)
SOH = state of health (%)

Required Battery Percentage = { R/(B*SOH) }*100%

Remaining Battery Percentage = C – { R/(B*SOH) }*100%

VI. SWITCHING BETWEEN MODELS

Since matching previous data is faster and accurate than ANN prediction, it has the highest priority over ANN prediction model. But due to low probability of available matching data in database there is a higher chance to switch prediction model to ANN based prediction model.

VII. PROTOTYPE & RESULTS

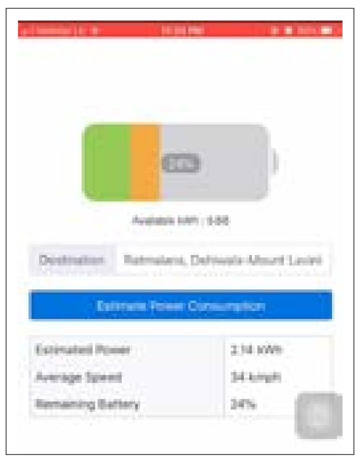

Figure 7. Power estimation GUI Front

Figure 7 shows the front end view of the power estimation application. Although there are several main inputs such as SOH, SOC, starting point, end point, power use of auxiliary devices etc., user just have to provide end location only. All other mention inputs will be read directly from the CAN Bus data stream over OBD2 interface. Since all collected data for the prototype test is based on a specific location, prediction accuracy for the specific location is higher than predicting required power for other location which has different weather and traffic conditions. But overall system provides accurate predictions although system has limited number of data records. Another important fact is that the estimated power consumption value is based on the traffic data provided by the Google Maps API and on average electric vehicle drivers' power usage values. In that case if a driver uses to drive aggressively or at higher speeds; this value might be not accurate.

VIII. CONCLUSION & FUTURE WORK

Cloud based power consumption estimation system for electric vehicles was introduced to overcome range anxiety of electric vehicle users by providing the value of required power consumption to achieve selected location or range by the user. This framework collects all the power consumption records from system users, traffic records, and weather changes. The system consists of 2 major prediction models and the model which uses Artificial Neural Network to predict power consumption is used to train its model on daily basis in order to improve the accuracy of the prediction. Prototype mobile application was developed to measure the accuracy of prediction, and as future works the prototype application will be developed for production and will collect more historical data in order to strengthen the dataset and the model to improve the accuracy.

ACKNOWLEDGMENT

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WATER INTAKE RECOGNITION SYSTEM BASED ON PRESSURE SENSORS AND BLUETOOTH TECHNOLOGY

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Abstract- Dehydration is a very common problem especially among the elderly people and patients, and monitoring daily fluid intake of a person is vital to avoid dehydration and many other diseases. When we talk about the importance of water, it is an essential element of life. Automating the fluid intake monitoring can help to avoid the risk of losing the recommended daily fluid intake. An automated system can monitor and keep tracking the daily fluid intake and send reminders to the users and guide them towards wellbeing. In this research, a system is developed to help elderly people as well as patients to monitor their fluid intake. The system is developed with a special stand using pressure sensor and Bluetooth and an android application which provides records and reminders. It was observed that the system provides accurate results and it is a low cost solution.

Keywords- Fluid intake monitoring, Pressure sensor, Bluetooth

I. INTRODUCTION

Water is the fundamental element of life. It has proven that the approximately 60 present of body weight consists of water. Our body needs water in all its cells, organs and tissues to manage the body temperature and the functions. (Jequier E, Constant F, Eur J ClinNutr. 2010). Normally, body loses water when breathing sweating and digestion. So, it is vital to get rehydrated by drinking enough water and by eating food which contains much water. The water requirement depends on many factors like, climate, age, health problems and physical activeness. This has proved that drinking water is very important and that it is also important to take a recommended daily water intake. (D. Bunn, F. Jimoh, S. H. Wilsher, and L. Hooper 2014)

(Jaehyoung Yu Harnsoo Han 2008) measured the water level in a river or a tank such as applications related to flood and farming applications. The application that has been built to measure the water level is based on main 4 types such as pressure, heat, image and the 4 supersonic waves.

According to Welch, hydration is important for a good physical health of a person. Liquid intake from drinking water and beverages are major sources of hydration. We tend to forget to drink water because of our busy schedule and that may lead to unwanted problems. In this study, we will be developing a smart system to elderly people and patients to guide them with their daily water intake. The system consists of a hardware unit (smart measure) and an android application.

Pressure sensor is used in order to measure the liquid intake of patients. Then the readings where send to an android application, which will calculate the water consumption, mange records and give alerts. This system is simple, low cost and maintenance-free. Monitoring drinking behaviours of people living at home alone is important not only to ensure that they maintain an adequate fluid intake but also to identify the drinking patterns. This system can easily have adapted to patients to monitor their fluid intake.

In recent years a review of literature regarding the application of various wireless system techniques used in the area of measuring the water level as well as Hardware

Design of Wireless Sensor Platforms which have been developed using such Water level monitoring techniques. Significant developments in the area of measuring liquid intake as well as the strengths and weaknesses of existing systems are also discussed the implementing of a remote measuring station in this the remote stations are considered as simple measuring units with a communication interface so that they may be operating under the control of base station. The advantages of this paper are that there are no mechanical parts required, remarkable accuracy and resolution, and disadvantage of this system is the water level monitoring is developed slowly and it required temperature companion (Daniels 2009). According to them they present a method to spot gestures when receiving data through sensors. The method is a natural way of getting continuous signals and is based on two stages. (H. Junker, O. Amft, P. Lukowicz, and G. Troster 2018)

A Wireless system for monitor and control of water level in greenhouse. They had used ZigBee network and several sensors nodes. The advantage is low cost and high network capacity. The ZigBee network for water irrigation control monitoring system. Here they used lots of sensors to monitor the water level of a tank and it was based from the signal that is coming from the sensors. (Morley JE, Miller DK, Zdodowski C, Guitierrez B, Perry HM 1998). According to (B.Y.Lee and B.Y.park, 2008) the pressure sensor is easy to use but it has some limitations where it should be replaced because of a breakdown which may occur by the high water pressure.

According to Zhou when we have to monitor and control the conditions of the environment such as temperature and humidity the main techniques used is WSN. This technique reduces the time when we have to monitor the environmental conditions. Also, the network technology that will be used is called ZigBee. This can be used in mining industry. (Zhou Yiming 2017). Here they use RFID Tags as a wearable sensor device to measure the liquid intake. Also, they use sliding window-based techniques to measure the activities (R. L. Shinmoto Torres, D. C. Ranasinghe, and Q. Shi 2013). In this review we provide the need for water and its importance for humans. Also, there are diseases related to dehydration, and how to monitor the amount of water consumed. (Bar-David Y, Landau D, Bar-David Z, Pilpel D, Philip M. U 1998).

According to Gender when the data has been measured and collected by the sensor the computer then takes the data from the database and monitor to see if the data is accurate, and if it is ready for communication. For this purpose, the computer chip is monitored by a micro controller which can measure the data that is being stored in the random-access memory and the Read only memory and other data monitoring software.

II DESIGN AND IMPLEMENTATION

A. The High-level Architecture of The System

The system is consisting of two parts. The first we design a hardware measuring stand, which is embedded with a pressure sensor, Bluetooth module and Arduino Microcontroller. Then we have developed and android application. The application takes the data from the hardware unit, calculate the measurements and provide user interface. Application is providing information to the users regarding the daily water intake and send them alerts of reminds to take water during the day to meet their requirements. Application also keep the past record to generate reports.

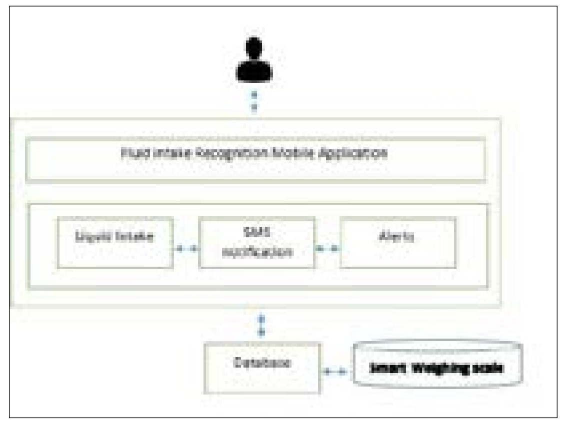

Figure 1. Overall System Architecture

Implementing android application will have the communicating media of a Bluetooth service. Only the registered users will be able to do the Measuring of liquid intake through implemented android application in the media of Weight Sensors.

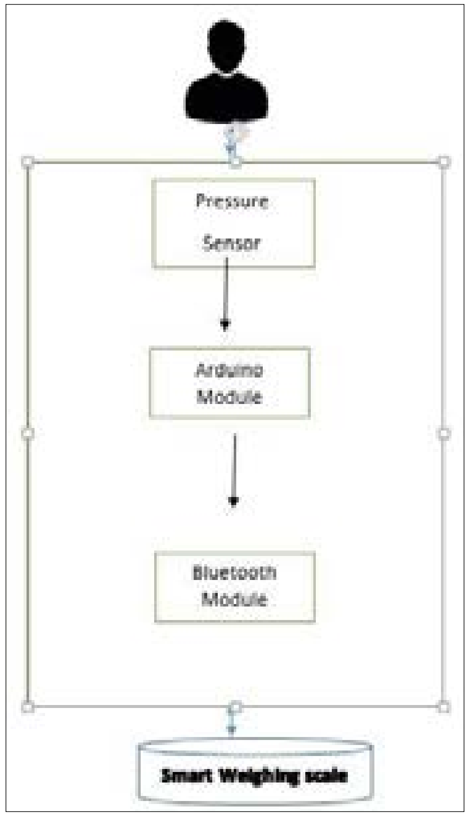

Figure 2. Identified Variables between Technologies

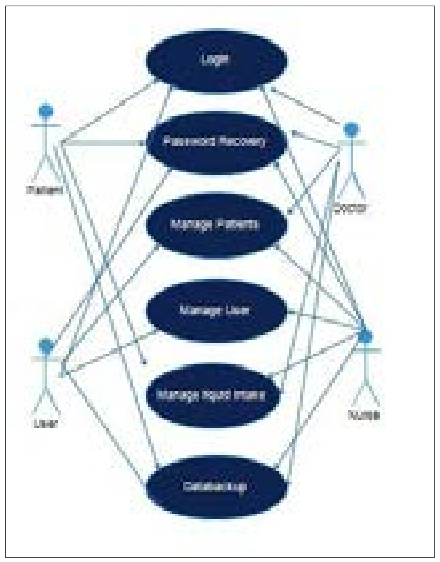

Figure 3. High Level Use Case

B. The design of the system core.

The core of the system is developed using Pressure Sensors, Arduino and Bluetooth Modules. However, the application should consist of user friendly and responsive interfaces which will allow user to access the platform on any mobile device. When we talk about the development of the mobile application, the interface module will consist of two basic Levels to input the data such as The Patient Level and the internal level.The interface will be for the patients to enter their details and check their status, and also the other interface will be for the authorized internal personal to enter the patient's records and see the status of the patients.

Figure 4. Sensor Input Data

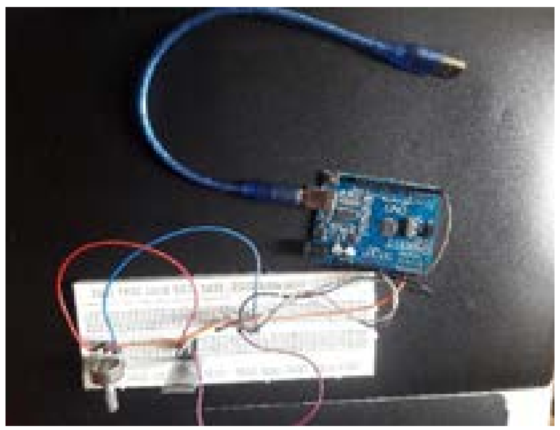

Figure 5. Hardware Interface

III. TECHNOLOGY USED

A. Use of Pressure Sensors

The reason to use the MS5837-30BA for the project is because The MS5837-30BA is because when we use a water proof pressure sensor the human interaction is limited and therefore we cannot get the accuracy of the data in a proper manner. When we talk about pressure sensors it introduces a good and accurate solution to measure the water intake of a person. Even though pressure sensor is easy to use, it also has certain limitations that has to be changed because of the pressure of the water.

B. Use of Bluetooth Module Connection

When we talk about wireless communication the first thing that comes to our mind is the Bluetooth connection. So, in order to communicate with a smart phone, and also in relation to the project we decided to use the Bluetooth module to transfer data from the pressure sensor to the mobile device. The reason to use this Bluetooth module is based on the following facts, such as Bluetooth consumes less energy than Wi-Fi and therefore it is easy to use.

Here we will be using the HC-06 is a class 2 slave Bluetooth module where it is used to transparent wireless serial communication. So, when it is connected to a Bluetooth device such as an android phone the operation will be transferred to the user, and all the data that is being received will go through a serial input and be transmitted over the air. It is easy to transfer data from multiple devices such as in this project, from the sensor you transfer all the date into one smart phone over a short distance.

C. Use of Arduino Microcontroller Technology

For the purpose of this project we used the Arduino – UNO because it can be easily used as both a hardware and software component. This consist of a circuit board and also it is built upon a readymade software called the Arduino IDE (Integrated Development Environment) which can be used to write the upload the code to the computer to the physical board. We need a microcontroller to measure the process from the pressure sensor and send it to the Bluetooth module, as well as to turn the Bluetooth module on and off when required. We use this platform because of its easy to use design development environment.

According to a study by KIipnisit is important to measure and monitor the physical conditions of a patient. When we monitor those conditions, we can get the internal data from the patient's body and get the accurate data of their health. And recognize the symptoms and help us to prevent them from dangerous body failure.

D. Android Studio

In order to make the mobile application we will be using the Android Studio Software in order to design interfaces.

Hardware interfaces are arranged as shown in the figure 5. The Programming Sensor Input are developed using Android Bluetooth Controller integrated with Bluetooth technologies which facilitates the need of responsive interfaces. Figure 4 shows the test data inputs taken by the hardware unit.

IV. HOW SYSTEM WORKS

The prototype model of the smart measure is shown in figure 5. After that we will connecting it to the Arduino using Breadboard and Jumper Wires. Next, we will take all the signals we get from the Arduino and connect it to the Bluetooth Module in order to have the communication with the android phone.

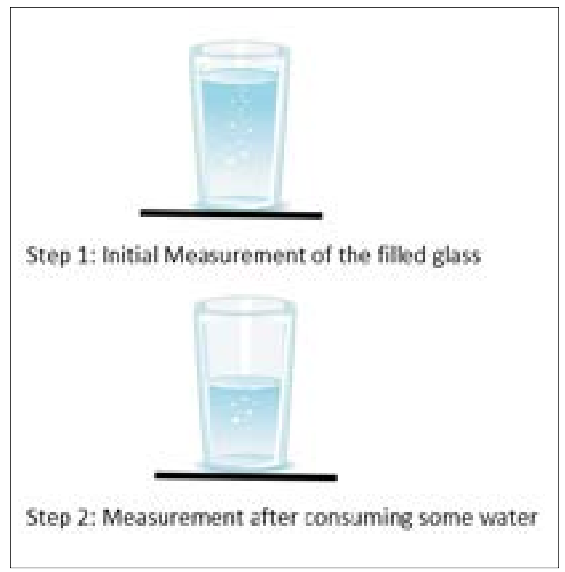

Figure 6. steps of measuring water consumption

PROCEEDINGS

Figure 6 shows the steps a person should follows when drinking water. First user has to fill the water and kept that on top of the measure as shown in step 1, then it will record the filled amount. After finish drinking user have to keep the glass on measure record data as in step 2. Then the system will calculate the water consumption using the difference (1 millilitre (ml) of water weighs 1 gram (g)) and keep records. This system automates the water intake, so it will be a great advantage rather than taking and keeping these records manually.

We will be recording all the data in the Database and sending all the relevant details to the mobile application so that every time the user drinks the water he/she will get the notification and the results of his behaviour. We will also be implementing a Mobile Application so that the patient can log on to the application and check the details whenever required. This system can be helped to elderly people who lives home alone, and patients need to monitor their water intakes.

- The users can log in to the system with authentication. Then the user can monitor the liquid Intake and browse the amount of water that they have consumed.
- This will also help the secondary users like gradients or medical officers to follow the records and analyze.

The system will provide the following outputs

- Daily water consumption
- Notifications regarding the remaining needs
- Water intake analysis report

V. CONCLUSION AND FURTHER WORK

When we talk about mobile applications and its development we see that it is one of the most technical future. When we talk about the future of businesses in order to win and live in the society they should always explore and come up with new ideas to improve their business and innovations. When we talk about hardware platforms it will reduce the work of the current users as well as new users and bring out a good solution.

Also, when we talk about good user experience we can use this and extend this to a wide area such as their mobile devices based on their location. Also, we can use this system in hospitals, where it would be easy for the doctors to check the amount of water consumed before being taken to the operation theater. In this study we use pressure sensors and Bluetooth modules to monitor the liquid intake of patients. Here we propose a smart weighing scale where we keep the cup to measure the amount of water consumed per day.

In conclusion we show the efficient and easy method of recognizing the amount of water intake consumed per day in order to have a good fluid balance life, based on pressure sensors and Arduino modules. We believe that this project will be very useful for patients, doctors as well as people who are interested in the medicine field. In future the system can improved to manage records on all types of fluid taken buy a person. This also can be modifying and improve to use in hospitals to monitor liquid intake and the output to create balance charts to help many patients.

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