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Smart Home Energy Management System Using Least Square Regression Analysis

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Abstract: Smart home is a residence with several electrical and electronic appliances that are capable of communicating with each other and can be controlled remotely from any room in the home or from any location in the world. Easy control of home appliances/devices and energy management has been the main goal that leads to the invention of smart homes. However, most of the systems developed for these homes are either complex or could not manage energy wastage efficiently which incurring more electricity bills cost. In this work, an intelligent home energy management system that is based on Least Square Regression (LSR) analysis is presented. The system is trained based on the historical data of occupant's interaction with the appliances over a period of time. It monitors and computes the power consumption of home user over a period of time. This system takes decision and controlled the output using LSR based on what it learnt by alerting the home user on condition of accept or reject response through Android GUI Apps. The system performance evaluation based on the frequency prediction which is given as 0.77 RMSE, the activation time prediction is given as 127.89 seconds RMSE which is slightly above 2 minutes with a regression coefficient of (R=0.999988). The RMSE of 257.90 seconds for activation of duration prediction with regression coefficient analysis of (R= 0.989071).
Keywords: Android, Communication, Electricity bills, Electronic appliances, Energy management, Intelligent, Least square regression, Smart home.

INTRODUCTION

Smart homes are homes where different appliances, machines and other energy consumers are connected in one network which is controlled according to inhabitants' needs and behaviors, outdoor climate and other parameters. Smart home refers to home where information and communication technology (ICT) can anticipate and respond to the needs of occupants, in order to enhance their comfort, convenience, security and entertainment [1, 2]. Described smart home as a home-like environment that possesses ambient intelligence and automatic control capable of increasing occupant's comfort, convenience and luxury. Since the primary objectives of a smart homes are to increase home automation, facilitate energy management, and reduce environmental emissions. This is possible due to the advancement of wide variety of sensors and high processors technologies using service modules based on any short-range technologies such as Wi-Fi, ZigBee, Z-wave among others [3-5].

In literatures [6-8] revealed that, smart home systems is grouped into six primary categories which include: security and access control systems; lighting, window and appliance control systems; home appliances; audio-visual and entertainment systems; healthcare and assisted living systems and energy management systems.

Energy management is a term that integrates both power control and power management, with an emphasis on total energy conservation rather than just the efficiency of a specific system component in a smart home. Smart home energy management system refers to the application of supervisory control and data acquisition with energy management systems, including the generation, the transmission and distribution systems of the electrical network. Smart home energy management system deals with the real-time monitoring and arranging of various home appliances, based on user's preferences via intelligent ambient systems controlled by a human–machine interface.

Revealed that, the full potential of smart homes still lies fallow due to the complexity and diversity of the systems, as well as the frequent problem of suboptimal energy management system [9, 10].

Intelligent energy management system is the infrastructure connecting energy demand and supply using the latest developments in digital technology and communication technology in order to increase efficiency, reliability and security of the system. According to [11-13] discuss intelligent energy management system as the collection of all technologies, concepts, topologies, and approaches that allow the silo hierarchies of generation, transmission, and distribution to be replaced with an end-to-end, organically intelligent, fully integrated environment where the business processes, objectives, and needs of all stakeholders are supported by the efficient exchange of data, services, and transactions.

All the highlighted works had contributed immensely to smart homes but some improvements can be achieved in the area of power consumption, reduction in complexity of the system and some level of intelligence can be incorporated as in [14, 15]. In this work, an intelligent home automation system is proposed to monitor energy consumption via the wireless network and internet of things (IoT) technology. It then required training with the pattern activities of the occupant in relation to the appliances and alerting the home user when action is taken in real-time.

MATERIALS AND METHODS

The Intelligent Home Energy Management System (IHEMS) consists of several integration of hardware systems module (includes, sensing, transmission/receiver, processing and power supply unit), wireless technologies and program design (software). The system block diagram is shown in Figure 1 and Figure 2 illustrate the system architecture.

The Sensing Module

The sensing unit is design to preform functions of monitor and control of home appliances. It includes television, fan, and refrigerator located in the living room, electric cooker and water heater in the kitchen. In this case, each smart home appliance are attached with the sensor for adequate control and monitoring.

The Transmission/Receiving Module

This module responsible for the data transmission using IEEE802.15.4 standard transceiver through intelligent gateway. This device is considered in the system development due to its low power consumption and ease of interfacing with the Arduino and Rapsberry Pi microcontroller. The IEEE802.15.4 classes and power consumption is presented in Table-1.

Table-1: IEEE802.15.4 classes and power consumption

Power Class	Max. O/P	Nominal O/P	Min. O/P
Class 1	100mW (20dBm)	NA	1 mW (0 dBm)
Class 2	2.5mW (4dBm)	1 mW (0 dBm)	0.25mW (-6 dBm)
Class 3	1mW (0dBm)	NA	NA

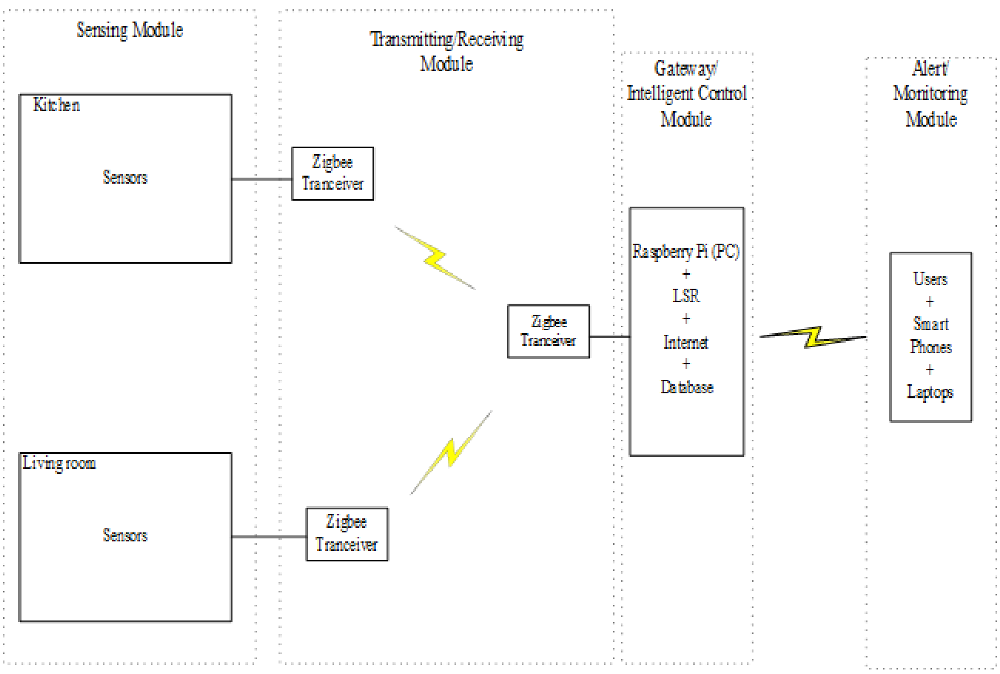

Fig-1: The IHEM block diagram

The Gateway/Intelligent Controller Module

This module comprised of a raspberry Pi board which serves as the controller to the sensing devices and a link between the sensing devices and the user. The Least Square Linear Regression model is adopted on raspberry pi. The acquired data are trained with the historical data collected and interaction with the occupant user of devices over a period of time. The home occupant devices are intelligently controlled by prediction output of the LSR model. The controller is used to monitor the power consumption of the devices and provides the detail through an android application. Details on the prediction model are described in subsequent section.

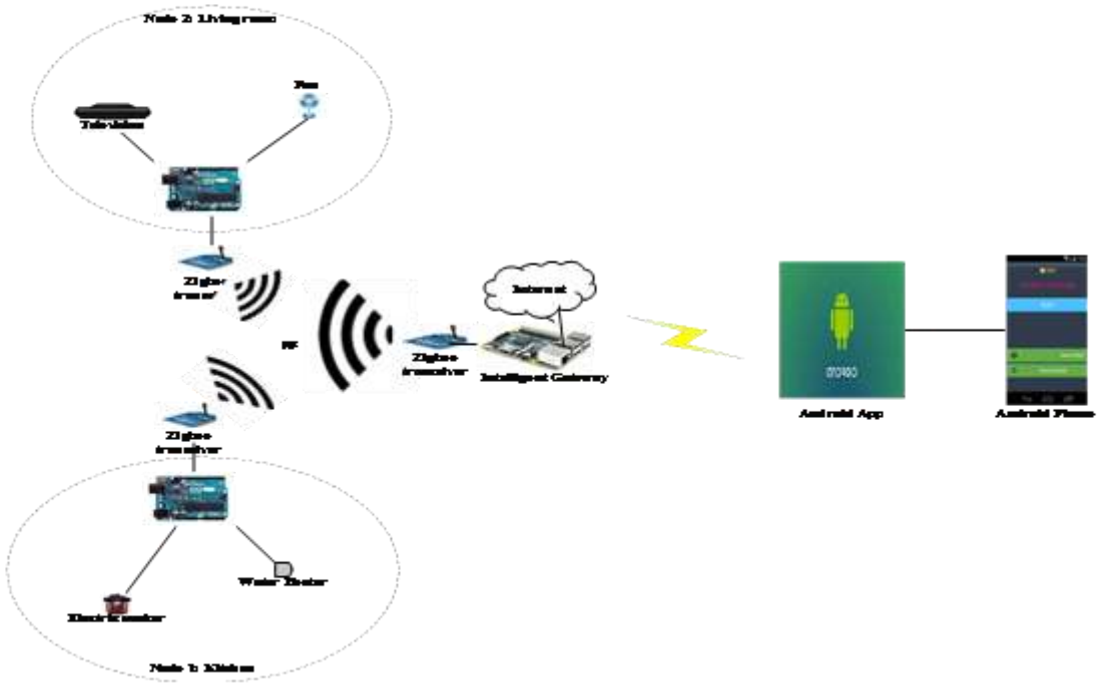

Fig-2: The IHEM system architecture

Alert/Monitoring Module

This module comprise of an android application designed to receive alert from intelligent controller. The alert pops up asking the user to accept/reject the control decision taken by the device as illustrated in Figure-3a, 3b and 3c**.**

Fig-3a: Android GUI apps for smart HEM

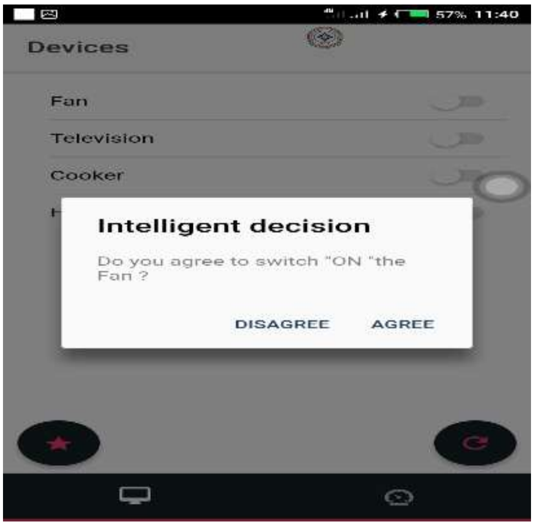

Fig-3b: Android GUI apps for smart HEM

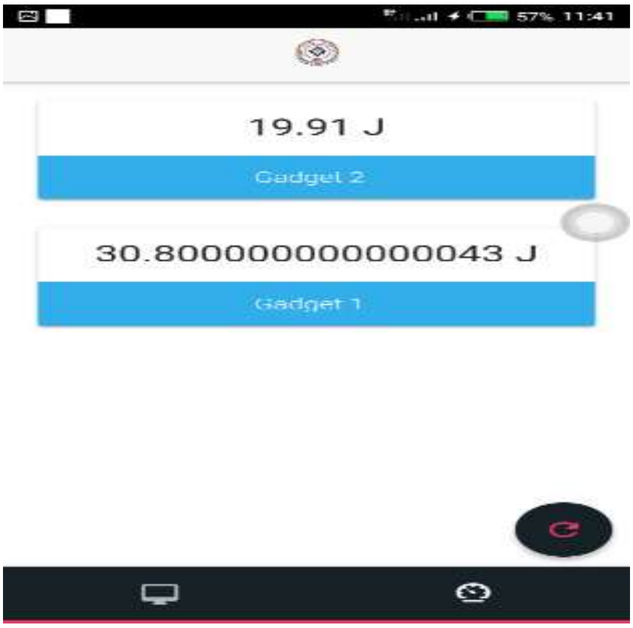

Fig-3c: Screenshot android GUI apps illustrate the consumption per gadget

Least Square Regression (LSR)

The design process of LSR machine learning model based HEMS is divided into two stages: training and testing of the model. Figure-4 illustrate the steps involved in the training and testing of the LSR model. This includes data acquisition, data division, LSR training and LSR testing. In this work, Multiple Linear Regression technique of the LSR was used and this was implemented using PHP.

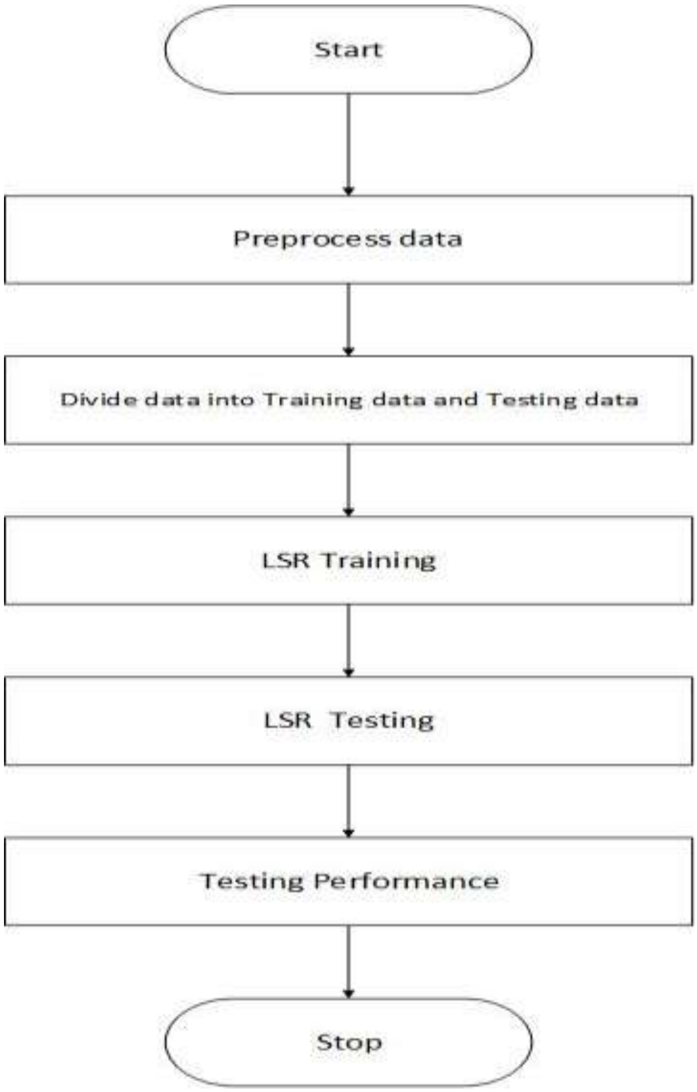

Fig-4: Flowchart of LSR prediction model design for IHEMS

Data Description

A log of the occupant's daily interaction with the interested devices for a period of approximately six months (20/01/2017-13/07/2017) was used as training and testing data for the LSR model. The collected data comprised of the date, the number of times the device comes ON per date and the duration per activation. The LSR after training was able to understand the pattern of the time the occupant switches ON/OFF the said devices. A total of 174 data were collected for each device for the first training. The size of the data kept increasing because, at the end of each device operation, the detail is added to the training data and will be used for the subsequent predictions.

Data Pre-Processing Steps

- Step 1: Group data by date per device
- Step 2: Sort the grouped data according to frequency of activation (ON) per device per date
- Step 3: Identify the dates with the same frequency of activation per device and group them together. The dates per device is the training data sample while the frequency of activation per date is the target data for the LSR
- Step 4: Identify per device, the dates with the same frequency of activation and group them together
- Step 5: Identify the activation times per group, per activation, per device, per date. The activation date is the data sample while the activation time is the target data for the LSR
- Step 6: Identify the duration per activation. Group another data with the activation time as sample data and activation duration as the target data for the LSR.
- Step 7: Put all the sample and target data of steps 3, 5 and 6 in array formats
- Step 5: Use the data to train the LSR model
- Step 6: Use the trained model to predict the next activation frequencies, activation times and activation durations per device in 24 hours

LSR Training/Testing

The LSR training was carried out using the pre-processed data as highlighted above. The sample and target were supplied and the PHP commands were issued to train the model. The model was developed to predict three outcomes; frequency of activation per day, the activation time per day and the activation duration. The data samples and targets for frequency of activation, activation times and activation duration were supplied for the training as illustrated in Figure-5. The LSR testing follows the days and times that data will be fed to the network to predict the status of each device (ON or OFF) based on the training.

$regression = new Least Squares;

$regression->train ($samples, targets);

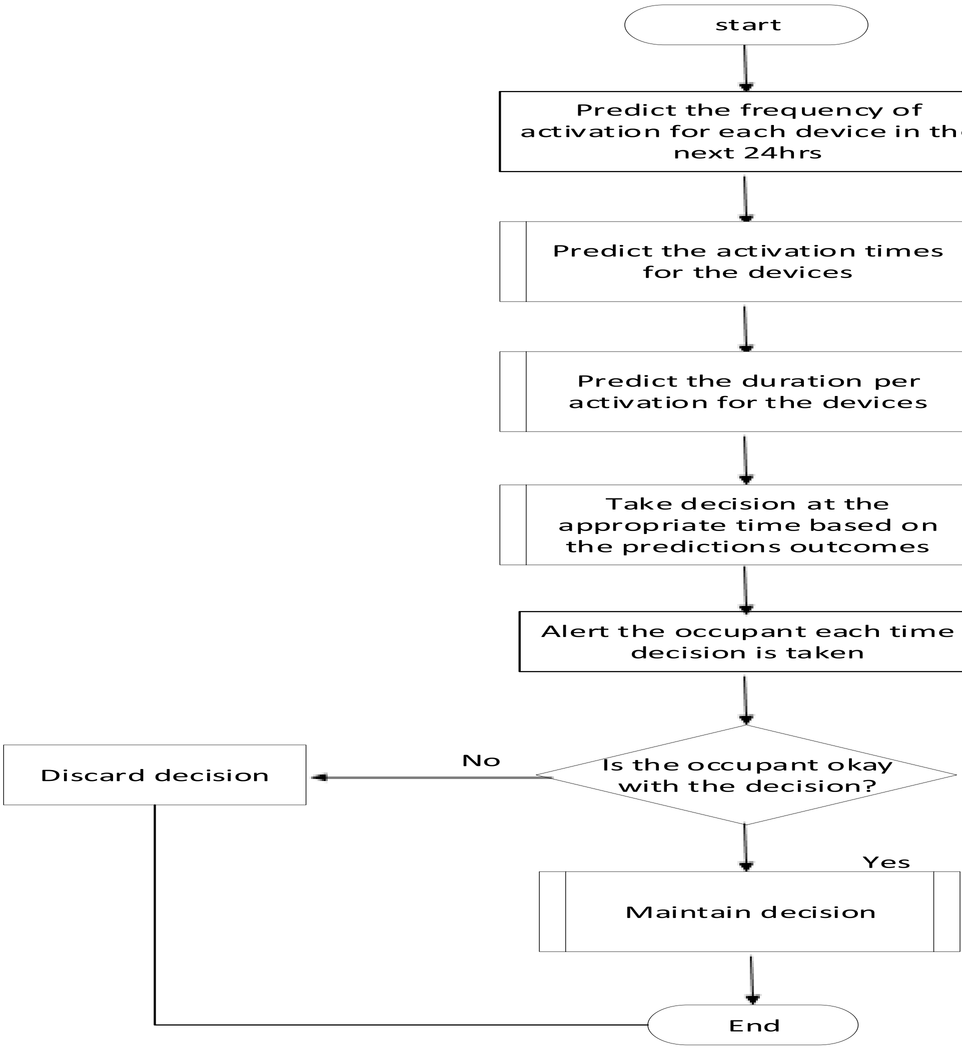

Fig-5: LSR Prediction flowchart for HEMS

Computation Model of Energy Utilization in the Smart Home

The intelligent controller keeps record of the power consumed for each device during the ON time and consequently, then computes the power consumed by all appliances in the smart home for a given period of time using Equation 1.

$$Consumed\ Power = \sum_{\substack{i=1 \\ j=1}}^{N} (I_i V_i)_j t \quad (1)$$

Where,

J= stands for the node number

i= stand for the device in the node.

I= stand for current

V= for voltage

The system performances are evaluated based on LSR model and the entire system operations. Performance evaluation of the LSR was carried out using average response time computed from twenty network responses for two different network conditions as expressed in Equation 2.

Average Response Time is;

$$T_{AR} = \frac{1}{N} \sum_{\substack{i=1 \\ j=1}}^{N} t_i - t_k \quad (2)$$

Where,

T_{AR} is the average response time

N is the number of system responses considered,

t_i is the time alert is received by the occupant,
t_k is the time intelligent control was taken by the system.

RESULTS AND DISCUSSION

The results comprises of Root Mean Squared Error and correlation coefficient for the Least Square Regression (LSR) model prediction. This is used for an intelligent decision and the response times for alerting of IHEMS.

Activation Frequencies Prediction

The predicted activation frequency and actual activation frequencies of the device are compared for 5 days as shown in Table-2. It is observed that, RMSE recorded error is 0.77 which is good for this system. The regression plot for the prediction is shown in Figure 6. which shows that the predicted values are not far from the actual values, hence, recorded regression coefficient is close to 1 (R= 0.992903) signifying minimal errors.

Table-2: Actual versus predicted activation frequencies

Actual Activation Frequency	Predicted Activation Frequency	Actual Error	Squared Error
4	4	0	0
12	12	0	0
9	8	1	1
1	2	-1	1
10	9	1	1
			3.00
		RMSE	0.77

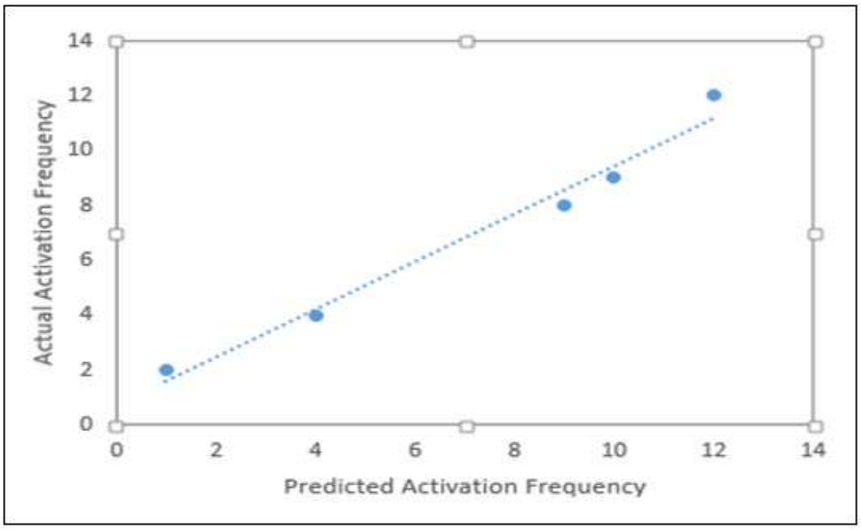

Fig-6: Regression plot of actual versus predicted activation frequencies

Activation Times Prediction

The activation time predicted versus actual activation times in seconds for the same device 1, is shown in Table 3. This illustrate the difference between the actual and predicted values, presented in the third column, is considerably small (less than 5 minutes). The RMSE recorded is 127.89 seconds, which is slightly above 2 minutes. This makes it adequate for the IHEMS. The regression plot for the prediction is shown in Figure 7. It can be observed from the plot that almost all the points fall on the trend line which shows that the predicted values are almost exactly like the actual values, hence, recorded a regression coefficient are very close to 1 (R=0.999988) signifying almost zero errors.

Table-3: Activation actual time versus predicted activation times

Actual Activation Time (s)	Predicted Activation Time (s)	Actual Error	Squared Error
73.00	72.75	0.25	0.06
21666.00	21862.63	-196.63	38663.66
43242.00	43466.85	-224.85	50557.52
64842.00	64918.29	-76.29	5820.52
22.00	115.9269	-93.93	8822.27
7229.00	7444.835	-215.84	46584.58
14522.00	14438.86	83.14	6912.64
21668.00	21730.18	-62.18	3865.97
28969.00	28785.22	183.78	33776.78
36072.00	36194.93	-122.93	15111.03
43285.00	43254.77	30.23	914.13
50444.00	50443.40	0.60	0.36
57796.00	57782.33	13.67	186.74
64983.00	65066.03	-83.03	6894.11
72118.00	72179.27	-61.27	3754.39
79372.00	79460.95	-88.95	7912.10
58.00	45.63	12.37	152.90
9683.00	9693.35	-10.37	107.04
19208.00	19351.42	-143.42	20570.18
28884.00	28905.60	-21.60	466.39
38432.00	38635.77	-203.77	41521.90
48066.00	47861.87	204.13	41670.94
57666.00	57698.48	-32.48	1054.75
67208.00	67208.37	-0.37	0.14
76867.00	76811.33	55.67	3099.49
55.00	199.76	-144.76	20955.90
147.00	93.34	53.66	2879.15
8644.00	8581.44	62.56	3913.95
17311.00	17561.30	-250.30	62652.02
26075.00	25970.21	104.79	10981.43
34651.00	34615.01	35.99	1295.17
43216.00	43218.19	-2.19	4.81
51975.00	51700.25	274.75	75485.45
60593.00	60558.53	34.47	1187.86
69213.00	69359.25	-146.25	21389.06
77831.00	77608.67	222.33	49430.97
		TOTAL	588596.40
		RMSE	127.89

Activation Duration Prediction Result

The predicted activation duration versus actual activation durations in seconds for the home appliance is shown in Table-4. RMSE value of 257.90 seconds was recorded. The regression plot for the prediction is shown in Figure 8. It can be observed from the plot that a large number of the points fall close to the trend line which shows that the predicted values are close to the actual values, hence, recorded a regression coefficient close to 1 (R= 0.989071). This signifies that, the duration of activation as predicted for the device is slightly close to the pattern of the occupant’s use of the device.

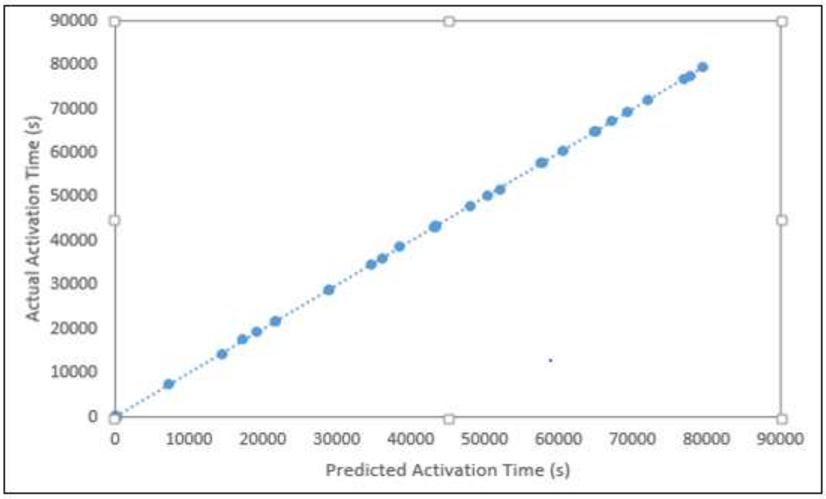

Fig-7: Regression plot of actual versus predicted activation times

Table-4: Table of actual versus predicted activation durations

Actual Activation Duration (s)	Predicted Activation Duration (s)	Actual Error	Squared Error
10812	10846.59	-34.5923	1196.628
10776	10707.43	68.56538	4701.212
10826	10641.67	184.3269	33976.41
10664	10280.01	383.9885	147447.1
3557	3947.312	-390.312	152343.1
3625	3346.696	278.3038	77453.03
3307	3500.1	-193.1	37287.61
3372	3325.75	46.25	2139.062
3419	3512.765	-93.7654	8791.947
3642	2950.423	691.5769	478278.6
3492	3231.196	260.8038	68018.65
3562	3727.058	-165.058	27244.04
3226	3329.112	-103.112	10631.99
3392	3377.235	14.76538	218.0166
3416	3174.054	241.9462	58537.94
3487	3426.238	60.76154	3691.965
4807	4640.223	166.7769	27814.54
4640	4658.338	-18.3385	336.2992
4875	4916.296	-41.2962	1705.372
4707	4775.073	-68.0731	4633.944
4762	4384.696	377.3038	142358.2
4675	4854.504	-179.504	32221.63
4668	4928.904	-260.904	68070.82
4780	5034.1	-254.1	64566.81
4795	4941.377	-146.377	21426.2
43053	43600.01	-547.012	299221.6
4115	3697.977	417.0231	173908.2
4436	4318.608	117.3923	13780.95
4462	4379.112	82.88846	6870.497
3992	4096.819	-104.819	10987.07
4104	4250.512	-146.512	21465.63
4111	4366.935	-255.935	65502.53
4320	4443.788	-123.788	15323.58
4280	4052.265	227.7346	51863.06
4283	3994.669	288.3308	83134.63
4050	4738.127	-688.127	473518.7
		TOTAL	**2394472**
		RMSE	**257.90**

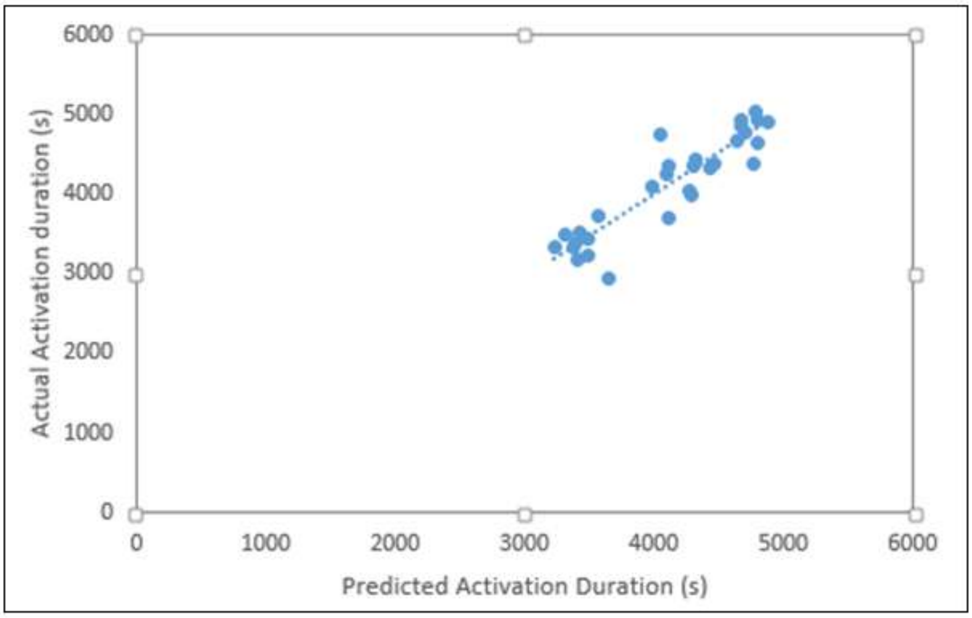

Fig-8: Regression plot of actual versus predicted activation durations

CONCLUSION

This paper presents smart home energy management system architecture to monitor, control and compute the power consumption among the home appliances over a period of time. Thereby allows the occupant to monitor the electricity bills incurred and control their operations. This techniques is achieved with the aids of programming an intelligent microchip (raspberry PI) and statistical analysis methods using least square regression (LSR) model for the prediction of frequency and time activation of smart home energy appliances. The deployment of this system on smart home energy appliances take decision and control based on the output of LSR analysis. This system learnt and alerting the home user on condition of accept or reject response through Android GUI Apps. The system performance evaluation based on the frequency prediction which is given as 0.77 RMSE, the activation time prediction is given as 127.89 seconds RMSE which is slightly above 2 minutes with a regression coefficient of (R=0.999988). The RMSE of 257.90 seconds for activation of duration prediction with regression coefficient analysis of (R= 0.989071). Successful implementation of this system will save more energy in smart homes, and reduce irregular bills of energy supplied by the agent.

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