Real-Time Fusion of Wireless Sensor Network Data for Wellness Determination of the Elderly in a Smart Home

A thesis presented in partial fulfilment of the

requirements for the degree of

Doctor of Philosophy

in

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New Zealand

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Abstract

In this research, I have explored a methodology for the development of efficient electronic real time data processing system to recognize the behaviour of an elderly person. The ability to determine the wellness of an elderly person living alone in their own home using a robust, flexible and data driven artificially intelligent system has been investigated. A framework integrating temporal and spatial contextual information for determining the wellness of an elderly person has been modelled. A novel behaviour detection process based on the observed sensor data in performing essential daily activities has been designed and developed. The model can update the behaviour knowledge base and simultaneously execute the tasks to explore the intricacies of the generated behaviour pattern. An initial decline or change in regular daily activities can suggest changes to the health and functional abilities of the elderly person.

The developed system is used to forecast the behaviour and quantitative wellness of the elderly by monitoring the daily usages of household appliances using smart sensors. Wellness determination models are tested at various elderly houses, and the experimental results related to the identification of daily activities and wellness determinations are encouraging. The wellness models are updated based on the time series analysis formulations. The integrated smart sensing system is capable of detecting human emotion and behaviour recognition based on the daily functional abilities simultaneously. The electronic data processing system can incorporate the Internet of Things framework for sensing different devices, understand and act according to the requirement of smart home environment.

Dedication

I dedicate this thesis to the elderly people living alone.

Acknowledgements

Firstly, I would like to express my sincere gratitude to my Guru: Prof. Subhas Chandra Mukhopadhyay, who has given me the opportunity to undergo my Ph.D. study under his excellent supervision. Prof. Subhas has taught me how to handle complex situations by inducing constructive concepts with fruitful cooperation and providing facilities in a timely manner. I also thank Dr. Ruili Wang and Dr. Ramesh Rayudu who have been my co-supervisors for providing me with valuable suggestions at different stages of my research.

I would particularly like to thank the elderly people (names and addresses are not mentioned due to privacy issues) for their immediate acceptance in deploying the developed home monitoring system at their houses and being tolerant to frequent visits/consultations during the troubleshooting phases of various tasks of the project.

I would like to also thank all my previous and present research scholars working in the School of Engineering and Advanced Technology, Massey University for their kindness and friendship. Many thanks also go to SEAT staff for being supportive in hard times. Financial support from Massey University Doctoral Scholarship program and the School of Engineering and Advanced Technology is also gratefully acknowledged.

I am extremely grateful to my parents, for their sacrifice and giving me the opportunity that they never had. I would also like to express my gratitude to my wife and children for their support in undertaking and sharing the family responsibilities in my absence.

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List of Publications, Contributions and Achievements during the PhD study (2011-2014)

Awards/Recognition:

1. Recipient of **Massey University doctoral scholarship** for three years (Aug-2011 to Jul-2014).
2. **Winner - Best Student Paper**-2013 for the paper titled: "A Smart Healthcare Monitoring System for Independent Living" presented at the HINZ Conference & Exhibition-27th Nov-2013, Rotorua, New Zealand.
3. Selected as one of the 10 finalists to the Best Student Poster Award of the IEEE - I2MTC 2013 held at Minneapolis, MN, USA, May 6-9, 2013.
4. Selected (as one of six papers) for the special issue as extended paper presented at International Conference on Intelligent Environments (IE'12), 2012, Guanajuato, Leon-Mexico.

Journal/Magazine Publications: (6)

1. **Suryadevara N.K**, Mukhopadhyay S.C, "Determination of Wellness of an Elderly in an Ambient Assisted Living Environment," Accepted for publication in IEEE Intelligent Systems-May 2014, (Acceptance rate for manuscripts is under 10%, **5 Yr Impact Factor: 2.538**) (Thomson Reuters(SCI)-World's leading journals Review)
2. **Suryadevara N.K,** Mukhopadhyay S.C, Wang R, Rayudu R.K, "Forecasting the behavior of an elderly using wireless sensors data in a smart home", **Elsevier: Engineering Applications of Artificial Intelligence**, Vol: 26, Issue: 10, Page(s): 2641-2652. **5 Yr Impact Factor : 1.947 (**Thomson Reuters(SCI)-World's leading journals Review)
3. **Suryadevara N.K**, Mukhopadhyay S.C, "Wireless Sensor Network Based Home Monitoring System for Wellness Determination of Elderly", **IEEE Sensors Journal**, Vol: 12, Issue: 06, Page(s):1965 – 1972. **5 Yr Impact Factor: 1.758 (**Thomson Reuters (SCI)-World's leading journals Review)
4. **Suryadevara N.K**, Gaddam A, Rayudu R.K, Mukhopadhyay S.C, "Wireless Sensors Network Based Safe Home to Care Elderly People: Behaviour Detection", **Elsevier: Sensors and Actuators: A Physical** (2012), Vol: 186, Page(s):277-283. **5 Yr Impact Factor: 2.084** - **(**Thomson Reuters (SCI)-World's leading journals Review)
5. **Suryadevara N.K**, Mukhopadhyay S.C, Kelly S.D.T, Gill S.P.S, "WSN-Based Smart Sensors and Actuator for Power Management in Intelligent Buildings", **IEEE Transactions on Mechatronics**, (Early Access Article) : doi: 10.1109 / TMECH . 2014. 2301716. **5 Yr Impact Factor: 3.39** (Thomson Reuters (SCI)-World's leading journals Review)
6. Kelly S.D.T, **Suryadevara N.K**, Mukhopadhyay S.C, "Towards the Implementation of IoT for Environmental Condition Monitoring in Homes", **IEEE Sensors Journal**, Vol: 13, Issue: 10, Page(s): 3846 – 3853. **5 Yr Impact Factor: 1.758 (**Thomson Reuters (SCI)-World's leading journals Review)

Conference Proceedings: (16)

1. **Suryadevara N.K**, Gaddam A, Rayudu R.K, Mukhopadhyay S.C, "Wireless Sensors Network Based Safe Home to Care Elderly People: Behaviour Detection", Elsevier Proceedings of the EuroSensors XXV-2011, Procedia Engineering: Vol25, Pages: 96-99.

2. **Suryadevara N.K**, Mukhopadhyay S.C, "Wireless sensors network based safe home to care elderly people: A realistic approach", Proceedings of the IEEE Recent Advances in Intelligent Computational Systems (RAICS)-2011, DoI: 10.1109/RAICS.2011.6069262, Page(s):001–005.
3. **Suryadevara N.K**, Quazi M.T and Mukhopadhyay S.C, "Intelligent Sensing Systems for measuring Wellness Indices of the Daily Activities for the Elderly", Proceedings of the Eighth International Conference on Intelligent Environments (IE'12)-Guanajuato-Mexico-2012, IEEE Computer Society, DOI 10.1109/IE.2012.49,Pages:-346-350.
4. **Suryadevara N.K**, Gaddam A, Mukhopadhyay S.C, Rayudu R.K, "Wellness determination of inhabitant based on daily activity behaviour in real-time monitoring using Sensor Networks", IEEE Proceedings of the Fifth International Conference on Sensing Technology (ICST), 2011, DoI: 10.1109 /ICSensT.2011.6137025, Page(s):474–481.
5. **Suryadevara N.K**, Mukhopadhyay S. C, Rayudu R.K., Huang Y.M, "Sensor data fusion to determine wellness of an elderly in intelligent home monitoring environment", Proceedings of IEEE International Conference Instrumentation and Measurement Technology (I2MTC)-Austria-2012, DoI:10.1109/I2MTC.2012.6229645,Page(s): 947 – 952
6. **Suryadevara N.K**, Mukhopadhyay S.C and Rayudu R.K, "Applying SARIMA Time Series to Forecast Sleeping Activity for Wellness Model of Elderly Monitoring in Smart Home" Proceedings of the IEEE 6th International Conference on Sensing Technology (ICST), India-2012,Page(s):157-162.

7. **Suryadevara N.K**, Mukhopadhyay S.C, Wang R, Rayudu R.K and Huang Y.M , "Reliable Measurement of Wireless Sensor Network Data for Forecasting Wellness of Elderly at Smart Home", Proceedings of the IEEE International Conference on Instrumentation and Measurement Technology (I2MTC)-Minneapolis-2013, Page(s):16-21.(Top 10 of the best student papers)
8. **Suryadevara N.K**, Chen C.P, Mukhopadhyay S.C, Rayudu R.K, "Ambient Assisted Living Framework for Elderly Wellness Determination through Wireless Sensor Scalar Data", Proceedings of the IEEE 7th International Conference on Sensing Technology (ICST), Wellington-NZ-2013, Page(s): 632-639.
9. **Suryadevara N.K**, and Mukhopadhyay S.C, "Smart Healthcare Monitoring System", *www.hinz,org.nz*. Health Informatics New Zealand, Pub: 20 Dec 2013. Retrieved on: Thu. 10 Apr 2014. <http://www.hinz.org.nz/uploads/file/2013conference/Smart Healthcare Monitoring System - Suryadevara.pdf>.

10. Mukhopadhyay S.C, **Suryadevara N.K**, "Homes for Assisted Living: Smart Sensors, Instrumentation, Energy, Control and Communication Perspective", Proceedings of IEEE International Conference on Control, Instrumentation, Energy & Communication (CIEC)-Kolkata-India, 2014, ISBN: 978-1-4799-2043-3, Page(s):9-14.

11. Kelly S.D.T, **Suryadevara N.K** and Mukhopadhyay S.C, "Integration of Zigbee-IPv6 Networks for Smart Home Sensor Data Transmission to Augment Internet of Things", IB2COM-Australia-2012, ISBN: 978-0-9872129-1-7, Page(s)-44-49.
12. Gill S.P.S, **Suryadevara N.K** and Mukhopadhyay S.C, "Smart Power Monitoring System Using Wireless Sensor Networks", Proceedings of the IEEE 6th International Conference on Sensing Technology (ICST), India- 2012, Page(s):444-449.

13. Kam M.H, **Suryadevara N.K**, Mukhopadhyay S.C, Gill S.P.S, "WSN Based Utility System for Effective Monitoring and Control of Household Power Consumption", Proceedings of IEEE I2MTC 2014 conference, IEEE Catalog number, CFP14IMT-USB, ISBN: 978-1-4673-6385-3, Page(s):1382 – 1387.

14. Quazi, M.T.; Mukhopadhyay, S.C.; **Suryadevara N.K**.; Huang, Y.M. "Towards the smart sensors based human emotion recognition", Proceedings of IEEE International Conference Instrumentation and Measurement Technology (I2MTC)-Austria-2012, DoI: 10.1109/I2MTC.2012.6229646, Page(s): 2365 – 2370.

15. Alabri, H. M, Mukhopadhyay S. C, Punchihewa G. A, **Suryadevara, N.K,** Huang Y.M, "Comparison of applying sleep mode function to the smart wireless environmental sensing stations for extending the life time", Proceedings of IEEE International Conference Instrumentation and Measurement Technology (I2MTC)-Austria-2012, DoI: 10.1109/I2MTC.2012.6229641, Page(s): 2634 – 2639.

16. Chen C.P, Jiang J A, Mukhopadhyay S.C, **Suryadevara N.K**, "Performance Measurement in Wireless Sensor Networks using Time-Frequency Analysis and Neural Networks", Proceedings of IEEE I2MTC 2014 conference, IEEE Catalog number, CFP14IMT-USB, ISBN: 978-1-4673-6385-3, Page(s):1197-1201.

Book Chapters: (5)

1. **Suryadevara N.K,** Quazi T, Mukhopadhyay S.C, "Smart Sensing System for Human Emotion and Behaviour Recognition", M.K.Kundu et al. (Eds): PerMIn 2012, Springer: Perception and Machine Intelligence, Verlag Berlin Heidelberg, Lecture Notes in Computer Science, 7143, pp: 11-22, 2012.

2. **Suryadevara N.K**, Kelly S.D.T, and Mukhopadhyay S.C, "Ambient Assisted Living Environment Towards Internet of Things Using Multifarious Sensors Integrated with XBee Platform", Smart Sensors, Measurement and Instrumentation, Vol. 9, Internet of Things: Challenges and Opportunities, ISBN 978-3-319-04222-0, Springer-Verlag, by S. C. Mukhopadhyay, 2014, pp. 217-236.

3. Mukhopadhyay S.C and **Suryadevara N.K**, "Internet of Things: Challenges and Opportunities", Smart Sensors, Measurement and Instrumentation, Vol. 9, Internet of Things: Challenges and Opportunities, ISBN 978-3-319-04222-0, Springer-Verlag, by S. C. Mukhopadhyay, 2014 pp. 1-18.

4. Mukhopadhyay S.C, **Suryadevara N.K** and Rayudu R.K, "Are Technologically Assisted Homes Safer for the Elderly", Smart Sensors, Measurement and Instrumentation, Vol. 2, Pervasive and Mobile Sensing and Computing for Healthcare: Technological and Social Issues, ISBN 978-3-642-32537-3, Springer-Verlag, by S. C. Mukhopadhyay, and O. Postolache, 2012, pp. 51-68.

5. Significant contribution to the book chapters 5 and 6 for the book titled "Intelligent Sensing, Instrumentation and Measurements", Springer International Publishing, 2013, ISBN: 978-3-642-37027-4.

Google Scholar Citations:
http://scholar.google.co.nz/citations?hl=en&user=S28OdGMAAAAJ

Significant Contributions/achievements

IEEE Sensors Journal Top 25 Download

1. Article titled: "Wireless Sensor Network Based Home Monitoring System for Wellness Determination of Elderly", IEEE Sensors Journal, Vol. 12, No. 6, June 2012, has been one of the 25 most downloaded Sensors Journal papers for 8 out of 12 months in 2012 and Jan-2013.

2. Article titled: "Towards the Implementation of IoT for Environmental Condition Monitoring in Homes", IEEE Sensors Journal, Vol. 13, No. 10, October 2013, has been one of the 25 most downloaded Sensors Journal papers in the months of September, October 2013.

Elsevier: Most Downloaded Engineering Applications of Artificial Intelligence Articles

Article titled: "Forecasting the behavior of an elderly using wireless sensors data in a smart home" Elsevier: Engineering Applications of Artificial Intelligence, Vol: 26, Issue: 10, Page(s): 2641-2652, 2013, has been one of the most downloaded articles in the month of March-2014.

Tutorial Offered

1. Practical demonstrations on design and development of Wireless Sensing system and the Graphical User Interface system was delivered at 5th International Conference on Sensing Technology, Nov. 28th - Dec. 1st, 2011, Palmerston North, New Zealand.

2. Practical demonstrations on design and development of Wireless Sensing system Graphical User Interface system was delivered at 6th International Conference on Sensing Technology, Dec.18 - Dec.21, 2012, Kolkata, India.

3. Practical demonstration on the application of wireless sensor network was delivered at IEEE-I2MTC-2014 conference May 11-14, 2014 held at Montevideo, Uruguay.

Keynote Talk

On Behalf of Prof.S.C.Mukhopadhyay a Keynote talk was delivered at 4th International Conference on Signal and Image Processing (ICSIP) held at Coimbatore, Tamilnadu–India -13 to 15 December-2012. Title of the talk: "Are WSN Assisted Homes Safer for the Elderly? A Smart Signal Processing Perspective", Date: 13-Dec-2012.

News Letter Articles

Article titled "Internet of Things: A Review and Future Perspective" by N.K.Suryadevara and S.C.Mukhopadhyay was contributed in the May/June 2014 edition of The European Business Review.URL: http://www.europeanbusinessreview.com/?p=4431

Article titled: "An Intelligent Integrated Healthcare Platform for Wellbeing and Independent Living" by By Subhas Mukhopadhyay and Nagender Suryadevara was contributed in the IEEE Life sciences-March -2013 Issue. Url: http://lifesciences.ieee.org/publications/newsletter/march-2013/293-an-intelligent-integrated-healthcare-platform-for-wellbeing-and-independent-living

In News: (http://telecommunications.verticalnews.com/articles/7081324.html)
Date: 06-Jun2-2012, Vertical News: Telecommunication: Study Data from Massey University Update Knowledge of Sensor Research.

Seminars/Presentations

I have presented my research outcomes in the following occasions:

Special Presentations:

1. Title: Wellness determination of an elderly using Wireless Sensors Data in a Smart Home
Date: 03-May-2013
Venue: Electrical and Computer Engineering Department
College of Engineering, University of Missouri, Columbia, MO, USA

2. Title: Wireless Sensing System for Elderly Independent Living
Date: 01-May-2013
Venue: The Aware Home Research Initiative
479 10th st NW, Atlanta, GA 30318, USA

3. Title: Applying SARIMA Time Series to Forecast Sleeping Activity for Wellness-
Model of Elderly Monitoring in Smart Home
Date: 18-Feb-2013.
Venue: IEEE-I&M Chapter-NZ
Workshop on Smart Sensors - Instrumentation and Measurement
University of Waikato, Hamilton-New Zealand

4. Title: Time Series Analysis of Sensing Data for Smart Home
Date: 11-April-2012.
Venue: IEEE-I&M Chapter-NZ
Workshop on Smart Sensors Measurements and Instrumentation: Applications to agricultural and environmental monitoring
Lincoln University, Christchurch-New Zealand

Conference Presentations: (Oral)

1. Title: Wellness determination of inhabitant based on daily activity behaviour in real-time monitoring using Sensor Networks
Date: 30-Nov-2011, Venue: IEEE-Fifth International Conference on Sensing Technology (ICST), 2011, Massey University-Palmerston North, New Zealand

2. Title: Intelligent Sensing Systems for measuring Wellness Indices of the Daily Activities for the Elderly (Doctoral Colloquium)
Date: 27-June-2012, Venue: IEEE-Computer Society-Eighth International Conference on Intelligent Environments (IE'12)-Guanajuato-Mexico.

3. Title: Applying SARIMA Time Series to Forecast Sleeping Activity for Wellness Model of Elderly Monitoring in Smart Home
Date: 18-Dec-2012, Venue: IEEE-6th International Conference on Sensing Technology (ICST), Kolkata, India- 2012

4. Title: Ambient Assisted Living Framework for Elderly Wellness Determination through Wireless Sensor Scalar Data
Date: 04-Dec-2013, Venue: IEEE-7th International Conference on Sensing Technology (ICST), Wellington-NZ-2013

5. Title: Performance Measurement in Wireless Sensor Networks using Time-Frequency Analysis and Neural Networks
Date: 15-May-2014,Venue: IEEE-I2MTC-2014,Montevideo,Uruguay

Poster presentation:
Title: Reliable Measurement of Wireless Sensor Network Data for Forecasting Wellness of Elderly at Smart Home
Date: 07-May-2013.
Venue: IEEE-International Conference on Instrumentation and Measurement Technology (I2MTC)-Minneapolis-USA-2013.

Contribution to the post graduate student thesis supervision's

I have contributed to the supervision of the following students while they were studying under Prof.S.C.Mukhopadhyay, SEAT, Manawatu Campus, Massey University-New Zealand.

Student Name	Degree, Year	Thesis Title
Anuroop Gaddam	Ph.D., 2012	Wireless Sensor Network Based Smart Home for Elder Care
Tauseef Qazi	Master, 2012	Sensors System for Emotion Recognition
Sean Kelly	Master, 2013	Design and Implementation of Internet of Things for Home Environment
Satinder Singh Gill	Master, 2013	Smart Power Monitoring Utility System Using Wireless Sensor Networks.
Vinok Verma	M.Eng. Studies, 2014	Data Fusion from two communication protocols
Mohammed Serhan Al Ghamdi	PG. Diploma, 2012	Medicine Dispenser for Eldercare
Hatim Al Abri	Bachelor Honours, 2012	Smart Wireless Environmental Sensing Station
MunHaw Kam	Bachelor Honours, 2013	WSN based Smart Grid for Utility System
Mohammad Anas	Bachelor Honours, 2014	Energy Harvesting Techniques for Sensor Node in Wireless Sensor Network (WSN)
Manaseh Togagi	Bachelor Honours, 2014	WSN and IoT in relation to a Tourist Perspective


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March 11, 2013

TO:
Mr. Nagender Kumar Suryadevara, Massey University, New Zealand
Dr. Subhas Chandra Mukhopadhyay, Massey University, New Zealand

Dear Mr. Suryadevara and Dr. Mukhopadhyay:

On behalf of the IEEE Sensors Council I am pleased to congratulate you, the coauthors of the paper *Wireless Sensor Network Based Home Monitoring System for Wellness Determination of Elderly,* IEEE Sensors Journal, Vol. 12, No. 6, June 2012, for your paper being one of the 25 most downloaded Sensors Journal papers for 8 out of 12 months in 2012. It is exciting to note that included in this count are all Sensors Journal papers published since its foundation, about 1000 papers in total. You can view the latest Top 25 papers at:

http://ieeexplore.ieee.org/xpl/topAccessedArticles.jsp?punumber=7361

Thank you for your contribution to the IEEE Sensors Journal!

Best regards,

Vladimir Lumelsky

Dr. Vladimir Lumelsky
President
IEEE Sensors Council

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University of Wisconsin-Madison
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Glossary

AAL	Ambient Assisted Living
ADL	(Basic) Activities of Daily Living
WSN	Wireless Sensor Network
IoT	Internet of Things
HMS	Home Monitoring System
SHMS	Smart Home Monitoring System
SAP	Sensor Activity Pattern
PSN	Pervasive Sensor Network
PAI	Predictive Ambient Intelligence
PIR	Passive-Infra Red
The Elderly/ An Elderly person	A person aged above 65 years

Chapter 1. Introduction

The present research work is about the application of computing technologies to determine the wellness of an elderly person living independently in their home. There is a world-wide tendency to transform the approach adopted by national healthcare systems to treat elderly people as more and more people choose to live in their own homes; however they still need professional medical supervision. Thus, monitoring important daily activities through the observation of everyday object usages is one way to let medical personnel know about the activities of the elderly, and, if there is a problem, a nurse or doctor can adequately respond in a timely fashion. The elderly people can be monitored continuously in their own home with the set-up of an Ambient Assisted Living (AAL) environment. It is necessary to develop artificially intelligent programs for analysing real-time data coming from heterogeneous smart sensors of the AAL.

The elderly well-being conditions can be known from the AAL set-up's principal values such as location (S), time (T) and context (C). Based on S, T and C, the complex elderly behaviour processes can be realized into a function Ż (computer program) for quantitative well-being assessment. The values of the <Ż (S, T, C)> can be realized with the help of the elderly Activities of Daily Living (ADL). The processing of Ż is based on the time series sensor data originated from various unobtrusive and non-invasive smart sensors of AAL. There are many ad-hoc methods available to deal with the assessment of the ADLs with only either spatio-temporal or contextual reasoning performed through an offline mode. Very few methods are available for online processing of spatio-temporal data of Ż. One of the motivating tasks in this situation is the longitudinal well-being assessment of the elderly with computational resource constraints. Another problem is to define a Ż (spatio-temporal functions) in terms of online processing of ADLs assessments.

The systematic integration of smart sensors with Wireless Sensor Networks (WSN) has led to the development of flexible, reliable and manageable intelligent healthcare informatics systems. Based on the measurements of smart sensor data types, the number of smart sensing channels and the sensor data sample intervals, the throughput of the wireless sensing system is efficiently deployed.

The data sensed by the WSN is sent to a centralized computing system for efficient recognition of the well-being status of a person. A novel combination of model driven and data driven based approaches for processing of $\dot{Z}$ are presented. The spatio-temporal smart sensor stream data is well-defined and modelled in terms of three wellness parameters: i) '$\beta1$' inactive usages of household appliances, indicating the status of inactivity of daily living, ii) '$\beta2$', excess usages of household appliances, indicating abnormal activity of daily living conditions, and iii) 'τ'- the trend in usage of household appliances indicating the conduct of ADL. The developed model can forecast the behaviour and wellness of the monitoring of individuals and generate appropriate warning messages when there is an anomaly state of ADL. The precise determination of the well-being state of a person is known by augmenting $\dot{Z}$ with the physiological parameters monitoring system.

The developed smart sensor fusion technology framework is capable of collecting and analysing both physiological parameters and ADL sensor stream data online. The integrated healthcare platform is smart and consists of indigenously developed sensing modules, together with wireless communication technology. An intelligent program has been developed to assess the well-being of an elderly person at different scenarios of the home environment. The developed system is capable of providing an early warning of any complicated health problem by effectively monitoring the wellness of the people both physiologically and in physical fitness for self-regulated daily activities. It is expected that proper use of the developed system may cut down the rising healthcare cost. The healthcare providers can remotely monitor the well-being condition of the people through a secured web-based system and provide advice at appropriate times.

The AAL technologies are complex and vary widely depending on their contextual application. The presented methods and tools in this research are not the only optimal solution to handle complex human behaviour assessments. Nevertheless, they do offer a resilient foundation for the AAL environments with support for real life implementations of the Internet of Things (IoT) paradigm. The architecture of the developed system support interconnection of multiple homes and can simultaneously monitor the inhabitant behaviour. Fig 1.1 shows the basic functional blocks of the developed health informatics system.

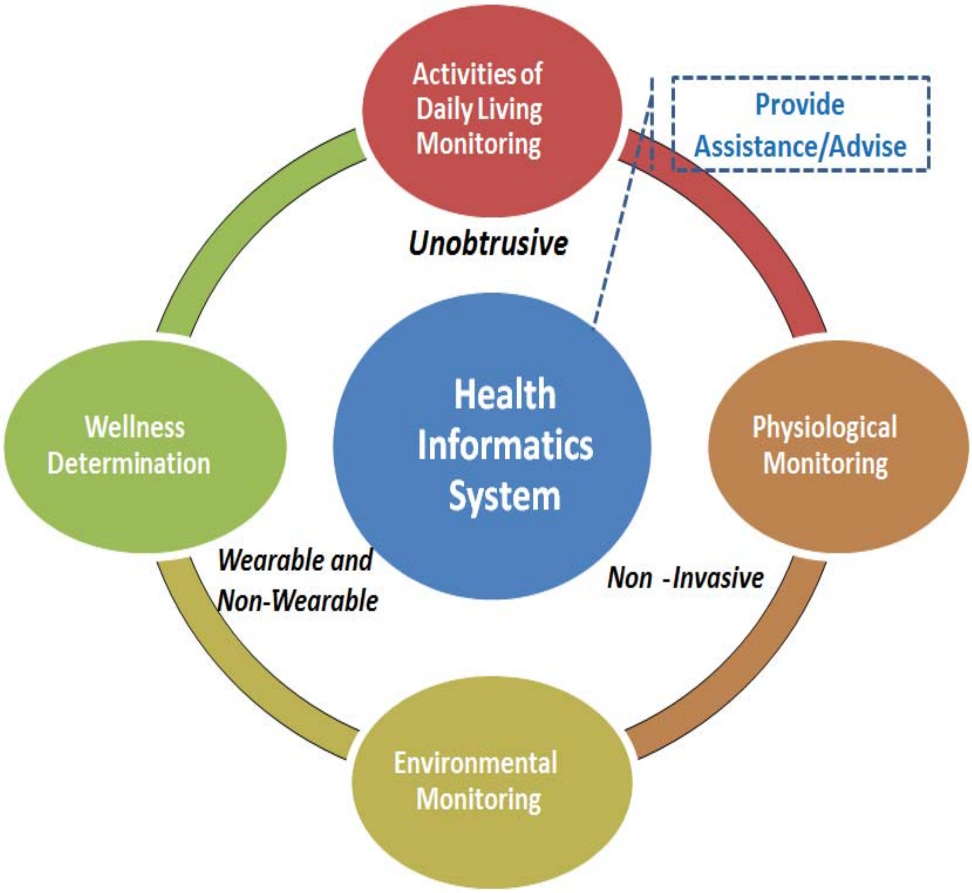


Figure 1-1 Main Functional Blocks of a Home Monitoring System for a Health Informatics System

1.1 Background

The elderly population who spend most of their time at home is growing rapidly. The research into well-being of the elderly in New Zealand is lacking despite it being an important area of research overseas. A report from "An Ageing World" shows that within the next decade, elderly people will be more than children [1] [2]. In New Zealand, the population of people aged 65yrs+ will increase from 550,000 in 2009 to 1 million in the late 2020s and will exceed the number of children aged 0–14 years [2] [3]. Our ageing population expects that this better longevity will help them to lead an independent and quality life in their own home. However, those who are in poor health condition require assistance in the form of medical help that can be delivered directly in times of need. Several nations are preparing national policies for handling the ageing requirements. At the national level, the main concerns are the increased cost of providing healthcare services and the sustainability of the services [4]. The existing healthcare system is unsustainable. According to a news report, the cost of healthcare in New Zealand is increasing rapidly [5]. Hence, there is a need for an alternative, low-cost, and sustainable arrangement of healthcare for now and the near future. One solution is to transform the normal home to smart home through ubiquitous computing technology to support the care of the elderly living independently.

Currently, a wide range of research on smart homes is carried out world-wide. One of them is the "Aware Home" of the Georgia Institute of Technology, USA. Based on ubiquitous computing methods the system senses and identifies imminent emergency conditions of an elderly person [6]. It also takes care of deteriorating aged memory and looks for behavioural changes [6]. "Gator Tech Smart House" is a product of "Florida University" that provides intelligent house for disabled and aged persons [7]. "Place Lab" is a fragment of "Massachusetts Institute of Technology (MIT)-house of the future" [8]. "Health Insight Solutions (HIS) project at Grenoble" and "Prosafe" at Toulouse [9] France are a few other research projects.

The ubiquitous technology is emerging as a vital role in improving the quality of life for the general public. The sensing technologies can be deployed at feasible points in a home and assess the inhabitant in the vicinity of the situation. Under the situation of no-obligation, the camera or vision based system has a very low acceptability among the inhabitants especially among the elderly. The developed system in this thesis does not use any camera or vision systems; thus, it will be more acceptable to the people.

1.2 Problem Statement

The thesis addresses the design and development of a framework for fusion of data from the multiple heterogeneous sensors of a home monitoring system to determine the well-being status of an elderly person. The wellness determination of an elderly person living in their own home is based on continuously monitoring the usages of household objects. The developed system can forecast the behaviour and wellness of a person by monitoring the daily usages of household appliances. Based on the usages of household appliances, the routine daily activities of the person have been estimated using time series analysis techniques.

1.3 Need for Determining Wellness of an Elderly Person

In general, a typical person performs their daily activities at regular intervals of time. This indicates that the person is leading a regular life. This also tells us that the overall well-being of a person is above a certain standard. If there is decline or change in the regular activity, then the wellness of the person is not in the normal state. If an elderly person needs assistance with some of their basic ADL, an index or scale which measures an elderly/patient's degree of independent living is very much required. The daily activities routine in preparing food, self-grooming, using the toilet, eating and movements within the home can inform the well-being status of a person. Professional health-care providers accessing the elderly daily activity reports will have a longitudinal assessment of the elderly and can provide appropriate care services, based on the daily functional assessments of the person [10].

There are several "wellness" conceptions proposed by professionals from several domains, each of which is defined from their specialist perspective and contain several dimensions of wellness [11] [12] [13]. Several authors are of the opinion that the wellness is not just the state of mind or being free from illness and disease; it is not a single state [11] [12] [13]. Wellness does have multiple dimensions or levels. However, an integrated definition does not exist. Hence, there are various instruments and methods in place for assessment of wellness for an elderly person. Wellness is a very wide and multifaceted perception. It is difficult to define the term wellness completely because the term wellness develops over time and is changed by different influential factors such as culture, experience, belief, religion and context [14].

The meaning of wellness in our context is how "Well" an elderly person living alone has the ability to perform his/her essential daily activities in terms of the usage of the house-hold appliances. Novel wellness functions were introduced to determine the wellness of an elderly person under the monitoring environment.

1.4 Scope of the Research

The objective of this research study was on understanding the intricacies for design and development of a framework for real-time data analysis of heterogeneous sensor data. Sensor data analytics was based on the wireless sensor network data for monitoring the daily activities. The system acts intelligently after analyzing the captured data and forecasts the investigated pattern of data for determining the wellness of an elderly person. The system can generate alerts for unusual behaviour for the necessary entities.

The system has been developed to observe elderly people specifically staying independently in their own home. Developed wireless sensing system is capable of simultaneously monitor the basic physical activities of daily living, physiological parameters and environmental parameters. It uses multimodal, unobtrusive, non-invasive novel sensing systems placed at focal locations throughout the home. Continuous in-home monitoring can be done with one computer server. The designed and developed software modules will be in execution on a windows software working environment. Internet connection is not required for knowing the wellbeing status of a person, however, for remote monitoring and cloud data storage management internet connection is required. The system in this research has been designed to function effectively with only "XBee" radio communication modules. Fig.1.2 shows the overall functional description of the developed smart home monitoring system.

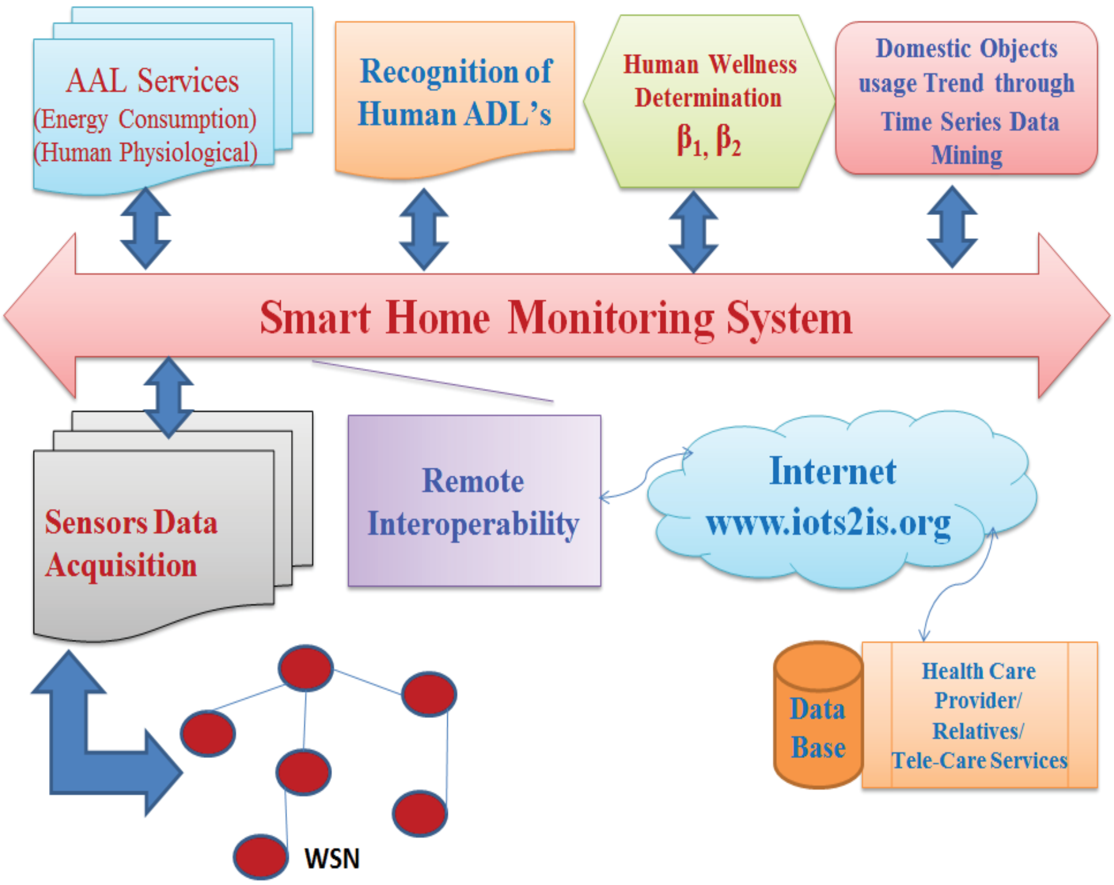


Figure 1-2 Functional Description of the Developed Smart Home Monitoring System

1.5 Research Direction

The Research was directed towards finding answers for the following:

- Determining parameters of the wellness model with effective time series analysis.
- Using the quantitative aspect of wellness to determine the tracking of well-being of an elderly person in performing their daily activities.
- How robust, flexible and efficient is the real-time data processing system in the presence of few sensing units in case of home monitoring.
- Identifying several operations involved in the performance of time series analysis and detection of early signs of unusual activity on data that represents the operation of Home Monitoring Systems (HMS) primarily as part of the wellness determination model.
- Dealing with various issues that include development, installation and maintenance costs of Home Monitoring Systems.
- How can we apply these models on a large scale, without the necessity of training data?
- To formulate strategies for collecting datasets that will benefit researchers across domains.

1.6 Novel Contribution of the Research

The following are the novel contribution of the research:

- Effective integration of wireless communication systems and information processing systems for measuring the well-being condition of people living independently.
- An integrated home monitoring system having functions such as well-being status monitoring of the person and household electricity (energy) consumption indices.
- Wellness determination from online sensor streams based on the time series analysis.
- Quantitative Wellness functions definitions (Beta1 and Beta2) to track the well-being of an elderly person in performing daily activities.

- Sensor Activity Pattern (SAP) matching procedures for recognition of frequent sensor sequences in wellness determination and mobility processes.
- The usage behaviour of domestic appliances and their corresponding ADLs are used to forecast in the wellness determination process.
- Anomaly detection related to the behaviour of the elderly by the combination of novel Wellness functions, SAP matching and forecasting procedures.
- Achieving high throughput of the wireless sensing system consisting of heterogeneous smart sensors for well-being monitoring of the elderly.
- Providing an integrated platform for the Internet of Things paradigm to handle wireless sensing systems and information processing efficiently.

1.7 Research Significance

- Designed algorithms will be used as a good protocol for data capturing and analyzing in real-time sensor data.
- Provide just-in-time information presented by wellness determination model in the home and to help people stay healthy as they age.
- Provide activity detection algorithms that work for non-techies in real life in complex situations using practical and affordable sensor infrastructures.
- Providing room-type human behaviour sensing environments using distributed sensors.
- Real-time analysis framework of sensing data through time-series forecasting methods.
- Procedures for modelling trends for different types of time series analysis models like Nonlinear and Nonparametric will be useful in intra domains.
- Fitting smooth transition and applying filters for structural models and cyclical behaviour for effective time series analysis.
- Diagnosis of the model for forecasting and evaluation will be useful for analyzing sensor stream data of different applications.

1.8 Outline of the Thesis

The present thesis is broadly divided into three parts. Part.1 has two chapters. Chapter.1 begins with the introduction of the present research work and then discusses the motivation, main objectives, and scope of the presented research work and the original contribution of the thesis. Chapter.2 deliberates about the literature review performed in relation to elderly people and independent living, smart home systems for monitoring the inhabitants and the technologies in use.

Part.2 consists of chapter.3 describing the design and development of wireless sensor network based ambient assisted living set-up. In this chapter, details about the deployment of wireless sensor networks and the implemented strategies for achieving high throughput in WSN systems and efficient data handling and processing mechanisms were presented.

Part.3 describes the designed and developed computing techniques for determining complex events from time series sensor streams. This part has four chapters.

Chapter.4 describes the importance of the sensor data analytics of the monitoring system for determining wellness of an elderly person living alone in their own home. Chapter.5 presents the implemented methods to recognize the daily living activities of an elderly person living alone in their own home and presents the novel wellness functions designed and developed for the determination of the well-being of an elderly person in the AAL set-up environment.

Chapter.6 provides details of the new methods of forecasting processes for incorporating with the time series sensor streams for effective recognition of the behaviour of an elderly person. Chapter.7 presents the development process of matching the activity patterns of the sensors obtained as time series sensor stream. The effective recognitions of the mobility of a person and the details of the combined methods for detecting the outlier (anomaly) situations in the wellness determination process are presented.

Chapter.8 presents the conclusion of the present research study and suggestions for future work.

Chapter 2. Literature Review

2.1 Introduction

This chapter presents the existing research works related to a home monitoring systems and elder care assistive technologies. The methods designed and developed for the AAL set-up of various tasks are compared and deliberated comprehensively to provide a better understanding.

The preliminary research database search was undertaken in the year 2011. The following key databases: Scopus, Discover, Web of Science under the Massey University Library related to computer science and information systems were searched. These databases were selected as they cover the technological issues in the design and development of home monitoring systems related to the elderly's home environments. Several keywords such as "elderly" and "smart home" were searched to retrieve information related to the smart home environment functionalities for the well-being monitoring of the elderly.

It was understood that the term "Home" is a natural environment surrounded by personal belongings, a sustained place to stay, live independently, a retirement village place or a health-care service integrated accommodation [15]. It was also observed that inhabitants do not like to make alterations to their houses for investigation purposes. Few researchers have selected to use purpose constructed intelligent homes affiliated with research laboratory such as "CASAS Lab-Washington State University" [16], "iSpace Lab-University of Essex" [17], "Smart Home-Duke University" [18], "Domus Lab" [19] . These setups were also considered as home environments wherein people were adjusted to live in these smart home settings.

The health center environments rarely provide inhabitants with substantial physical home setting environments; hence, the well-being monitoring studies of the elderly performed in nursing hospitals and clinics were omitted in the present research study. According to "Medical Subject Headings" (MeSH) definitions the term "older people", were categorized under the age group of 65+ years and the age group between 45-64 years were termed as middle aged people. Thus, the literature search includes any participants aged above 65 years was considered for our methodical research review.

The initial literature research is comprised of published works that are thoroughly examined. It includes chapters of periodicals, articles in journals and proceedings of conferences. The following are the key words used in search engines: 'tele-homecare', 'e-health', 'smart home', 'ambient assisted living', 'tele-health', 'tele-medicine', 'tele-monitoring', 'wearable device', 'assistive technology', 'implantable device', 'user satisfaction', 'cost', 'ethics', 'socio-economics influence', 'laws', 'intrusiveness', 'eldercare', 'machine learning', 'activities of daily living' and 'wellness systems'. The keywords are exercised as standalone terms or are used in combination. The following information is the collected research findings of the smart home monitoring systems for the elderly care.

2.2 Elderly People and Independent Living

The age span of humans has increased over the last decade and elderly people (aged over 65 years) are estimated to rise by 2050 to 19.3% worldwide [20]. The elderly population who spend most of their time at home is growing rapidly [21]. For the 21st century, the life expectancy is projected to grow for individuals 46-89 years to 66-93 years [22]. The population of aged people (retired group) is going to escalate by 24 percent to 32 percent [1]. The age group above 75 years is predicted to double from 8.5 percent to 17 percent in the next three decades [23].

As per the United Nations(UN) forecasts, major deterioration in the child population and fertility rate have resulted in a greater population of elderly people compared to children [24]. The ratio of a child to elder i.e. 15 to 65 years would come down from 9:1 to 4:1 in 2050 [24] [25]. The estimated trend would result in a drastic decline of aid from younger people operating from home, and healthcare for older people. The following conditions prevail over industrialized nations: raise of disease and disabilities a growing trend of the annual cost of Alzheimer diseases alike increasing from $33 billion to $61 billion suggests a greater health risk for elder people [26]. Rapid increase in healthcare demand and cost a greater section of public spending now goes to healthcare, which consumes 13 percent of national income. Increased demand for tele-homecare minimizes the cost for nursing home care and long duration hospitalization. However, there is a greater requirement for enhanced skills and technology for the implementation of tele-home care [27]. Fig 2.1 shows the elderly population trend in the near future.

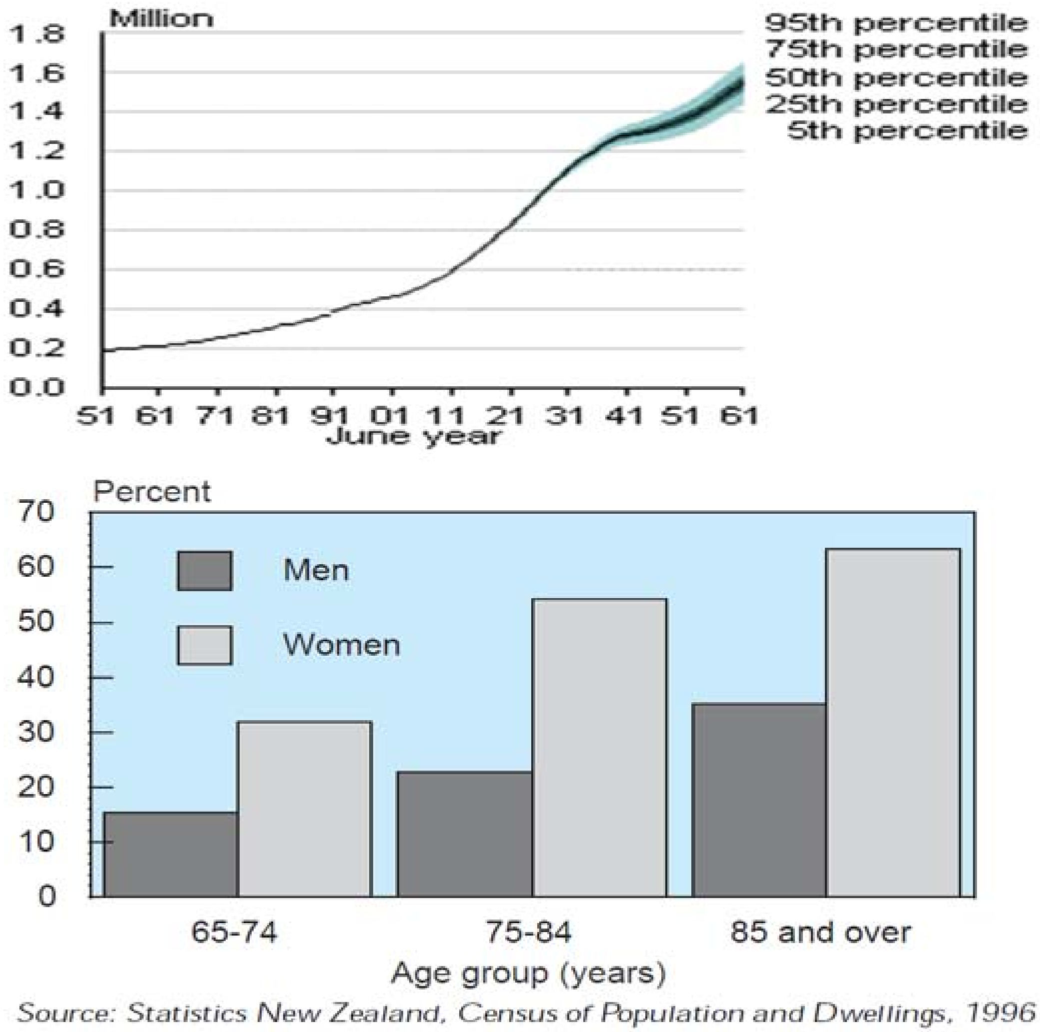


Figure 2-1 Increasing Trend of the Elderly (Aged 65+ years) Population

The estimated growth of elderly people has significant consequences on the cost of health-care hence cost effective health care systems are very much needed [28]. There have been several researches reported in recent times on the systems development to monitor the daily activities of elderly living so that assistance can be provided before any unforeseen situation occurs [29] [30]. One of the interesting facts is that elderly people prefer to live independently, and their lifestyle expectations are highly desirable [31]. However, at old age, elderly living alone have high risks in relation to their wellbeing. Newspaper headlines like: “Elderly man lay dead for days”, Second Lonely Death, “Body lay in flat for months”-Thursday, Feb 23, 2012 - *The Dominion Post*, are quite common in news bulletins in recent times.

With the improvement of health consciousness, quality of food and medicine, the lifespan of humans has increased. But, people at old age are susceptible to different types of injuries and accidents, and consequently elderly people require more medical care facilities [10] [32]. The increasing expenditures of healthcare for the elderly will have greater financial impact on healthcare providers; hence, there is a need for new approaches and systems to address the health-care monitoring issues [32]. Pervasive computing and healthcare experts felt that medical expenditures can be minimized with the help of home monitoring systems to assist the elderly with their individual wellbeing assessments [10]. Moreover, healthcare professionals have suggested that the health monitoring tests generally performed in laboratories can be implemented in homes for longitudinal tracking [33]. Accordingly, researches are proceeding on the development of intelligent systems to recognize elderly Activities of Daily Living (ADL) [16] [34] [35] [36]. The use of sensor networks in pervasive computing for healthcare is mainly for helping healthcare professionals to collect data about health, physical habits of the elderly and providing appropriate health information [10] [34].

"In recent times, the health information exchange has changed and millions now look online for apt health information" [35]. Today's online users are not only "people in poor health who want to get healthy, but also healthy people who want to remain healthy" [35]. Accordingly, to assist the elderly with their health information in real-time, Pervasive Sensor Networks (PSN) were deployed in home environments to prompt appropriate actions when irregular ADL events were happening.

The "Ubiquitous Monitoring" systems might be more readily adopted by the elderly if the monitoring systems were designed and developed as a custom-made tool [36]. The tool can be used for longitudinal monitoring of well-being of the elderly and also provide the opportunity of self-investigation. The collection of longitudinal data will help the healthcare providers to know the past behavior of elderly. It is cited "well-practiced behaviours in constant contexts recur because the processing that initiates and controls their performance becomes automatic" [37]. Moreover, frequency of the past behaviour reflects the "habit strength and has a direct effect on future performance" [37]. Additionally, a normal elderly person is assumed to be well if he/she performs basic daily activities at regular intervals of time. This implies that the wellness of a person can be assessable and can be quantified in terms of wellness indexes.

The following section provides the insights of the recent research and development on providing AAL systems (i.e., Smart Home systems) for the well-being monitoring of individuals, especially elderly.

2.3 Smart Home Systems

A "Smart Home" is an expression utilized for dwellings outfitted with technologies that enable proper scrutiny of residents, promoting autonomy and upholding of better health [38]. Every individual has distinct requirements based on which custom support must be provided to each individual.There are several smart home test beds designed and developed in the recent past. Their main purpose is to monitor people with visual or cognitive disabilities. The focus is on the potential to efficiently monitor and prompt appropriate health care actions that lead to a better health outcome [39].

With the advancements in sensing technologies, embedded processors and communication systems, the deployments of smart home settings has been easy and manageable. This enabled the health care sector to provide appropriate services using smart home technologies for independent living people [40].

The improvements in Information Technology (IT) have resulted in the well-ordered and enhanced function of sensors, networking and computation technologies [41]. The developments of smart home technologies are towards risk-free sheltered as well as comfortable real life settings for the residential home environment. This supports the regular security and safety process by employing intelligent monitoring system as well as access commands.

The smart home integration system is made of about three important entities: First, the physical components (electronic equipment – smart sensors and actuators); Second, the communication system (wired/wireless network) which usually joins the physical components; and Third, the information processing through artificial intelligence program to manage and control a smart home integrated system.

2.4 Components of the Smart Home Systems

A typical scenario in the smart home environment can be viewed as monitoring various household appliances for recognition the ADLs to know the well-being of the inhabitant. It consists of various electronic components in terms of instrumenting the objects to be monitored, and a wired/wireless communication system to have interconnection among the instrumented components to derive proper information.

The information gained will be able to determine the quantitative measurement of the well-being of a person. Fig.2.2 shows the basic elements of a Smart Home Monitoring System (SHMS).

Figure 2-2 Basic Components of the SHMS

In a smart home environment the physical constituents (smart sensors) sense the natural environment and pass to the home monitoring command system through networks and infer the sensor fusion stream to adapt the inhabitant behavioral pattern. Fig. 2.3 depicts the interconnections among the basic elements of SHMS.

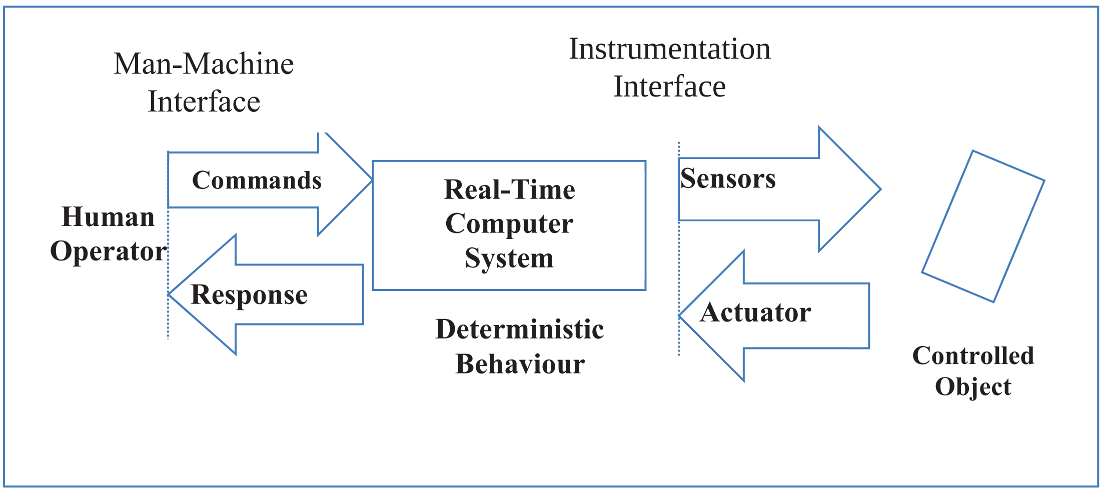


Figure 2-3 Interconnection among the components of the SHMS

2.4.1 PHYSICAL COMPONENTS

The physical sensing components and their placements are vital in the smart home environment. These physical sensors measure the ambient home environmental information and communicate with the central controller to accumulate and infer appropriate ambient information. Usually, sensors, microcontrollers and actuators are embedded with intelligent programs to gather vital data and are considered as the physical components of the smart home system. Different applications deploy different sets of physical components to fuse and collect appropriate ambient information. Table.2.1 provides the sensing types, sensing parameters, as well as their corresponding applications.

Table 2-1Sensing types, parameters and applications

Sensing types	Sensing Parameters	Application
Ambient	Pressure, Temperature, Humidity, Light Intensity	Health Safety, Energy Efficiency [42]
Motion and Presence	Position, Angular, Velocity, Acceleration, Direction	Security, Location tracking, Falls detection [43]
Bio-chemical Agents	Solid, Liquids, Gases	Security and Health Monitoring Maintenance [42]
Multimedia	iButtons, Sound, Image	Identify objects, Control, Speech Recognition, Context Understanding [42] [43]

2.4.2 COMMUNICATION MECHANISM

The communication mechanism will be functioning to exchange information between physical components as well as the intelligent managing processes with the home environment settings. Communication methods can be implemented either using wired or wireless operations. The wireless system provides a huge flexibility in terms of installation of sensors at home. To avoid frequent replacement of batteries, the electrical power at home may be considered. The commonly used wireless technologies in the ubiquitous monitoring systems are the Bluetooth, Wi-Fi, Wi-MAX and ZigBee.

Bluetooth consumes a lot more electric power and has the disadvantage of transmission distance. WiMAX provides enough wireless broadband accessibility, and it is an alternative to cable television relationship; however the power consumption is high. Wi-Fi is less secure for data transmission. Hence, ZigBee radio technologies can be ideal for smart residence environment monitoring for its low price, electric power consumption and flexible integration with smart sensors of home monitoring systems. A brief comparison of the common wireless communication medium [44] is shown Table 2.2.

Table 2-2 Features of Wireless Communication Technologies [44]

Protocol	IEEE Standard	Frequency band/Hz	Rate/ Bps	Power Consumption	Security	Coverage	Network Topology
Bluetooth	802.15.1	2.4G	0.72M	50mA	High	10m	Star
Wi-Fi	802.11 a/b/g,	2.4G/ 5G	11-54M	400+mA	Low	100m	Star, Tree, P2P,Mesh
Wi-Max	802.16	2-66G	80M	200mW-20W	Medium	50km	Star, Tree
ZigBee	802.15.4	868/ 915M, 2.4G	20-250K	40mA-50mA	High	100m	Star, Mesh, Cluster Trees

2.4.3 Information Processing

The key functionalities of the information processing system related to the smart home monitoring system are:

- Compatibility of sub-home monitoring systems
- Flexibility
- Robustness
- Real-Time Processing of Data.

In general, there will be various sub-systems of the smart home monitoring system for different purposes. Hence, there is a requirement of compatibility. Otherwise, information inference will be very complex, and it may be extremely difficult to realize the complex human behaviour.

2.5 Comparisons of Smart Home Systems

In recent times, a wide range of research on smart home has been carried out world-wide. Systematic literature searches have been followed in order to study the existing systems, and there are ongoing research investigations relating to the exploration of the intelligent home monitoring systems for the determination of wellness of the inhabitants. Various systems have been developed in European nations and the United Kingdom (UK). A supported interactive residence house was built for aged and disabled individuals [45]. Its sensor system evaluates key signs & actions and offered security surveillance. It also utilizes ecological controller tools. Similarly, a smart apartment was developed by implementing infrared (IR) sensors [46]. The infrared sensors are implanted in ceilings of a flat, enabling the evaluation of actions and movements. In France, a project on "PROSAFE" at Toulouse aspires to support independent living and activates alarms at the time of emergency [47].

Recently, Tao et al. proposed "A Pattern Mining Approach to Sensor-Based Human Activity Recognition" [48]. Fig.2.4 shows its usage. "(a)The sensor platform consists of RFID wristband readers, (b) iMote sets, (c) RFID wristband reader, and (d) tagged objects" [48].

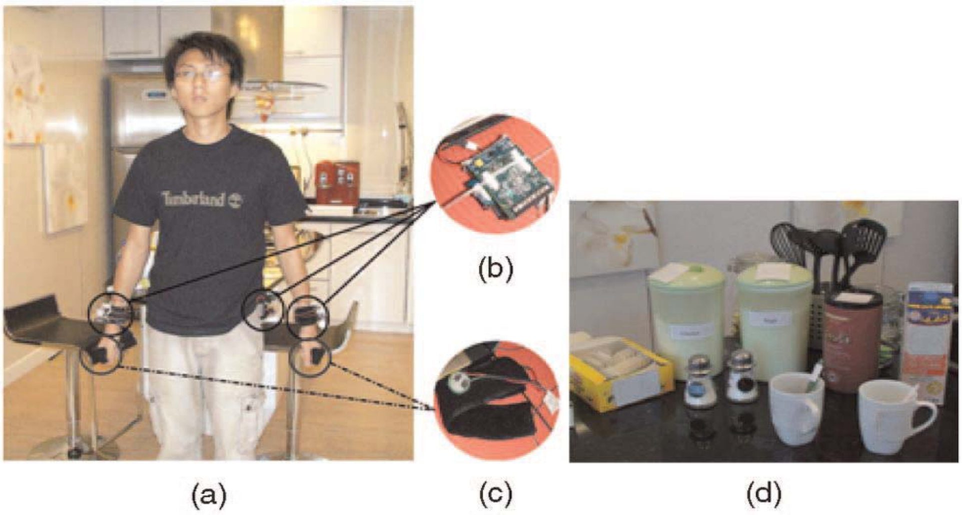


Figure 2-4 Sensor Platform with RFID Components [48]

The main drawbacks and the observations of the system [48] is that the system uses wearable sensors and requires radio frequency tags for all the objects in the monitoring environment. The acceptability of the system is a big question as the inhabitant feels uncomfortable to wear sensors all the time, and it is not feasible to ascertain tags for all the objects in the monitoring environment.

Several research works related to smart home technology developments such as well-being tracking systems "CASALA" [49] and techniques for long and short wellness monitoring [50] to examine the behavioural changes have been reported. There are research studies on recognitions of daily activities with the focus on the use of probability concepts and statistical analysis procedures [51]. A variety of sensing systems for monitoring and assessing the functional abilities of elderly behaviour in a smart home have been developed [16] [45] [52]. Behaviour prediction methods of human activities relating to abnormal behaviour with temporal rules have been proposed [53] [54]. Nouri and Hadidi [54] have demonstrated the "feasibility to produce simulated data which mimics the data gathered by the presence of sensors in field conditions and imagined to raise an alarm whenever the real collected data becomes significantly different from the simulated data" [54]. Also, there has been a generic ambient agent-based model to study the dynamic patterns of human behaviour [53]. Simulation experiments have been conducted with the generic ambient agent-based model, and the outcomes have been formally analyzed. However, these methods will lead to a high number of false alarms when their behaviour prediction techniques do not satisfy the conditions of the knowledge base. Moreover, most of the methods have limitations such as requiring large training data for proper reasoning with no assurance for identifying an anomaly situation rightly. For example, 'Health Insight Solutions' (HIS) project has IR sensing systems to evaluate actions. A model house is developed in 'Eindhoven' satisfying the needs of Dutch Senior Citizens [9]. These dwellings can be supervised with supportive technologies with the main objective of utilizing IT to aid interaction amid older people and their caregivers.

Japan aspires to amplify the utility of supportive technology, helping the older individual to live independently at their residence by nurturing intelligent and secure surroundings. A total of 13 'Welfare Techno-Houses' (WTH) [55] have been developed by the Japanese Ministry of International Trade and Industry. Information on inhabitants' actions is gathered by researchers from embedding rooms with IR sensors, bathrooms with totally independent biomedical devices and doors with magnetic switches [55]. The 'Ubiquitous Home' project is considered as a test function to position important service linking devices, appliances and sensors with data networks. These sensor systems supervise the movement of humans [56] [57]. Every room is laden with monitoring camera that recognizes and clips a user along with microphones to gather total audio-visual information. Inhabitant's movement and furniture location is ascertained by pressure sensors in placed on the floor [57]. Another interesting developed system is the Parisa Rashidi et al. based on “Activity knowledge transfer in smart environments,” [58]. Fig.2.5 shows one of the “CASAS test-bed” set up for monitoring the individuals.

Figure 2-5 One of the Test-Bed Sensor Installation of CASAS Project [58]

The main drawbacks or observations of the proposed test bed [58] set up are: i) many sensors need to be installed, ii) same type of sensors (motion sensors) is used to recognize the several ADLs, and it is iii) a test-bed environment. Setting up a house with many sensors is a big question for acceptability, as well as it will be a costly solution. Also, smart home systems implantable with microsystems and wearable are available [59]. These devices are normally worn by the inhabitants and linked by wireless or wired systems [60].

The main aim of the above mentioned systems is the context awareness, and sensors are used to find out where users are, and reminding them only if information is necessary. Likewise, in the United States, various smart home technologies projects include a garment with optical fibres, conductive elements and electronic sensors: i.e. the Life Shirt (Vivo metrics) [61], Sense Wear Armband (Body Media Inc.) [62]. “Smart Shirt” [63] is a lightweight garment.. Sense Wear is a wearable tool which is used for body measurements. Smart Shirt is a tool which is used to evaluate cardiac and respiration parameters using a shirt. Rantz et al. [64] have proposed a residential care system for elderly people “Tiger Place: An Innovative Educational and Research Environment”. Fig.2.6 shows the set-up of the system.

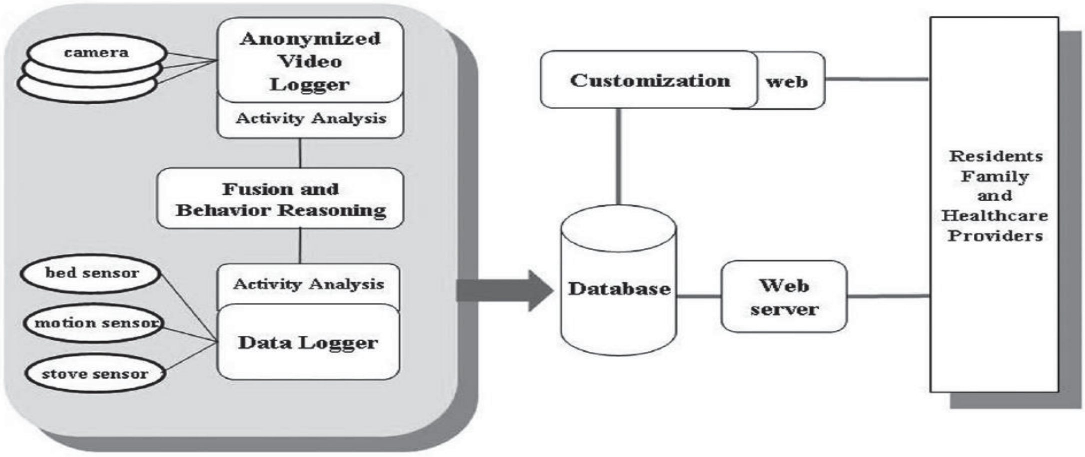


Figure 2-6 Block Structure of the Residential Elder Care Monitoring System [64]

The main drawback or observation of the system [64] is that it uses a camera. Usually, a camera based system has poor acceptability among the elderly. Similarly, there are several smart home projects such as systems using door switches, movement sensors, bed load cells, individual tracking badges [65] [66] [67], a reminder system for personal household assistant [68] a method to enable interaction and control of devices using EEG signals in smart home built in the laboratory setting were prototyped.

Shin et al. proposed a technique for "Detection of Abnormal Living Patterns for Elderly Living Alone Using Support Vector Data Description" [69]. The main drawbacks or observations of the system [69] are that the system uses motion sensors and the communication medium is "Bluetooth" modules for data transmission. Using Bluetooth as a communication channel has several drawbacks, such as short range coverage and radio signal interferences. Fig.2.7 shows the system set-up.

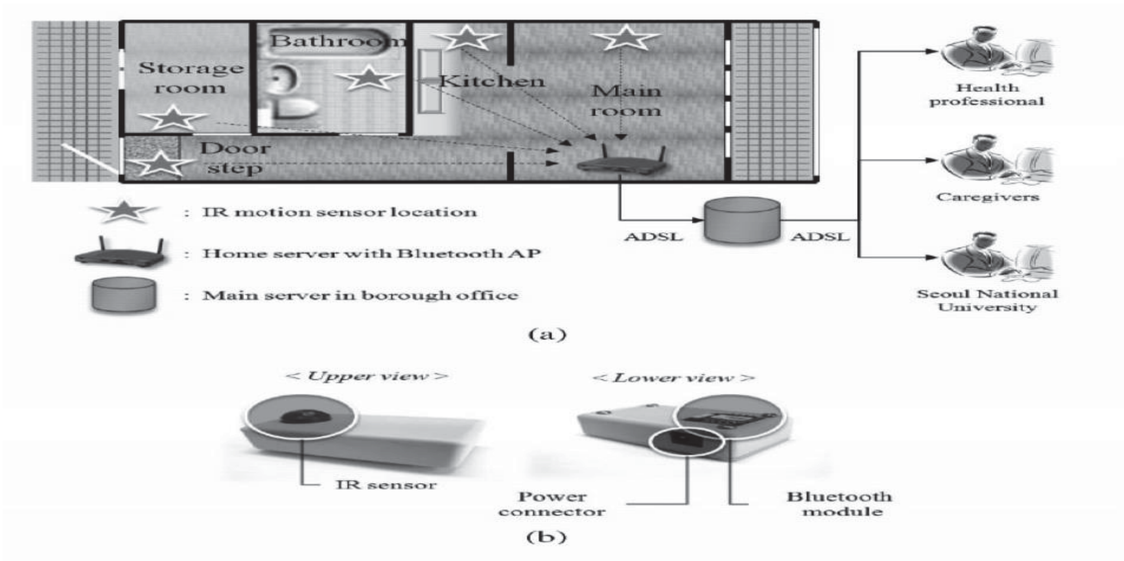


Figure 2-7 Ubiquitous Healthcare House Monitoring Systems [69]

The developments of intelligent home systems are mostly based on the importance of communication technologies and intelligent programs for various tasks of the smart home monitoring systems. The relative exploration of various smart home schemes having mainly wireless sensor network is presented in Table 2.3.

Table 2-3 Smart Home Monitoring Systems based on the importance of communication medium

Smart Home Monitoring system	Physical components/ Sensors /Actuators	Home Network based on	User GUI based on	Procedures
Implementation of Active Sensor Network pertaining to home appliances manage system [70]	Actuator, Generic Sensor	ZigBee	Internet based Application	A smart house energy managing program for controlling household objects. A Linkup Quality Indication Based Routing was proposed [70].
Keeping track of Elderly people at flat [71]	IR sensors, Contact switches, hygrometry	ZigBee	Application for Mobile devices	Numerous-sensor centric smart network computer architecture. Activities of Day to day living classification using Support Vector Machine technique [71]
Development of Wireless Sensor Network node for smart home system [72]	Wireless Sensor Node and Coordinator	ZigBee	Application using GPRS for external network	Applying Dijkstra Algorithm for increasing routing method inside a hybrid star topology [72].
Setup of an automation architecture [73]	Smoke Sensor and Light Sensor	ZigBee	Windows based Wi-Fi	Virtual home computerization system [73]
Supervising system using wearable pulse monitor sensor incorporated with a smart phone [74]	Smart Phone with a pulse sensor	Bluetooth	Wi-Fi, GPRS, WiMAX, HSDPA	A mobile health and fitness overseeing system by means of Wireless Bluetooth dimensions on the pulse sensor. Measured information is carried into a remote machine via several interaction systems [74]

Powerful intelligent home control system employing Android phone [75]	Generic sensors	Android platform network	GSM, Wi-Fi	An intelligent home control system using Android phone being a temporary home gateway. Based on the user behavior analysis unused devices are shutdown [75]
Applying a smart home with digital door lock as base station [76]	Temperature, gas, fire sensors	ZigBee	Internet	The doorway lock system contains RFID tag, touch LCD, motor module for enter and exit of door, sensor modules for detecting condition inside [76]
Implementing E-Healthcare using WSN [77]	Pulse sensor, Pressure sensor, fire sensor	WSN	Internet	WSN application for all day around continuous checking. A merged positioning procedure to determine the location in the elderly [77]
Arrangement of WSN inside a living laboratory home atmosphere [78]	Temperature, Pressure, Light, contact sensors	ZigBee	Windows based	Daily Activity Monitoring Supervising 42 everyday object usages with eighty one liaison sensors [78]
Implement a smart home security system [79]	Smoke, gas, temperature, biosensor	ZigBee	GSM	Microcontroller based WSN with GSM module. Send alert for unusual circumstance [79]
Prediction of user usages in energy management of a smart home [80]	Generator, consumer, and energy storage	photovoltaic system and a micro cogeneration unit	electric energy systems	Decision Tree approach Hybrid Algorithm(Prediction Algorithm) – Day Type Model, First order Semi Markov Mode [80]
Research of emotional characteristics of home user using multi agent system [81]	X10 based devices based on Mav Home project	WSN	Window based	Multi-agent Technique to trace user for process classification using clustering algorithm for smart home activities [81]
Friendly Smart Home Energy Management [82]	Smart meter, Smart Switch Smart Interactive terminal	ZigBee	Windows based	Interconnections with smart meters, switches, appliance controller to analyses the leading functions [82]
Implementing a proactive, adaptive, fuzzy home-control system [83]	Actuators, Light sensor	ZigBee	Windows based	Customize the environment based on user desires using Fuzzy control process weighting factors as well as for adding, altering and eliminating rules [83]

Agent based system to regulate an intelligent home monitoring [81]	Thermal Sensor	WSN	Windows based	Agent based system to interface with building automation installations [81]
Energy efficient smart home system [84]	Smart devices- PlayStation, Lamp, Coffee Maker	wireless smart meter plugs	Windows based	a middleware structure for Event Management and maximize the performance of energy consumption [84]

2.6 Review of Methodologies on ADL Recognition in SHMS

There have been several machine learning models for daily activity recognition from the monitored sensor data which differ nearly as very much as the kinds of sensors that are used in a smart home environment. A Predictive Ambient Intelligence (PAI) [85] environment gathers information from WSN including environmental changes and occupants' interactions with the objects within the monitoring environment. Collected data are used to determine the behaviour of an inhabitant at different times by using prediction methods.

The prediction involves the extraction of patterns related to sensor activations. This is then used to classify the sequence of activities and match it to predict the next activity [86]. Healthcare specialists believe that the best procedures to recognize health conditions of the elderly before they become sick is to look for the changes in the actions of everyday life such as basic ADLs and Instrumental ADLs(IADLs) [87] [88] [89]. Effective classification of ADLs is an important factor for detecting the changes in the routine habits of the elderly to determine their health conditions. There have been momentous research explorations in activity recognition and anomaly detection subdomains of a smart home monitoring system [87] [52] [16] [90] [91] [92].

Researchers discovered that dissimilar kinds of sensor data are helpful in grouping diverse activity forms. Many probability based algorithms are used to develop daily activity prototypes. The most usual models are the Hidden Markov Model (HMM) [93] and the Conditional Random Field (CRF) models [94]. The main purpose of activity identification is to make out normal human actions in the real life scenario. The precise recognition of actions is difficult due to the complexities and diversities of human actions. The precise objective of the HMM model is to establish the unknown class classification that matches with the experimental output. It also tries to understand model factors from the account of observed output sequences.

However, HMM faces limitations irrespective of its popularity and simplicity. Especially, it faces problems in indicating multiple networks of activities that are synchronized or interlinked [94]. HMM is inefficient in securing long range or transitive reliance of observations because of its firm self-sufficiency supposition for the observations. In addition, lack of appropriate training leads to non-recognition of probable observation sequences coherent with the specific activity by the HMM model.

The HMM and CRF are operated to discover hidden state evolution from observation classifications. HMM tries to discover activities using a joint probability distribution and CRF use conditional probability methods. CRF permits a subjective, dependent relationship amid an observation sequence, supplementing with flexibility. One of the huge disparities between the two models is the reduction of independence supposition where hidden state supposition relies on precedent and prospective observations.

The synchronized and interlinked daily living activities can be identified by Skip-Chain CRF and Emerging Pattern methods [94]. Apart from Emerging Patterns, every method needs organized learning, which consequently entails training data for true activity identification like greater restrictions in carrying out in programmed labelling. However, the alterations in the sensor environment must resemble in the individual models. A deeper comprehension of raw sensor data can be gained by adopting knowledge detecting methods such as finding patterns in sensor data [48] instinctively to recognize precedents of importance in the facts..

There are methods using the windowing concept. A window of user-defined dimension is rearranged by an "Episode Discovery" algorithm using sensor data to amass candidate episodes or progression of interests [95]. Most of the smart homes monitoring methods are relying on classifying the sensor data for ADL recognitions.

The main objective of classifying sensor data analysis is to categorize the information from sensor data to defined groups [96] [58]. Different categorization procedures related to sensor data have been formulated such as decision trees [97], Bayesian classifiers [98], neural networks [99], instance-based learners [100], support vector machines [101], clustering [102] and regression algorithms [103]. Categorization algorithms have several drawbacks because they vary depending on the nature of data handling, like class labels having distinct or true values, data consisting of omitted values or inaccuracies, magnitude of training data availability and the representation of concepts. Proper caution should be followed to avoid the over fitting of learning algorithms with the data leading to non-generalization of intellectual concepts to the latest data.

On the other side the development of unsupervised learning methods [104] and discovery of mildly controlled learnings [105] are carried out. These methods help to overcome the blockage from acquiring a greater quantity of training information. But, these algorithms too face limits when confronted with ambiguity of sensor data. Domingo et al. [106] demonstrated an application to exploit “Markov Logic Networks” (MLN). It’s basically an arrangement for statistical composition to find out daily activities recognition. But, this approach corresponds to activities identification presuming that the elderly perform only one activity at a time which is realized as an instance in formulation.

Hao et al. [107] demonstrated the multi-tasking as an essential attribute in the real daily routines, refusing the concept of considering activities as serial. Correlation graphs are used to model simultaneous actions and develop the corresponding model. There is also an alternative solution to HMMs called an Interleaved HMMs model (IHMM) [108]. Complex daily activity is realized from the correlation scores of the activity features. This method too has restrictions when a sliding time frame is taken into account for identifying specific characteristics.

Riboni and Bettini [109] proposed the activity recognition method from a knowledge base perception by using ontology concepts. The ontology concept is examined based on the subject’s context which decreases possible mis-calculation by the probabilistic algorithms. The probabilistic algorithms method does not deal with temporal relations among activities and is limited to merely sequential activities. Table 2.4 shows the some of the comparisons for various methods of sensor data analysis related to ADL’s. recognition in smart home systems

Table 2-4 Comparisons of various sensor data analysis related to ADLs recognition in SHMS

Method	Description	Advantages	Dis-Advantages
Hidden Markov Model(HMM) [110]	▪ generative probabilistic model ▪ model is generated from the past observed sequences of sensor data ▪ Maximize transition and observation probability(joint probability)	▪ For simple(sequential) activities [111]	▪ Composite or new sets of activities are difficult to recognize and cannot be put in the model ▪ Extensive training is required ▪ Difficult to represent multiple interacting activities ▪ Incapable of capturing long-range dependencies
Condition Random Field,-Skip Chain Conditional Random Field	▪ Alternative to HMM ▪ Use likelihood function as an alternative to mutual probability function, Composite activities can be modelled with sub-activities by capturing appropriate dependencies	▪ Flexibility for non-independent relationships among observation sequences [112]	▪ Lot of training is required for estimating the potential function. ▪ Potential functions are computationally expensive when there are multiple linear chains ▪ Lacks in scalability when multiple models are to be added/updated
Emerging Pattern	▪ Use support and growth Rate functions. Partially unsupervised	Recognize Concurrent and Interleaved activities [104]	EP mining required when there is a change of model
Clustering Techniques	▪ Set of discovered sequences (sensor observations) are grouped into a set of clusters. ▪ Use different methods such as edit distance and LCS	Cluster similar patterns together	▪ Only emblematic orders with no structures [113] (requires at-least temporal info to be attached) ▪ Reasoning about ordering information. Using clustering technique it is difficult to classify a real-time sensor values

Self-Organizing Map	▪ Similar raw sensor data points move closer together ▪ Different Gaussian vicinity functions are considered	Reveal patterns in the data after learning the process and branch out by its shape. Unravelling phase after the limits that regulate the tractability are high [114]	▪ Learning rate decay linearly based on the class. originally knowledgeable perceptions depreciate leading to sluggish conjunction ▪ "Self-Organizing Map" can be very unbalanced, particularly in the early phases of learning.
Episode Discovery Algorithm	▪ Employ automata theory ▪ Based on the limited past history of the sensor sequence, how can the following episode be identified	Useful for the forecasting methods from the known behaviour [95]	▪ The procedure is investigated based on the artificially generated data collection assuming the possible sequences of the sensor data of typical inhabitant behaviour.
Bayesian Classifier	▪ Have strong assumption that all variables effect a classification decision	▪ works well when limited to small datasets	▪ Frequency problems occur when assigning probability of 0 for a given activity during training stage, ▪ Parameter estimation is crucial [115]
Ontology Matching	▪ Activity recognition systems based on knowledge-driven techniques.	▪ ADLs are discovered based on the contextual information [109]	▪ Ontological approaches require chronological perceptive for improving the identification precision [109] ▪ Ontological reasoning is computationally expensive
Instance-Based Learner(IBL)	▪ Supervised learning or learning from examples ▪ IBL procedures adopt related occurrences require analogous groupings. ▪ This indicate to their local	▪ domain-specific systems	▪ do not retain a steady set of generalizations resulting from particular occurrences [116] ▪ requires large storage requirements

	preconception for categorizing novel occurrences conferring to their most alike neighbour's ordering		
Auto-Correlation	▪ Auto-correlation data is for constant patterns with negligible tolerance within the set of data that's being processed.	▪ High amount of autocorrelation is seen between neighbouring observations [117] ▪ To detect trends	▪ Anomaly detection is difficult for non-linear/quadratic graphs ▪ Require time series forecasting model
Support Vector Machines	▪ Make limits about the objective data by encompassing the objective data within a least parameters values; accordingly classify normal and abnormal behaviour patterns.	▪ Able to classify normal behaviour patterns [101]	▪ For developing a dependable irregular behaviour detection system, the irregular status of the system needs to be pre-defined, which is hard problem.

2.7 Smart Homes Technologies Users

The following benefits are offered from the technology assisted smart homes: Anyone living independently, who is not able to look for aid in some emergency situations such as unconsciousness, falls etc. Disabled or older people who are suffering from cognitive like dementia and/or physical injury like visual, hearing or suffering from chronic diseases. Individuals who require aid in day-to-day life for personal care actions like eating, bathing, dressing and instrumental activities like cooking healthy meals [118]. There are SHMS technology users like formal health care provider or informal family health care providers for handicapped or older. People who are living in rural or urban communities with unsatisfactory health service provisions.

2.8 Advantages of a Smart Home Technology

Smart homes enabled with tele-care systems are providing specific assistances to support older or handicapped people who are suffering from prolonged illness and living independently. The health assessment of behavioural patterns and physiological signs will be interpreted into exact forecasters as a proficient program to start proper activities. Smart home tele-care can provide facilities to overcome the transportation for organizing multidisciplinary care outside the hospital [119] [120]. Home tele-monitoring of chronic illnesses provides information empowering patients with health related information and potentially developing their health check-ups [120]. The important benefits are ease of understanding of locations and services of quality health care. Some of the respondents highlighted the significance of selection in terms of actions and accessing services ways. As per the patients view, they are usually favourable in the direction of telemedicine such as eliminating consultation timings and reduced costs, etc. Most of the patients favour tele-consultations as it saves money as well as time [121]. Information technology like 'e-prescribing', 'electronic health files', and 'decision support systems' has decreased costs of tele-health care systems [122].

2.9 Current Limitations of Smart Home Technologies

Application of wellbeing care equipment's in smart homes is hindered by the need for research associated with user requirements. This is further aggravated by poor understanding of customer requirements and substandard requests for services to be utilized at smart homes. Also, the industry is controlled by providers offering "a technology-push, rather than a demand-pull system" [123] [124], leading to customer dissatisfaction. Regarding health specialists, those external to networking systems are confronted with the need for skill to share medical information. The main reasons pointed by the medical doctors are the price and apprehensions on privacy as the key obstacles to execution of information technology [125]. Major difficulties in shared, moral and legal concerns hamper extensive use of these devices, notably Electronic Medical Records (EMR). Because of intricate automated devices plus inadequate access to funding costs by doctors and health care centres, and having substandard norms the sharing of medical information was not easy. A second obstacle arises with the amount of time need to understand the operation of these technologies. Distrust might result in suppression of data, revealing deceptive info to wellbeing care suppliers [126].

Smart home technology might unenthusiastically influence social communication associations. Individuals employing smart home type of technology could worry about equipment's substitute private communication with their doctors. Casual providers may apprehend that a better liability will be engaged on them. When a patient is not informed, the spouse or other legal heirs do not inevitably have permissible authority and the principles change for each country [127]. Establishing e-health arrangements evokes many concerns like unintentional revelation of people, communicating with incorrect people and inaccurate use of information [128]. A comprehensive regulatory structure for telemedicine is still missing.

European and global telemedicine processes were unsuccessful in deploying smart home tele-care systems because they were too costly for patients [129] [130]. A number of technologies are short of interaction between doctors and patients. The tele-medicine research is not strong enough, since it lacks in information evaluating of patients' insights. Practical faults such as trials, precise framework, and research design of the available study restrict the overview of the results.

Tele-consultation is good enough for various situations, but concerns associated to a patient gratification have to be discovered in detail concerning patient–doctor communication. There are not many randomized restricted tests comparing tele-health interferences with traditional health care practices. Most of the works in tele-monitoring of chronic ailments were regular tests exclusive of monitoring systems. The researchers proposed that potential appraisal should focus on randomized tests with a greater number of patients over a longer time.

2.10 Chapter Summary

Several smart home technology research tasks were conducted in different parts of the worlds both in the recent past and under current conditions. But, still the answer for the smart home monitoring system in terms of cost, acceptability, technology friendly and service has not been uniquely obtained. Most of the systems developed are based on technology push rather than user specific requirements. Mostly, systems currently designed and developed for the smart home monitoring are wearable, and huge sets of sensors are required to realize proper human behaviour recognitions. The methods developed are based on offline analysis and require set-ups to be changed for different requirements.

The existing methods related to ADL recognition approaches are either based on probabilistic approaches or specific rule based data-driven approaches. Thus, the capability towards combining common sense knowledge is lacking, which is believed to be the significant issue of smart home inhabitant daily activity recognition. There is a need to get optimal solutions for the smart home technologies such as:

- Collection and fusion of on-line/real-time data from heterogeneous sensors on a 24/7 basis. Development of on-line/real-time detection of irregular elderly behavior and better behavior prediction systems in a real home environment.
- Recognition of elderly daily activities including complex behavior using temporal reasoning. Quantitative measurement of "wellness" in terms of performance related to essential daily activities behavior.
- Predictive data mining for real-time sensor streams related to determination of wellness. Set-up of environmental sensing systems with less cost that are reliable, flexible and easily managed for effective elderly behavior recognition and the corresponding wellness.
- Development and finalization of WSN based systems with an optimum number of sensors for elder care in smart homes.
- Integration of human behavior recognition systems with co-systems like human physiological monitoring systems for better well-being monitoring, reasoning and predictions.

Chapter 3. Deployment of WSN in a Home Environment and Real-Time Data Fusion

3.1 Introduction

With the speedy growth of communication technologies and smart sensors, wireless sensor networks based systems became popular tools to encapsulate the physical world's information. The WSNs have been strengthened by the progress in processor technologies and wireless communication systems that gave way to the development of small, low-cost and low-power consumption, well-organized sensing systems. The WSNs facilitate the users to observe and study physical phenomena at a granularity degree of the aspect that was not possible previously. WSNs were initially applied in military and scientific projects. Applications of WSNs have boomed up as the expense of sensors drop, while the capabilities augment. In the past some years, WSNs have attracted significant interest from both the Network and Database communities. For example, an environmental researcher is interested in the temperature readings, while an ecologist is concerned with the level of soil moisture.

Similarly, in this research, the ADLs of an elderly person are captured by Wireless Sensing Systems (WSS). The important objective of this study is to identify the well-being performance of the older people through the collection of heterogeneous sensors by nominal sensing systems at their homes. For this, WSNs consisting of diverse sensors like electrical, force, contact, and Passive Infra-Red (PIR) sensing systems integrated with radio communication ZigBee modules have been fabricated and deployed at the elderly homes. The developed sensing systems are noninvasive, flexible and safe to use.

The fusion of wireless sensors to a centralized computing system (the sink or base station) is the most widely considered data collection method. There have several researches undertaken to realize a few goals efficiently, such as increasing the lifetime of nodes, and to conform to the application requirements. There are basically two major concepts that researchers have investigated in the fusion of WSN data. Firstly, data is interrelated (both across time and over space), and second, a number of applications recognize small variations in the data values they investigate. These ideas have given way to the development of a large number of methods that deal with the exactness for time implementation and energy savings. In this research, to have near real-time (online) sensor data analytics, a robust heterogeneous sensor data fusion system has been designed and developed. In this chapter, details of the near real-time sensor data collection, storage and handling of wireless sensor data fusion are presented.

3.2 Description of the Wireless Sensing Systems

The term wireless sensing system is a module with one or many sensing devices, radio component and restricted computational resources. It takes physical measurements of the AAL setup, e.g., temperature, humidity and the usages status of the domestic objects. A WSN comprises a base station and a set of sensor systems (nodes). Each node can directly be in contact with others within its radio coverage. The base station (coordinator of WSN), also called the data sink, is ready with a radio component, so that it is able to be in contact with the nearby sensor nodes and gather the encapsulated AAL data.

The sensors at a distant place may not be able to transmit data directly to the coordinator. Depending on the range of the monitoring area, data encapsulated by the sensing systems present on the boundary of the monitoring area might be required to relay (using multiple hops sensors) before they reach to the sink. To query the sensing data, appropriate programs are executed at the base station, which then reports the query outcomes. In the present research, the home monitoring communication system is based on IEEE standard 802.15.4 of ZigBee. The WSS have been indigenously designed and developed at our laboratory.

The overall structure of the WSN data fusion consists of two important modules: i) WSN and ii) an intelligent home monitoring software system to collect sensor data and perform data analysis for detecting behavioral changes of an elderly person. The household objects regularly used by the elderly person are attached with fabricated sensing units. The input signals from the sensing units are integrated and connected through radio communication interface XBee modules [131]. The rationale for observing the usage of household appliances is based on the fact that these are regularly used by the elderly person in various situations like preparation of food, relaxing, toileting, sleeping and grooming activities. Fig. 3.1 depicts the functional design of the developed system.

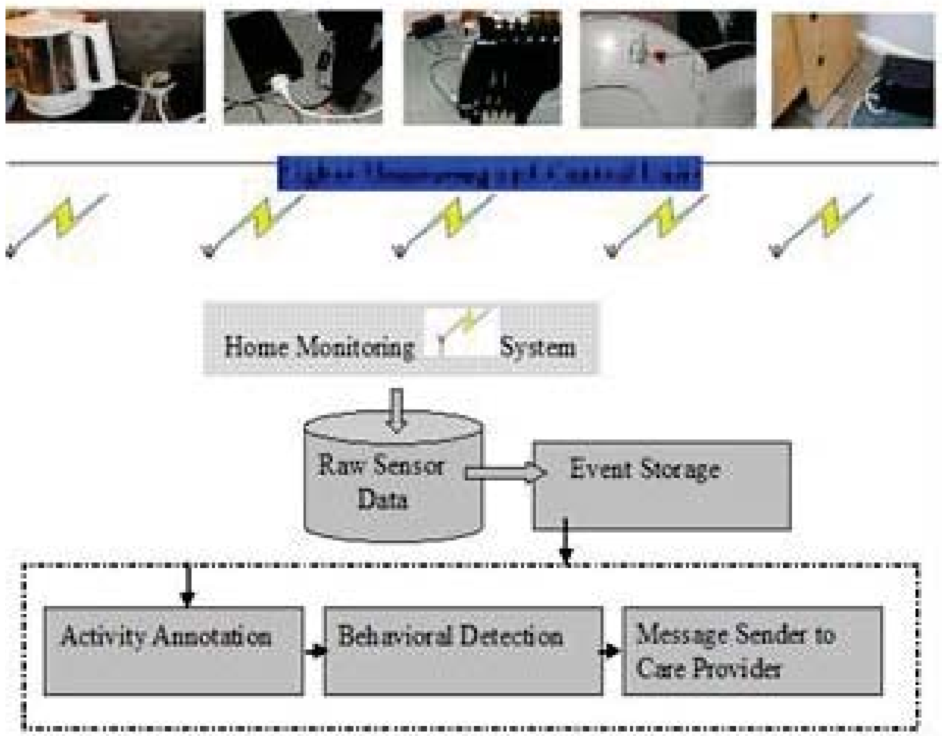


Figure 3-1 Architecture of the developed WSN based Home Monitoring System

The designed and developed sensing systems are useful to determine the wellness of the person in performing basic daily activities. In addition to the fabricated sensing units, emergency help and deactivate operations are developed with XBee modules to facilitate the corresponding operations during the real-time activity monitoring of the elderly. Since, the research objective is concerned with how "well" the elderly person is able to perform their basic-ADLs; a limited number of sensing systems that correspond to the daily usages of household appliances are investigated in the present home monitoring system.

The importance of the sensing system is that it has been developed for using in an existing elderly person home rather than a newly constructed house or a test bed scenario. Additionally, the WSS are compatible with the internet of things functionalities. These, systems are capable of operating from a remote location (i.e., the WSS are able to respond to the commands from remote server).The operational feature of these systems is that they are flexible in connecting with the regular household appliances.

3.3 Wireless Sensing Systems for Household Objects Monitoring and Control

The selection of sensors (sensing systems) is dictated by the lifestyle of the elderly person. There are different types of sensing systems indigenously designed and developed at our laboratory for the home monitoring system. Instead of connecting a household object to a power outlet, the household objects are connected to the fabricated sensing systems for recognizing the elderly person's basic ADLs. The following fabricated wireless sensing systems are designed and developed to monitor the behavior of an elderly person living alone in their own home.

Type #1: Electrical Household Objects Monitoring and Control Sensing System.

Type #2: Non-Electrical Household Objects Monitoring Sensing System.

Type #3: Contact Sensing System for Household Objects Usage Monitoring.

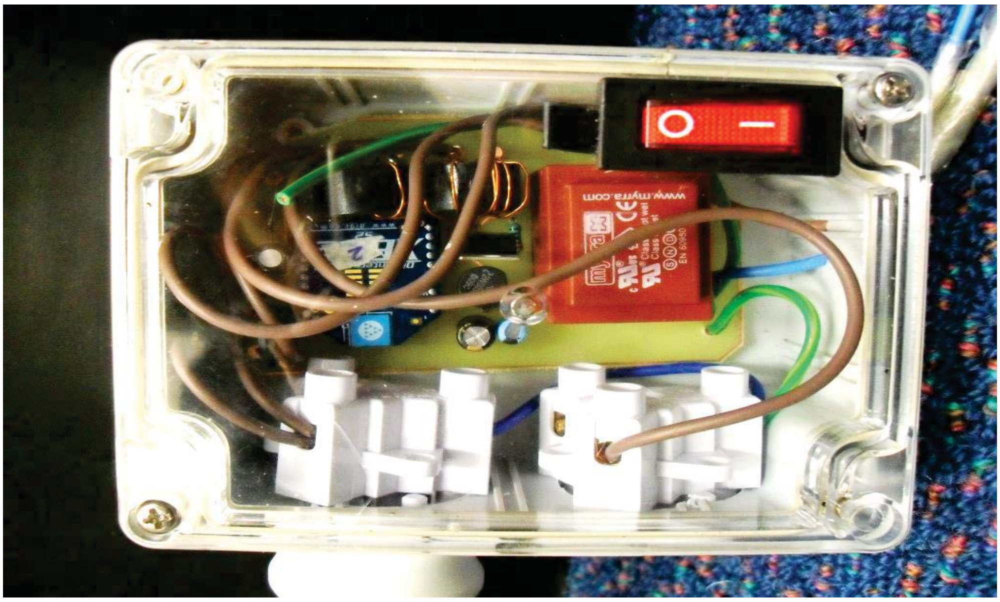
Type #4: PIR Sensing System for Monitoring Movements inside the house.

Type #5: Environmental Parameters Monitoring Sensing System.

Type #6: Human Physiological Parameters Monitoring Sensing System.

3.3.1 TYPE #1 ELECTRICAL HOUSEHOLD OBJECTS MONITORING AND CONTROL SENSING SYSTEM

The system has been designed for measurement of electrical parameters of household electrical appliances. From a consumer point of view; electrical power consumption of various appliances in the house along with the key parameters such as supply voltage and current may be useful. The following household objects were monitored: Room Heaters, Washing Machine, Microwave, Oven, Toasters, Water Kettle, Fridge, Television, Audio device, Battery chargers and Water pump. In total, ten different electrical appliances were used in the home monitoring system; however the current system can only be used for any electrical appliances of power rating of less than 2KW. The electrical sensing systems intelligently identify which electrical appliance is in use. Electrical sensing devices operate on the detection of current flow connected to household objects. Typically, a single electric sensor is necessary to sense an electrical appliance usage. However, in this research the design of the electrical sensing system is done in such a way that two electrical appliances can be connected to the same sensing system. Thus, the cost of the system is reduced. Fig.3.2 shows the fabricated electrical sensing system.



(a)

(b)

Figure 3-2 Fabricated electrical sensing system (at our laboratory) to monitor and control household electrical objects

Fig.3.3 shows the electrical sensing system Graphical User Interface (GUI) running at the base station. The fabricated electrical sensing system has distinct features:

i) Use of Triac with opto-isolated driver for controlling electrical appliances. Household appliances are controlled either remotely or automatically with the help of a fabricated smart sensing unit consisting of triac –BT138 [132].

ii) No Microprocessor/Micro-controller: The design of the smart sensing unit does not require a processing unit at the sensing end

iii) Flexibility in controlling the appliances: Depending on the user requirements, appliances can be monitored and controlled in different ways.

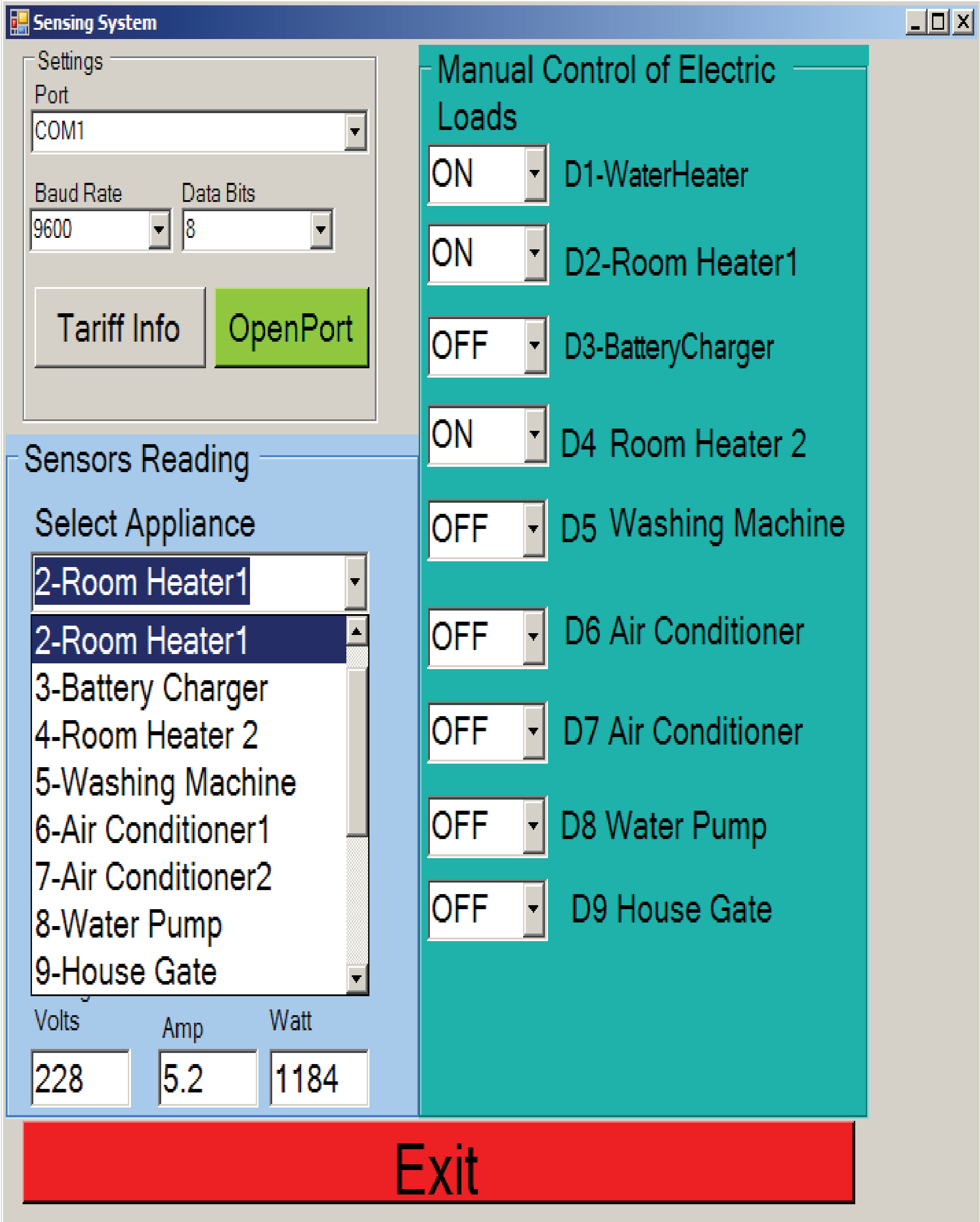


Figure 3-3 Electrical sensing system GUI running at the base station of the WSN

The same fabricated electrical sensing systems are connected to various household electrical appliances to recognize the basic ADLs of an elderly person. Fig.3.4 shows the different electrical domestic objects connected to the fabricated sensing systems.

Figure 3-4 Fabricated Wireless Electrical Sensing Systems attached to various Household Appliances

3.3.2 TYPE #2 NON-ELECTRICAL OBJECTS SENSING SYSTEM

The non-electrical household objects such as the single bed, chair, toilette and sofa are monitored using an ultra-thin, flexible and non-obtrusive Flexi Force sensor (Flexi) [133]. The force sensing system is indigenously designed and developed at our laboratory. Fig.3.5 shows connection of the force sensing system to domestic objects such as Bed, Couch, Chair and Toilet.

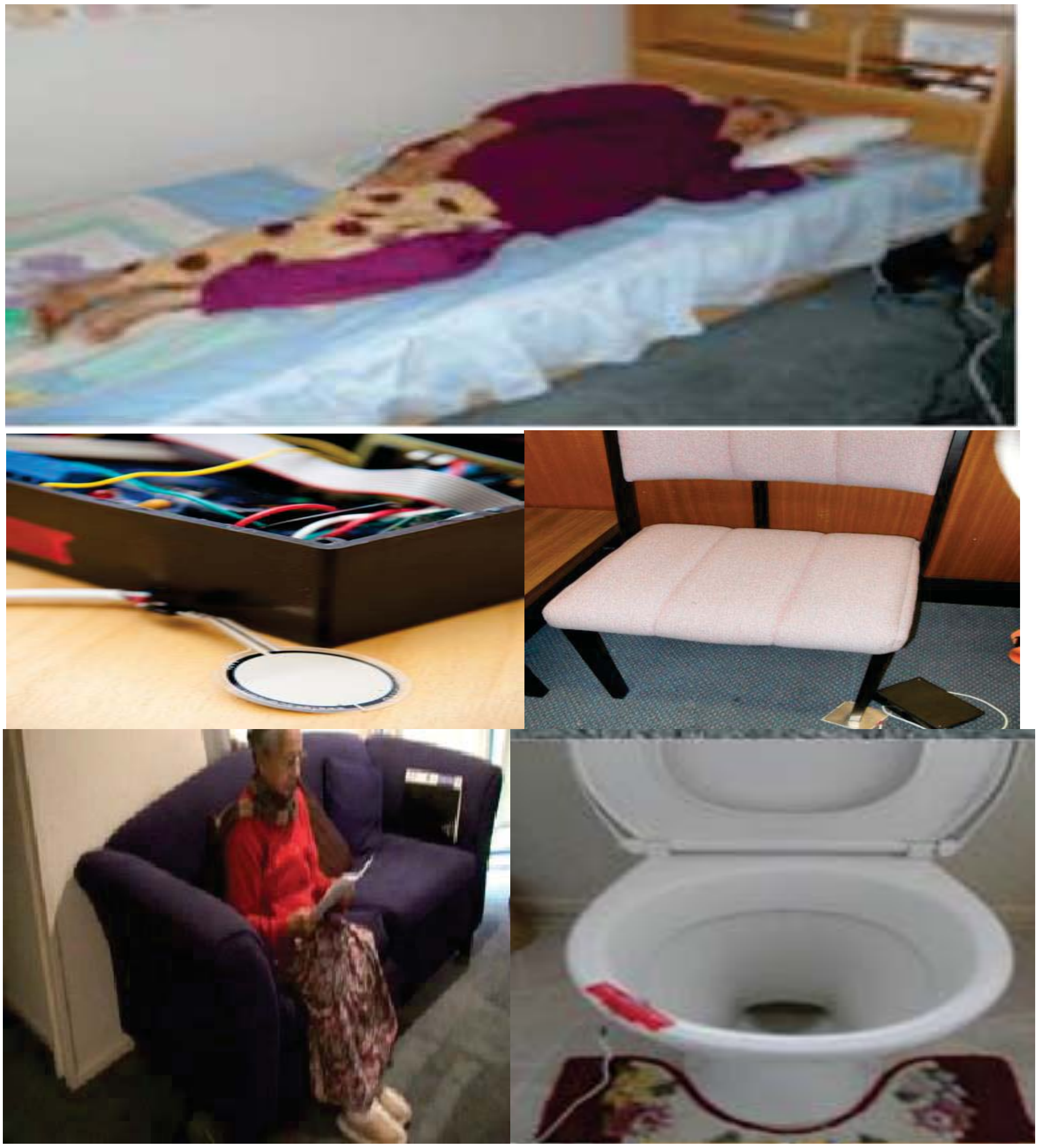


Figure 3-5 Fabricated Wireless Force Sensing Systems Connected to Various Domestic objects

Based on the analog values received at the coordinator from the force sensor, the data acquisition system can recognize the usage of these devices as active (in use) or inactive (not in use). The detection and measurement of the relative changes in force sensor values when the use/no-use is of the object is realized at the base station (sink). The software program running at the base station identifies the analog force values received at the base station (sink) and trigger the usage activity based on the threshold values of the respective sensing systems.

3.3.3 TYPE #3 CONTACT SENSING SYSTEM FOR DOMESTIC OBJECTS

The domestic objects such as self-grooming table, fridge door are connected using fabricated wireless contact sensing systems. Fig.3-6 shows the fabricated contact sensing system connected to a grooming table to identify the appliances usages. The corresponding usages of objects are identified at the base station based on the ON/OFF values.

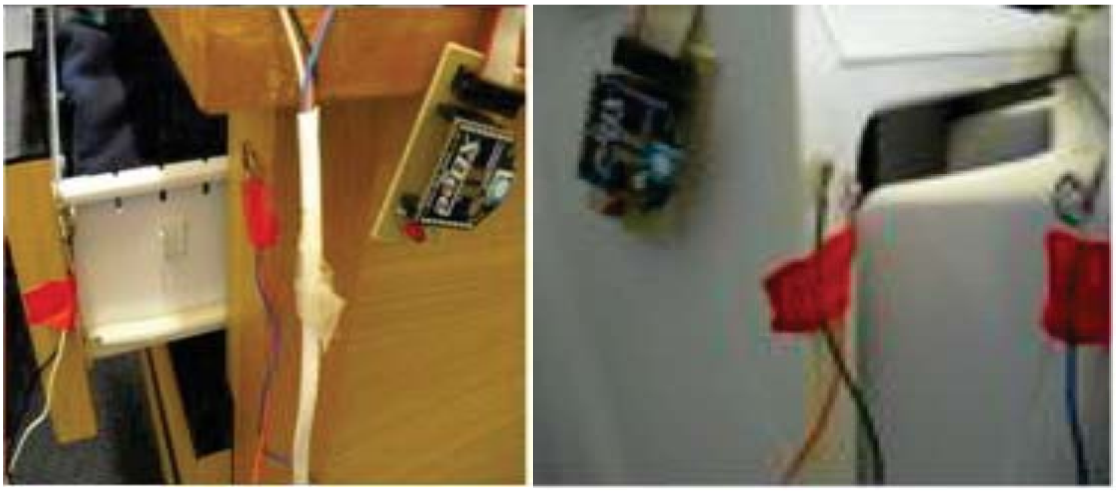


Figure 3-6 Fabricated Wireless Sensing Systems attached to doors of Grooming table cabinet and Refrigerator

3.3.4 TYPE #4 PIR SENSING SYSTEM FOR MOVEMENTS MONITORING

The Passive Infra-Red (PIR) motion sensing system is designed to detect movements within coverage of the sensing system. These are tiny, cheap, of low-power consumption, flexible and long lasting. They are often referred as "IR motion" sensors. This unit works from 5V to 12V.and can be interfaced with XBee. The PIR sensors provide a binary state output either "ON" or "OFF". Fig.3-7 shows the interface connection of PIR with XBee module and the fabricated wireless PIR sensing system.

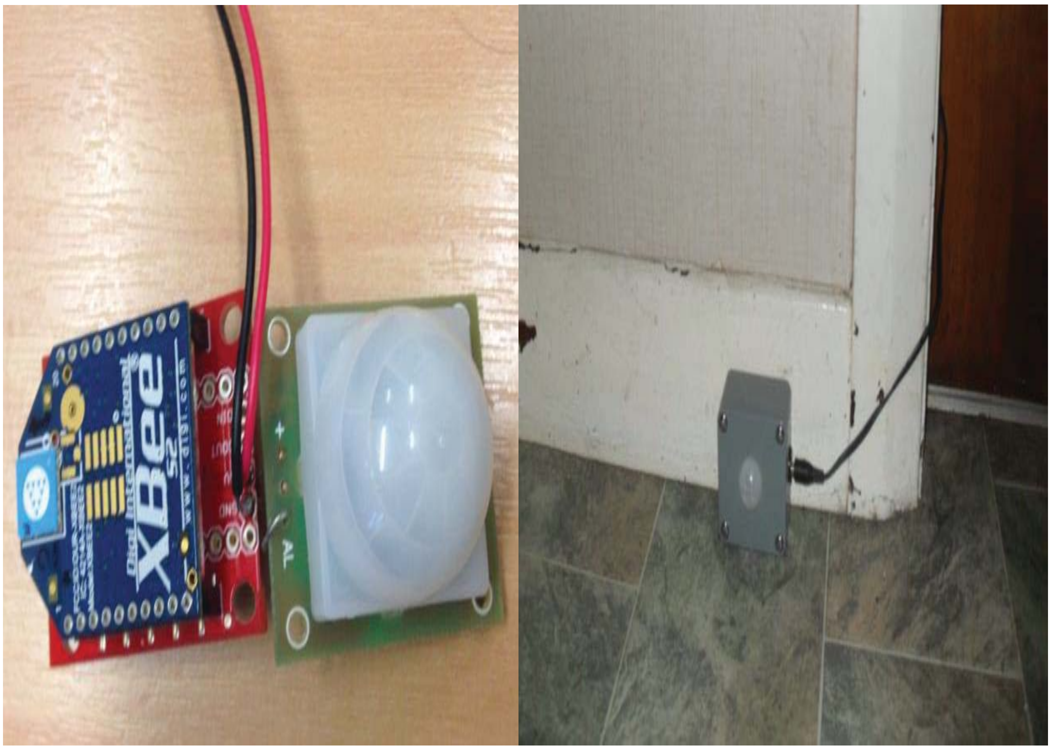


Figure 3-7 Fabricated Wireless PIR (motion) Sensing Systems

The deployment of a large number of sensing systems in the house to track the person will be costly and it may be difficult to convince the elderly person of its benefits. It is beneficial to use a restricted number of movement sensing systems to determine the physical location of the person at real-time. A limited number of movements sensing systems installed in an unobtrusive manner have been used in this research to know the location of the inhabitant, simultaneously supporting the wellness determination indices. The PIR sensing movement's data analytics is presented in chapter.6.

3.3.5 Type #5 Environmental Parameters Monitoring Sensing System

The fabricated environmental wireless sensing system measures the ambient temperature, humidity and light intensity inside the home at various locations. Fig.3.8 shows the fabricated environmental sensing system. The system can monitor and control sensing system based on the environmental conditions very efficiently

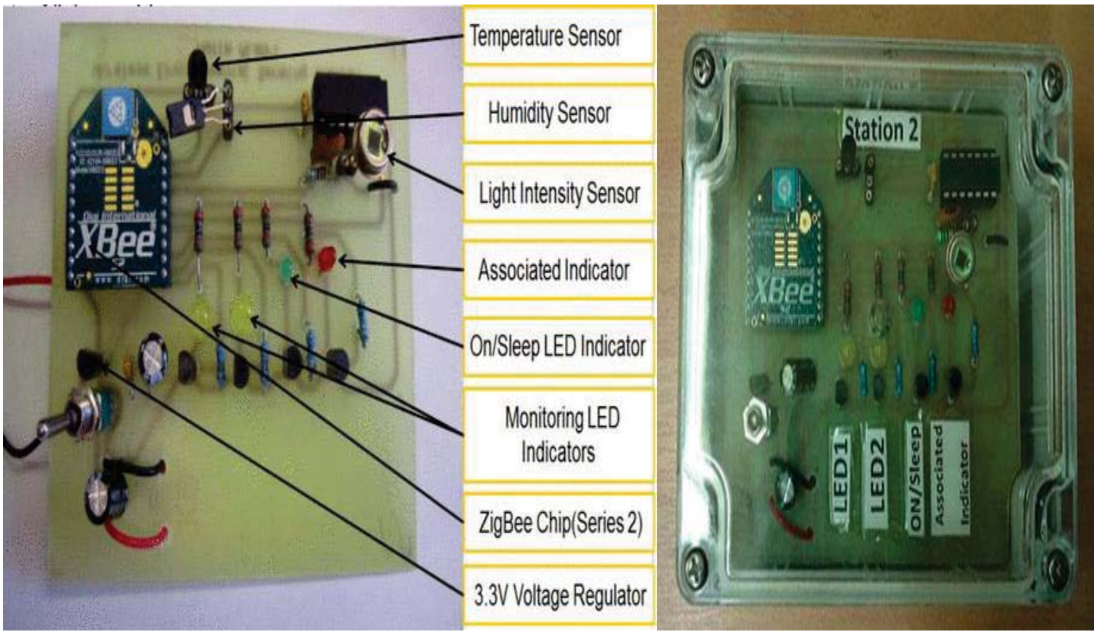


Figure 3-8 Fabricated Environmental Wireless Sensing System

The graphical user interface of the environmental sensing system is developed to offer manageable interface for the user needs. Fig.3.9 shows the GUI of the environmental sensing system at the base station.

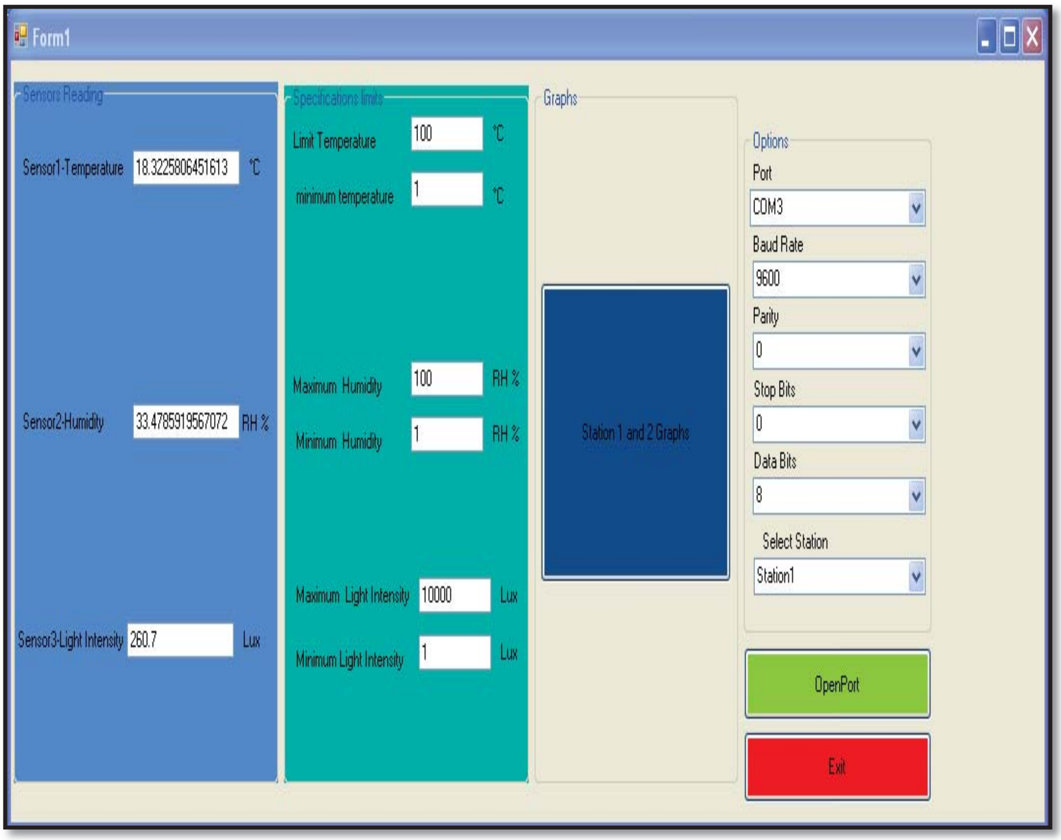


Figure 3-9 GUI of the Environmental Parameters Monitoring system

3.3.6 Type #6 Physiological Parameters Monitoring System

The human emotion recognition module consists of physiological sensors, a signal conditioning circuit, a C8051 (Silabs) microcontroller [134] communication medium (XBee) and a computer for displaying and storing the results. The IR LED, phototransistor, temperature sensor and GSR electrodes are positioned on the top (external) of the container which would be in direct contact with the hand as seen below in Fig 3.10.

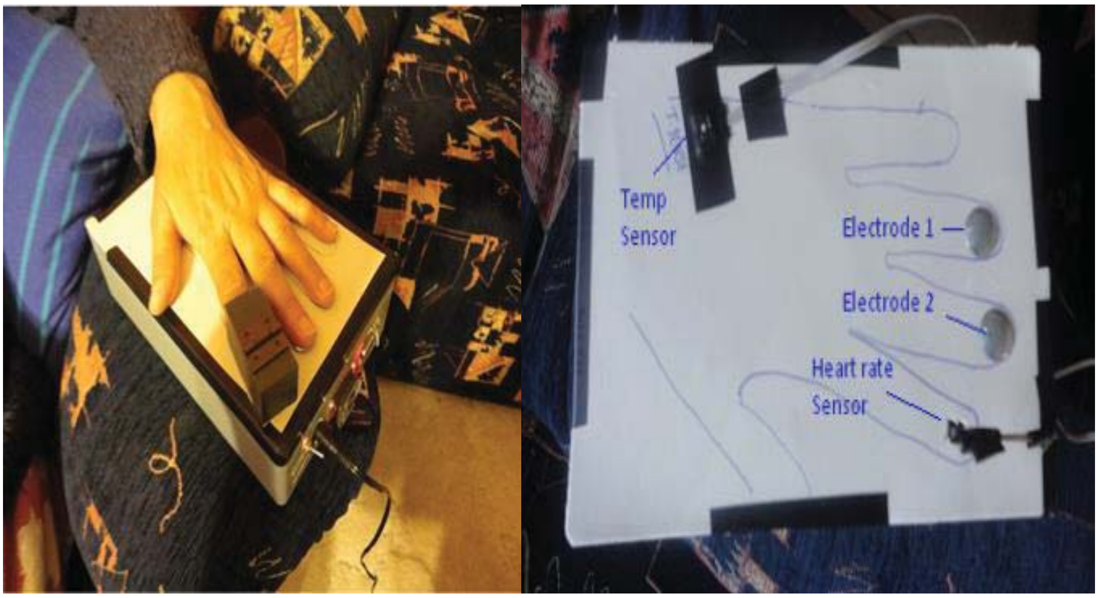


Figure 3-10 Wireless Physiological Parameters Monitoring System

The classification of different emotions is performed on different data set of classes aiming at distinctive emotions. K-means clustering's performed on the data collected from the features for distinguishing the emotions. This technique is a form of unsupervised learning that helps to find the intrinsic constitution in the data. It clusters different people's skin temperature, heart rate and GSR values to classify them into appropriate emotions like Happy, Sad, Neutral and Stressed. The centroid converges to a local optimum of the cluster to specify the number of centers.

3.4 Networking Wireless Sensing Systems

The developed sensing systems do not need any complex processing requirement; hence there is no need to consider a microcontroller at the sensing node. All of the research tasks related to the wireless communications are designed using the ZigBee (XBee) IEEE 802.15.4 protocol (referred to as XBee Series 2). The XBee can be interfaced to collect the sensing data and transmit directly to the base station (sink). The XBee is radio module manufactured by digi.com and follows the ZigBee protocol. The technology defined by the IEEE 802.15.4-2003 (ZigBee standard) is simple when compared to other wireless personal area networks such as Bluetooth. The use of XBee is for radio frequency applications requiring short-range, reliable, secure and high data rates [135] [136].

The XBee operates with 3.3V and uses 40mA. The XBee pins can be configured as Analog Input or/and Digital Input / Output [137]. It is possible to send the measured sensor data through the I/O pins of XBee to the central computer without the need of a microcontroller. The processing of sensor data needs to be done at the central controller (base station). XBee provides up to 250 kbps of data throughput between nodes on a Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) network. XBee provides a reliable mechanism for transfer of data between the network nodes.

3.4.1 ADVANTAGES OF XBEE MODULES

The XBee utilizes the IEEE 802.15.4 protocol which implements:

- Error Detection: Error check sum procedures are implemented for receiving data correctly.
- Media Access: Any two wireless sensor network modules do not transfer the data simultaneously which causes data collisions and errors in transmission. This follows a clear frequency calculation for the right to be established for data transmission.
- Acknowledgements & Retries: Reliable data transfer is followed to make sure the recipient network node receives data otherwise several retries are established.
- Addressing: Various addressing schemes are available such as point to point, point to multi point so that only the network node intended to receive the data will be active.

3.5 Topologies of Wireless Sensing System

The wireless sensing systems comprise a set of sensing nodes. A sensing node links to another sensing node if it is in the radio range, (i.e.,) it directly interacts with another sensing node. A raw technique for message transmitting among the sensing nodes called “flooding” can be applied in WSN for transmission of data to longer distances [138]. In flooding, whenever a sensing system receives a message, it transmits the message to its adjoining sensing nodes (i.e., sensors nodes within the radio range). Nevertheless, this easy method is high energy consuming due to the huge amount of transmissions. In order to aid effective messages transmission, the WSN protocols are set up into definite topologies. Network protocols for WSNs pursue several techniques based on the desired trade-off between communication expenses and sturdiness. There are three main types of topologies: the tree-based topology, the multi-path-based topology and the hybrid topology. In tree-based topologies, every pair of sensing system interacts through a single path [139]. This minimizes the transmission expense, but is very responsive to packet loss and sensing system breakdowns, which occur often in WSNs. Particularly, when a broadcast or a sensing system fails; the data from the matching sub-tree are misplaced.

Alternatively, multi-path-based topologies permit a message to spread through multiple paths until it reaches the base station, so that even if it gets misplaced in one path, it is able to effectively deliver through another one. The trade-off is the elevated communication expense and probably replicated results compared to the tree-based approaches. Hybrid techniques systemize part of the WSN (e.g., depending on sensing system with stable communication links) using a tree-based topology, and the remaining according to a multi-path technique.

In a network set up with high link quality, trees are preferred than multi-path topologies because of their energy efficacy. Alternatively, if the network is having problems such as low link quality, it is better to use a multi-path-based topology for strength. Typically, trees acquire no duplicate data transmissions, as contrary to multi-path based topologies. In this research, the fabricated sensing systems are configured in the form of mesh topology, so that reliable data communication is achieved.

The Quality of Service (QoS) in the configured mesh topology in terms of reliability and throughput in transmission of sensing information are given in sections.3.12.2 The XBee modules for the sensing systems are configured using "X-CTU (XBee *Configuration and Testing Utility*", a program provided by the XBee manufacturer) [140]. A sensor data collection program is developed and installed on the computer that can read the serial data, store and further process the data according to the application. Fig. 3.11 shows the screenshot of a remote sensing system XBee module configuration.

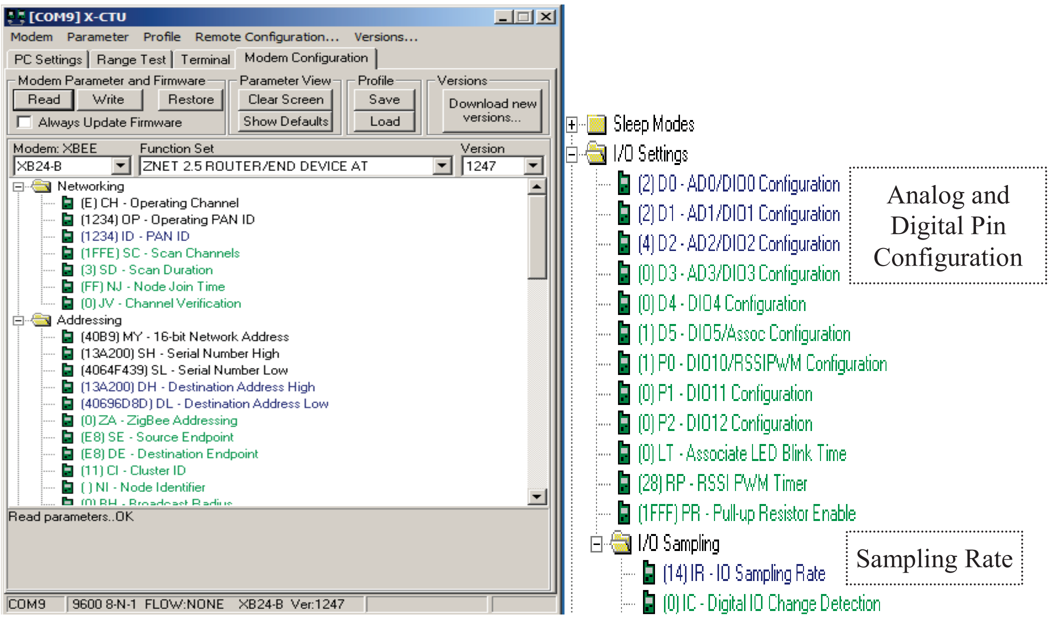


Figure 3-11 Screenshot of the remote ZigBee (XBee) Module Configuration

3.6 Placement of Different Sensing Systems in a Home

The fabricated sensing systems are deployed at an elderly person's home to assess the performance characteristics of the wireless sensing systems. Fig. 3.12 and 3.13 show the 2D view and 3D view of the house with domestic objects and placement of the sensing systems at different locations of the house.

Figure 3-12 2D-View of the house and the placement of different Sensing Systems

Figure 3-13 3D-View of the house and the placement of the domestic objects

3.7 Required Number of Sensing Systems at an Elderly Person Home

The basic ADLs of an elderly person are monitored throughout the day (i.e., 24 hours duration) and the lifecycle of the elderly is reflected in the usages of the household objects detected by the sensing systems. Fig. 3.14 shows the GUI indicating the frequency of the domestic objects usages.

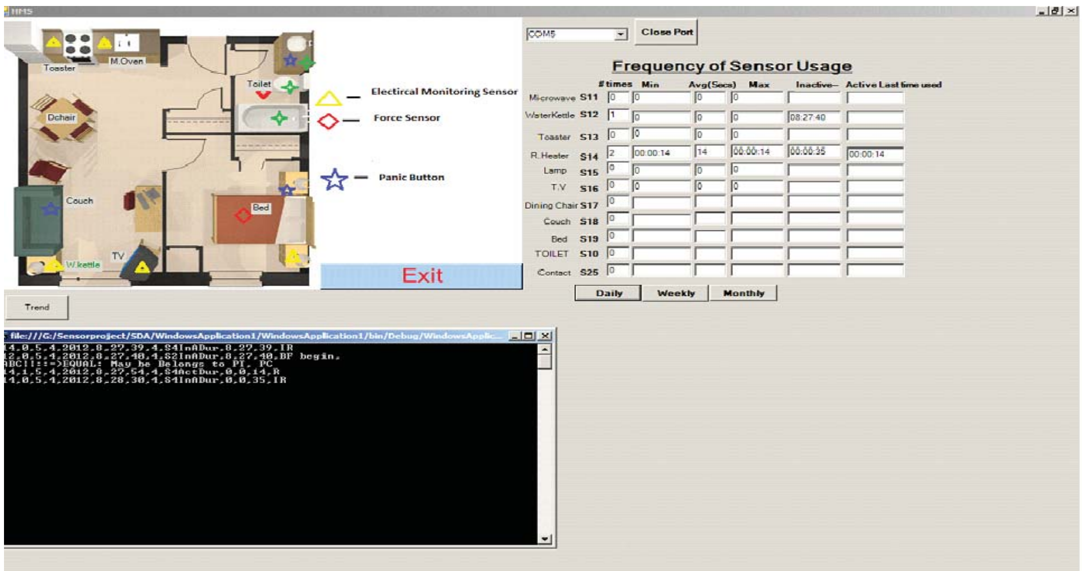


Figure 3-14 GUI of the HMS displaying the frequency usage of various domestic appliances

Based on the following Eq.3-1 the frequency (η) of a particular sensor type in the home is determined.

$$\eta^{c}_{T\,(loc)} = 1 / \sum_{s \in S^{l}_{c}}^{|s^{l}_{c}|} f_{T}(s) \tag{3-1}$$

Where
loc = *specific location in the house*
c = *sensor type*
s_c=*set of sensors of a particular type c*
$f_T(s)$ = *frequency of sensors over a time period T=,*

Table.3-1 indicates the frequency of household object usages at an elderly house. During the trial of the HMS it was identified that the storage room sensing system is of less importance.

Table 3-1 Frequency of Sensor Usages

Room Type	Sensor Type	Connected to Device	η	
			Trail	**Test**
Living	Force, Electrical	Couch, Chair, TV, Heater	0.03, 0.05, 0.05,0.1	0.03, 0.04, 0.03,0.1
Kitchen	Electrical	Microwave, Toaster, Kettle	0.05, 0.05, 0.02	0.04, 0.06, 0.00
Sleeping	Force	Bed	0.26	0.36
Wash Room	Force	Toilette	0.38	0.34
Stowing room	Contact	Cupboard	0.02	0.00

Fig 3.15 shows the block diagram to determine minimum number of sensors needed for an elderly.

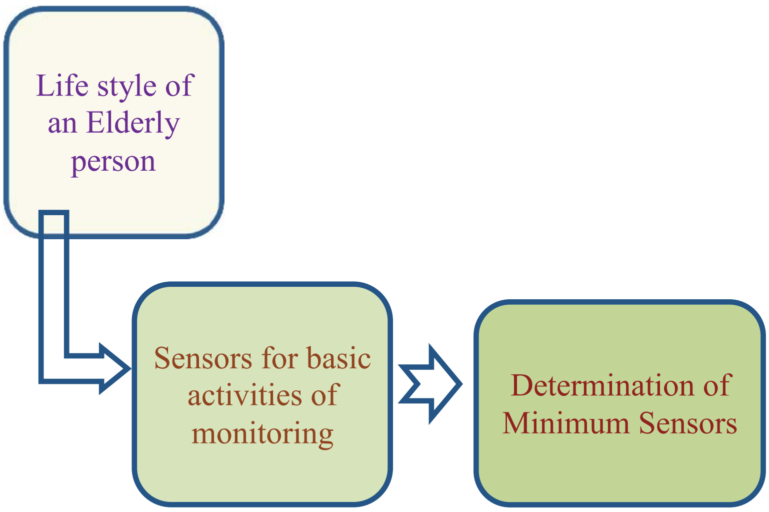


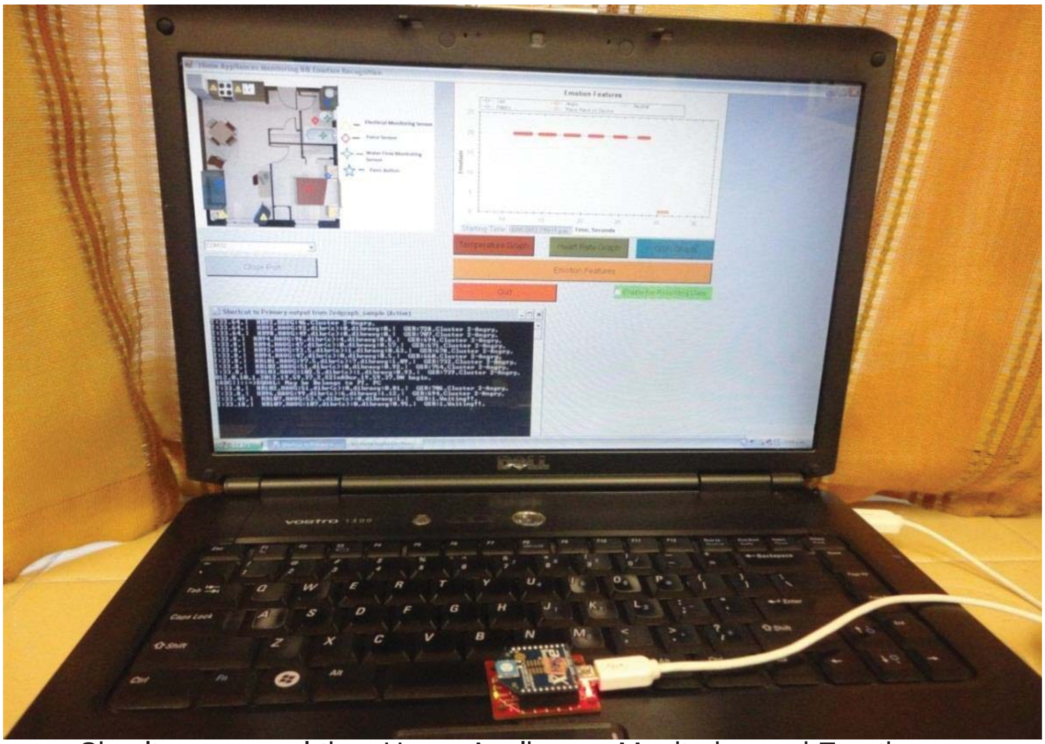
Figure 3-15 Block Diagram Showing the Required Number of Sensing Systems for monitoring the behaviour of an elderly person

3.8 Real-Time Heterogeneous Sensor Data Fusion

The WSS obtain samples of the environmental parameters at different time periods and the data from the WSNs are called "streams". There exist two query models in WSNs for sensor data collection: push-based and pull-based [141] [142]. In the push-based model, the user records a constant query at the base station. The query is executed at the base station during which the sensors constantly produce the outcomes that gratify the query.

This model is a very popular and realistic one in WSNs. A standard query over the WSN comprises the following information: (i) The sampling rate: how frequently the sensors take samples, e.g., once in a minute, (ii) the pretentious features: which attributes should be considered as a sample, e.g., ambient temperature, humidity etc., and (iii) restraints on the returned values: filtering out unwanted values. For the pull-based model, a snapshot outcome is returned for a query. Especially, a query is circulated into the network. On receiving the query, a sensing system returns its present reading. After the base station receives all the responses, it produces and returns the ultimate outcome at the present time stamp to the user. The major variation between these two models is that the push-based one gives back a stream of results, while the pull-based one gives back only one outcome which is the snapshot of the present network status. In the present research study the push-based query model is followed wherein the queries are recorded at the base station to retrieve the sensor data from the sensor database for efficient data processing.

The wireless sensing systems of the home monitoring application generate huge amounts of data set. The absolute number and size of the data set required to control the real-world application (home monitoring) require a more dense depiction of data progressions than the crude numbers itself, and applicable depictions have to be considered. The user interface of our developed system provides connections to the sensor network for capture of sensor data in real-time. Processing the corresponding sensor icon will be highlighted to display if the connected household appliance is active. At any point of execution the activity of the elderly person can be known by viewing the front end of the system. Captured raw sensor data are stored in the computer system in the form of event-based activity (i.e.,) when status (active or inactive) of the sensor is changed. Fig.3.16 shows the robust supervisory and control system and the corresponding user interface:



Simultaneous real-time Home Appliances Monitoring and Emotion Feature recognition

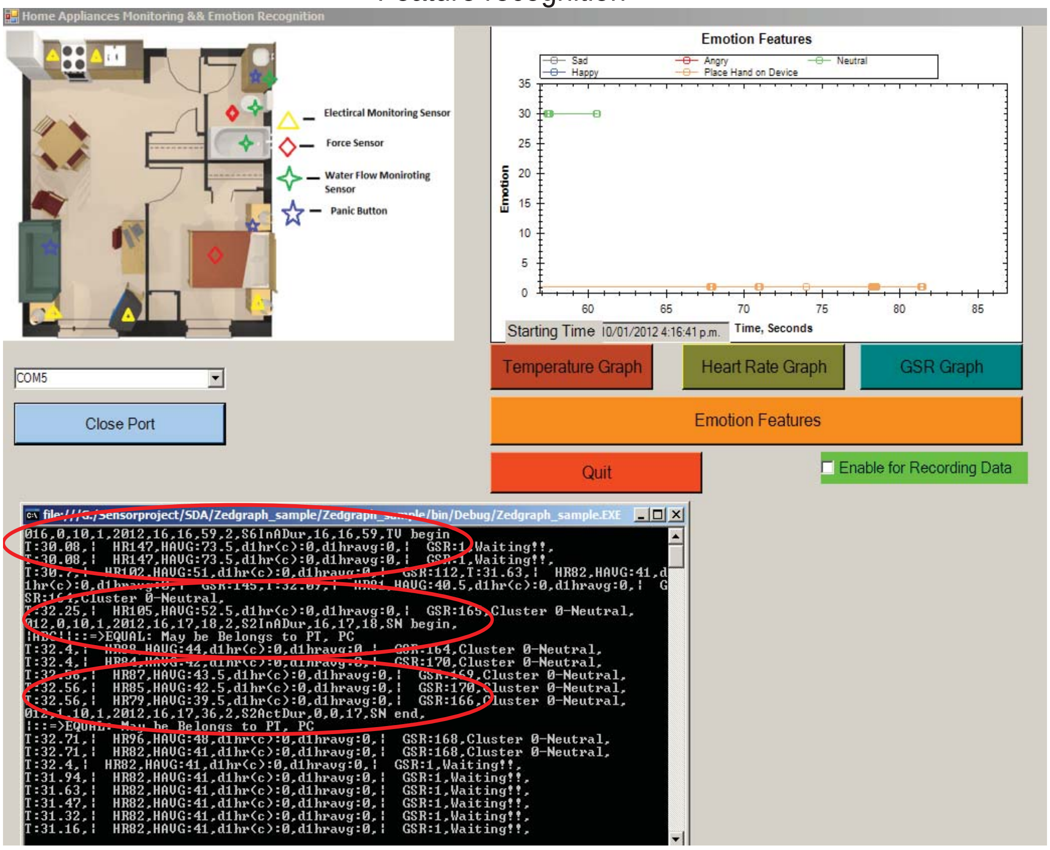


Figure 3-16 Home Monitoring System Showing the Robust Supervisory and Control Unit and the Corresponding GUI

3.9 Software System for Sensor Data Acquisition

The interpretations of fusion of WSN data were implemented for the start of the Internet of Things (IoT) framework modeling. The reasons for using WSN with IoT are i) low-cost, ii) long-term adaptable sensing and actuation abilities, and iii) dispersed resilient communications in the framework.

The IoT framework is capable of supporting i) real-time sensor data acquisition directly from sensing systems or able to retrieve the data from the databases in near real-time, ii) easy handling of real-time data analysis logic methods that process the streams of sensor data in the form of raw data processing and iii) Recognizing anomaly events on the sensor streams, and sending the outputs in a scalable manner to a visualization process.

The home monitoring software system consists of the following programs:

i) A Real-time heterogeneous sensor data fusion program coded using C#

ii) MySql scripts for handling/managing the near real-time sensor data storage on the data base server.

iii) PHP scripts, JGraph scripts and Ajax programming codes for near real-time sensor data display on the web application.

iv) A Sensor Activity Pattern matching process for inhabitant behavior recognition coded using java language.

v) Database replication procedures using MySQL scripts for connecting multiple home monitoring systems through internet and Open-VPN software.

3.10 WSN Data Storage Mechanism

Some applications do not require a base station (sink) to collect the sensors' data. In such applications, the nodes form a WSN as they do not have a base station. In order to gather data, scientists drive a vehicle with the data gathering equipment through the monitoring region. During the lifetime of the network, the nodes store the values until they are dealt with by the collector. There are two major confrontations for such applications: i) due to the restricted storage capacity, sensors memories at node end may run over and ii) workload may differ on various areas of the network, e.g., sensors in the areas with frequent activities will produce more data than those in areas with few activities. These matters raise challenges on how to amass data consistently in each node, and how to get back pertinent data in various parts of the network with low cost. The technique splits WSN storage methods into two categories: centralized and decentralized. In the centralized storage, data are preserved on the node that generates them. As an example, in TinyDB, [143] [144] [145] to carry out some kinds of collective queries, sensors may preserve a small set of data locally. This approach is not appropriate for a set up with recurrent burst activities as they rapidly use up the valuable memory resource. A common decentralized storage approach is the data-centric storage. In data-centric storage, the area to store a piece of data is examined by a set of attributes of the data. The benefit of this method is that the associated data could be stored together. Complicated algorithms are required to find out where a piece of data should be stored so as to balance the storage expense of all nodes. The data-centric storage scheme is regarded as the energy expense technique for storing and obtaining data in WSNs. Assuming that a piece of data *d* is produced by a sensing system s*src* and is stored at sensing system s*dest*. The complexity of storing data comprises of three components: (i) Reading *data* from the memory of s*src*, (ii) broadcasting *data* to s*dest*, and (iii) writing *data* to the memory of s*dest*. The total expenditure of getting back data contains three components: (i) Routing the recovery request to s*dest*, (ii) reading *data* from the memory of s*dest*, and (iii) giving back *data* to the base station.

The above-mentioned two approaches are not suitable for the present WSN home monitoring systems. Captured data are dynamically changing and demanding fast, real-time response time for recognizing the behaviour of the elderly person. To analyze the sensor data, an efficient process of storage mechanism of sensor data in the computer system has been executed. Issues like storage requirements for continuous flow of data streams and processing of data to generate patterns or abnormal events in real time have been effectively dealt with in the current system.

Since there is a continuous in flow of sensor streams, storage of the sensor data in the processing system is done only when there is a change in the sensor events. Event based storage (i.e.,) when status (active or inactive) of the sensor is changed then the sensor fusion data is recorded. This is a most efficient technique, as it reduces the size of storage to a large extent and more flexible for processing of data in real time. Event monitoring collection of data has enormous benefit over continuous flow collection of data in terms of the amount of data storage and processing of data in real-time applications like home monitoring. Fig.3.17 shows the advantage of the event-based storage mechanism in relation to the continuous storage mechanism.

Figure 3-17 Continuous Data Storage vs Event Based Storage Mechanism

3.11 Query Processing Mechanism for the WSN Data Stream

Another appealing and significant research direction in the WSN data management is that of well-organized data processing and analysis, and a significant amount of effort has been dedicated to it with supporting different types of complicated queries at the base station (sink) of WSN home monitoring system.

The incorporated methods are the SELECT * queries. In the following paragraphs, a framework that enables the development of a range of complicated processing applications in the home monitoring sensor network is presented. Although most of the data series symbolically treat every point of the data series in an equal manner, there are certain WSN applications for which the time position of a point brings in the variations of the reliability and its estimation [146] [147]. This would signify the most recent data with low error, and would be more lenient of variations in previous data. The trustworthiness estimation of variation reduces within a period; hence, it needs less retention of data from the recent past measures. For instance, the environmental observation and forecasting system functions is a method that permits for some sensors only discontinuous connections to the sink (via a repeater station that is not always handy). It is required to identify the extent of deviation allowed for every point in the approximation of the time series. In order to accomplish this objective, a function which gives back the acceptable estimated variation for every point of the data series is to be defined. It can be observed that the function can be either relative or absolute functions. A relative estimation function finds out the relative error and can tolerate for every point in the time series (e.g., can indicate that the estimate of a point is twice as old, and can accept twice as much error). Alternatively, an absolute function identifies, for every point in the data series, the maximum allowed variation for the estimation, which is beneficial while an application need assurance for the estimation of the data sequences.

The estimation functions permit the use as much memory as required so as to meet the error boundaries. Additionally, the concept of contextual time windows is needed in the estimation function [148]. The sliding window is the window that consists of all the values of the data series (from a given time point) up to now [149]. The sliding window model is more suitable for adaptability contexts. Contrary to the estimation and sliding window concepts, the usage of wavelets to symbolize data streams is proposed [149] [150]. An efficient, online approach for incrementally keeping up the present sensor data stream representation is required. The bias to the most recent values can be considered as similar to an estimation function, whose form in this particular case is dominated by the categorized property of the wavelet variation. This concept is biased towards the more current values.

In order to efficiently process (query processing) the WSN data in the present research study, the WSNs set-up data storage that can be taken into account as a database that comprises two sets of data schema: sensing meta-data schema and sensing data schema. Sensing meta-data schema refers to information about the sensing system, such as the sensing system identifier, settings, and other substantial traits. Sensing data schema are measurements gathered from the sensors over a period of time. In order to decouple the estimation of the time series from a specific dimension process or based on user-input to identify how the memory will be used for the variation estimations, efficient data mining techniques have been applied where the major objective is to have a model for time variation designs in a data set. More details are presented in the sections 5.4.1 to 5.4.4.

This research describes solutions for the online algorithms (human behavior recognition) that use linear and exponential estimation models. When a new point is obtained, the algorithms inform the estimation model in sub-linear time on the number of linear sections. It has been observed that the novel methods can be performed in a very effective way at the base station.

The meta data schema form a “relational table” Sensor_db (*sensing system ID, Date_Time, Channel_no, Sensing_value*) at the base station, where *sensing system ID* signifies the ID of a sensing system as Date_Time records the time stamp, and Channel_no stores the origin of the data from a sensing system, and the sensing value provides the corresponding sensed value. The sensing data schema values are produced by sensors at each time stamp. The present database system pursues a sequence model set up to entrench each reading with the time stamp when it is produced. Given a set of tuples imbedded with time stamps, a time series of the readings is built by sorting the records based on the time stamps.

The database consists of a Structured Query Language (SQL) declarative language. As an instance, a query is identified in the following form: The “SELECT” clause indicates that the sensing sample has a specific attribute and gives back only those readings falling within range. The clause “WHERE” indicates the sensing that are affected by the query. Another clause “from (table)” is an expression used to represent an incessant query where each sensing should give back a sample every period of time from a specific table of the database. The present database design supports aggregation (time window) queries based on time windows. The data produced by the sensing system form a single intangible table called sensors_db. Each type of measurement, such as electrical sensing parameters, force sensing, movement monitoring, ambient readings temperature, humidity or light strength, forms a topic in sensors_db. A tuple consists of the models of various measurements obtained by a sensing system at a single time-stamp. Recently obtained tuples are added at the end of sensors_db. A query in database comprises of “Select”, “From”, “Where” and “Group by” clauses.

Sensing system information will be ultimately directed to the data sink via a multi-hop networking architecture (mesh topology). Each tuple of the stream consists of a time stamp concerning the time it was generated. The base station openly scrutinizes the readings of a chosen portion of sensors, which report their analysis to the base station. The base station scrutinizes the variations on chains of nodes. As per the topology of the network, the base station is able to get each sensing system data for analysis from the readings of the directly observed sensing system and the chained variations. Due to the spatio-temporal interrelation, the readings of adjoining sensing systems are stored in the database.

In order to encapsulate diverse requirements, the home monitoring system submits queries at the base station. The query language is declarative and similar to SQL. Making sensing systems work in cycles is a general way for data storage in WSNs databases. Within a cycle (sampling rate), it collects measurements from the setting, receives data from other sensing system transmitted data to the WSN coordinator:

3.12 Results

The performance analysis of the deployed home monitoring systems at the elderly homes is investigated with the WSN parameters:

i) "Sampling Rate" of the WSS data fusion,

ii) Throughput of the WSN data fusion.

The "Sample Rate" corresponds to the number of sensed samples to be sent from the sensing system to the sink (base station) for appropriate sensor data processing. The data type of the received data at the sink (base station) is mostly analog data. The Type#1, Type#2 and Type#5 sensing systems have Analog to Digital Conversion (ADC) values sent to the base station for data processing. Therefore, an appropriate sampling rate of the sensing systems is very much required for the home monitoring system for efficient data analytics. Moreover, the sampling rate has a direct impact on the temporal reasoning of the data.

The sampling rates of the fabricated sensing systems for the home monitoring application are formulated by following an engineering approach. Rather than using an adhoc sample rates value, an experimental analysis is performed to derive lower limit and upper limit sample rates of the sensing systems based on the application parameters. Table 3.2 shows the XBee I/O pins configured for various types of sensing systems.

Table 3-2 Sensing Systems XBee Pin I/O Data Types

Type of the wireless sensing system	Number of Sensing (I/O) Channels	Sensing Channels	XBee Pins Configuration
Type #1: Wireless Electrical Objects Sensing System	04	Domestic object electrical par's: i)Voltage parameter, ii)Current parameter of plug1, iii)Current parameter of plug2, iv)Digital Input for control of domestic object	Pin 20: ADC for Voltage readings Pin 19: ADC for plug1 current readings Pin 18:ADC for plug2 current readings Pin 17: DI for ON/OFF control of appliance[1]
Type #2: Wireless Non-Electrical Objects Sensing System(Force Sensing systems)	01	Force Value	Pin 20: ADC for force readings
Type #3: Wireless Contact Sensing System for domestic objects	01	Digital Input of the object contact	Pin 20: DI for contact of objects
Type #4: Wireless PIR sensing system for Movements monitoring	01	Digital Input indicating the movement within its vicinity	Pin 20: DI for detecting the movements
Type #5: Wireless Environmental parameters monitoring sensing system	03	Environmental Temperature, Humidity, Light Intensity	Pin20:ADC for temperature readings Pin19:ADC for humidity readings Pin18:ADC for Lux readings

3.12.1 Sampling rates for Wireless Sensing Systems

An Analytical approach supported in determining better sampling rates for sensing ADC values that deliver continuous sensing data. The following is the procedure.

Let the sampling rate (number of sensed samples to be sent from the sensing system to the sink (base station)) be Δs. Based on the log of recorded ADC values from the various electrical sensing systems, Δs is considered the most suitable sampling rate in interval Δt. If Δs is the difference between two consecutive ADC values; and $\Delta s = \max(\Delta s)$then ${\Delta S}/{\Delta t}$ will provide the maximum rate of change for

[1] ADC: Analog to Digital converted value of the XBee module, DI: Digital Input

the sampling rate of the electrical sensing system. The objective is to obtain the best Δt for different electrical sensing systems of the home monitoring system for better data analytics. As $\Delta s/_{\Delta t}$ is the requirement for the max slope:

$$Max\ rate\ of\ Change(S) = \frac{\Delta s}{\Delta t} = \omega 2^{n-1} = 2^n \pi F \tag{3-2}$$

Where: 'n' is the number of bits for the ADC conversion, 'F' frequency.

Assuming, Er to be the maxi tolerable error considered as a measurement of the max range of the sensing signal. In practice, max error is considered to be 5%, and the remaining 95% as accurate in receiving the signal therefore, Er=0.05.

Then the sampling rate (min) for the electrical ADC values is derived as:

$$Sampling\ rate\ (min = Sr(min) = \frac{(\Delta S \mid \Delta t)}{Er.2^n} = \frac{\omega}{2Er} = \frac{\pi F}{Er} \tag{3-3}$$

In the home monitoring system application, the max rate of change for the electrical sensing system is equivalent to sampling a 50Hz signal and the XBee performs 10-bit ADC conversion to read the sensing signal. If the Er is considered to be 5% then, Sr(min) = $50\pi/_{0.05} = 3.1kHz$.

To derive the sampling rate (max) = Sr(max), Er=2^{-n} is substituted in the above equation to obtain: Sr(max) = $2^n\ \pi\ F$. The sampling rate for various sensing systems is given by the equation:

$$\frac{(\Delta s \mid \Delta t)}{Er.2^n} \leq Sr \leq \frac{\Delta s}{\Delta t} \tag{3-4}$$

Table.3-3 shows the configured sampling rates for various sensing systems of the HMS.

Table 3-3 Sampling rates of the Sensing Systems

For Electrical sensing systems sampling rates: (I/O channels configured as ADC)		
Electrical Sensing system connected to domestic objects	Minimum sample rate	Maximum sample rate
Room Heater (1200 watts)	1 minute	10 minute
Microwave	1 secs	65 secs
Water kettle	1 secs	65 secs
Rice Cooker	65 secs	10 minutes
Television	1 minute	10 minutes

Room Heater (600 watts)	1 minute	10 minutes
Refrigerator	1 minute	10 minutes
Toaster	1 secs	65 secs
Washing Machine	1 minute	10 minute

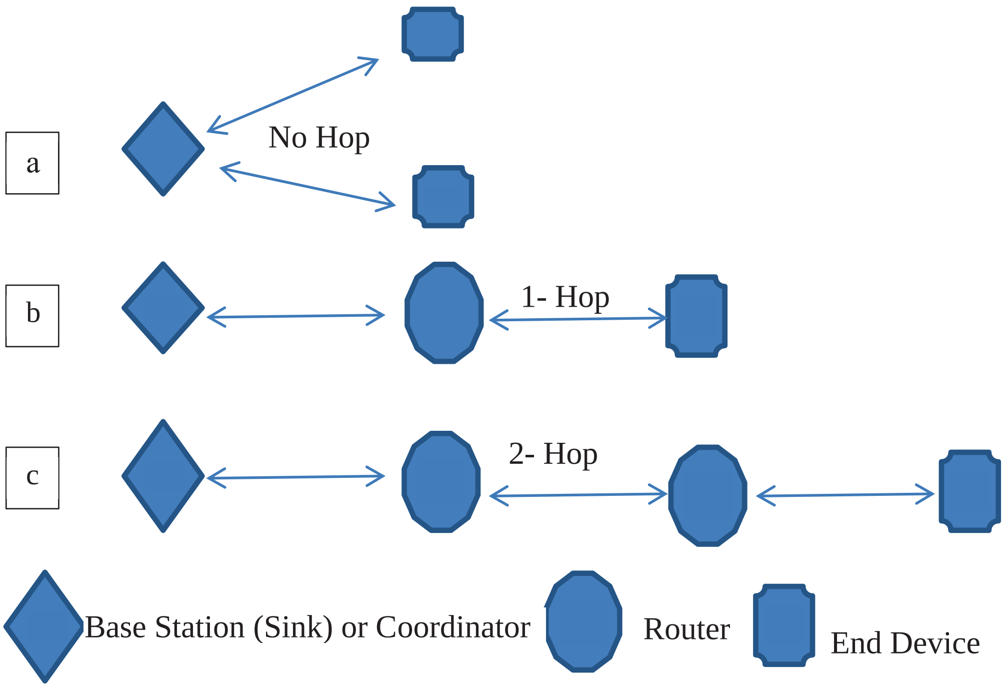
For Force Sensing Systems: : (I/O channels configured as ADC)		
Force Sensing system connected to domestic objects	Minimum sample rate	Maximum sample rate
Bed	1 secs	65 secs
Chair	1 secs	65 secs
Couch	1 secs	65 secs
Toilet	1 secs	65 secs

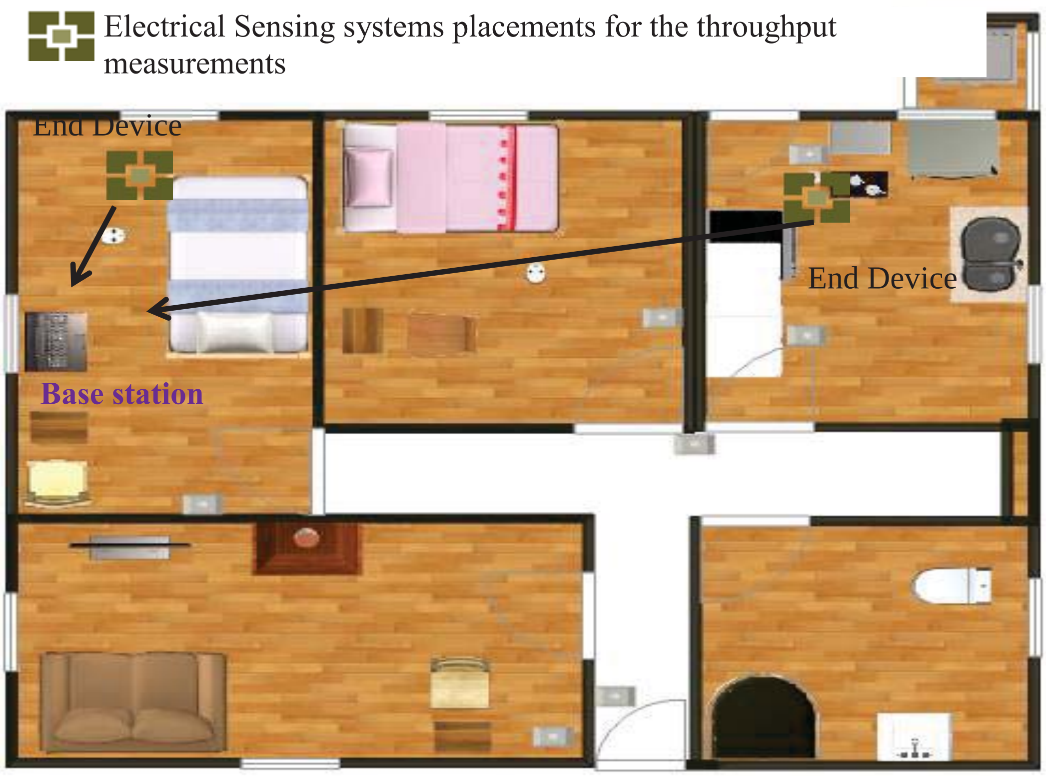
For Contact and Movements monitoring sensing systems: (I/O channels configured as Digital I/P)	
Contact and PIR sensing system sample rate	Whenever there is change in the digital I/O Detection of the XBee

For Environmental parameters monitoring sensing systems: (I/O channels configured as ADC)		
Environmental parameter Sensing system	Minimum sample rate	Maximum sample rate
Temperature	12 minutes	22 minutes
Humidity	1 minute	6 minute
Light Intensity	1 second	10 minutes

3.12.2 QUALITY OF SERVICE FACTORS OF THE WIRELESS SENSING SYSTEMS

The data from four electrical, four force, two contact, six pir and three temperature sensing systems for the time period of three months was analysed to determine the reliability, throughput and jitter of the wireless sensing system. A trial topological testing was done with the configurations as shown in Fig 3.18(a,b,c). In order to obtain experimental measurements, the sensing systems were configured such that every 10 seconds a sample (packet) was sent. The arrival times of these sensing system samples (packets) at the sink (base station) are recorded in the database. The following are reliability and throughput results of the Wireless Sensing System data transmission.





(a)

(b)

(c)

Figure 3-18 Mesh Topological Testing Setup [2]

[2] (a) No-Hop, (b) 1-Hop, (c) 2-Hop

3.12.3 RELIABILITY

The reliability of the wireless sensing system was determined by comparing the calculated value with the amount of sensor information received correctly. The difference between arrival times of successive sensing information gives the interval value. If the time interval was greater or less than 10 secs then there was an error. When the interval is less than 10 secs then the sample information received was incorrect or duplicated and therefore was erroneous. The system was configured and was running as a mesh network. If all the end nodes are within the range of the co-ordinator, the system may operate as star network. Otherwise, hopping takes place. If a node is used as a router (as well as node), then there is a small delay due to the configuration and accordingly reliability drops. For a HMS, Mesh networking of the sensing systems is the most optimal topology. HMS can have reliable data transmission if there is hopping property among the wireless communication devices. This is due to the fact that in real home environment there will be several obstacles like walls and objects which may hinder the data transmission. This can be easily handled with mesh topology Table 3.4 shows the reliability of the wireless sensor network data transmission for different hops in the home monitoring system.

Table 3-4 Reliability of the wireless sensor network data transmission for different hops

# HOP	Sensor ID	Router/End_ Device	From Coordinator (Meters)	# Obstacles	Period between packets 'T'(Secs)	Expected packets	Incorrectly received packets	Correctly received packets	Reliability (%)
0	407C602B	End_ Device	8	2 walls	10	7854	46	7808	99.4
	4079CDD6	End_ Device	3	no walls	10	8338	26	8312	99.6
1	407C602B	Router	8	2 walls	10	8056	16	8040	99.8
	4079CDD6	End_ Device	10	4 walls	10	8076	29	8047	99.6
2	407C602B	Router	8	2 walls	10	5561	15	5546	99.7
	4079CDD6	Router	10	4 walls	10	5575	64	5511	98.8
	407C5C8D	End_ Device	12	4 walls	10	5566	102	5464	98.1

3.12.4 THROUGHPUT MEASUREMENTS

The objective of the throughput measurement is to know the functionality of the wireless sensing system in relation to the number of sensing systems and the packet length for the transmission of sensing data. The throughput of the sensing system is the amount of data sent from the sensing system to the sink in a given time period [151]. As per the ZigBee protocol, the maximum allowable packet length is 128 bytes [152]. However, the packet length for the respective sensing systems varies. Table.3.5 provides the details of the packet length for various sensing systems in the configured home monitoring system.

Table 3-5 Wireless Sensing System packet lengths

Type of the wireless sensing system	Number of Sensing (I/O) Channels	Sensing Channels	Packet Length (Bytes)
Type #1: Wireless Electrical Objects Sensing System	04 (Analog-3, Digital-1)	Domestic object electrical parameters: Voltage parameter, Current parameter of plug1, Current parameter of plug2, Digital Input for control of domestic object	28
Type #2: Wireless Non-Electrical Objects Sensing System(Force Sensing systems)	01 (Analog-1)	Force Value	22
Type #3: Wireless Contact Sensing System for domestic objects	01 (Digital-1)	Digital Input of the object contact	22
Type #4: Wireless PIR sensing system for Movements monitoring	01 (Digital-1)	Digital Input indicating the movement within its vicinity	22
Type #5: Wireless Environmental parameters monitoring sensing system	03 (Analog-3)	Environmental Temperature, Humidity, Light Intensity	26

The throughputs of the various network topologies were studied for a period of seven days. Fig 3.19 and Fig.3.20 shows the throughput of an electrical sensing system placed in the real home environment.

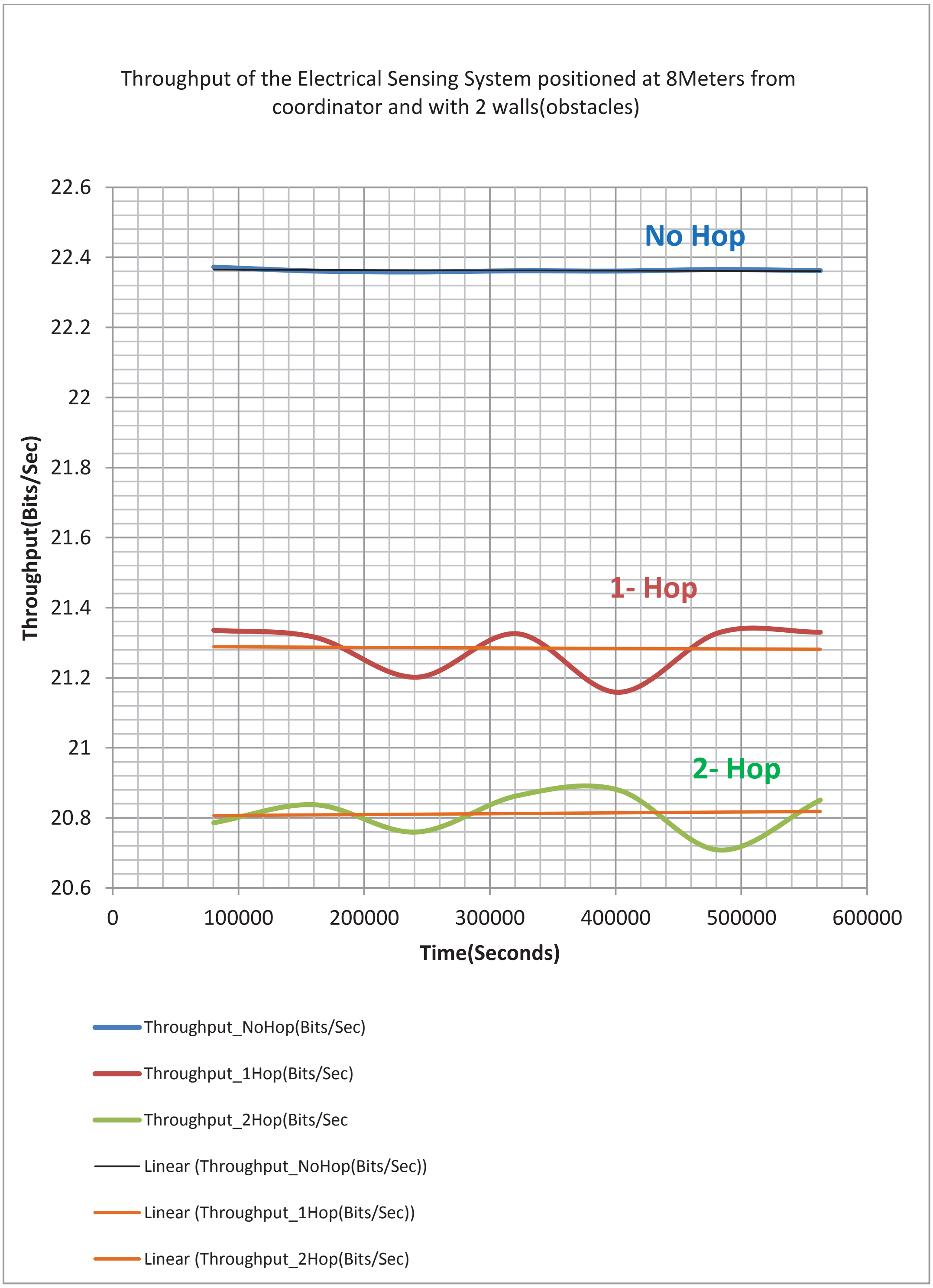


Figure 3-19 Throughput of the Electrical Sensing System Positioned at 8 meters from the Base Station with Two Walls Obstacles

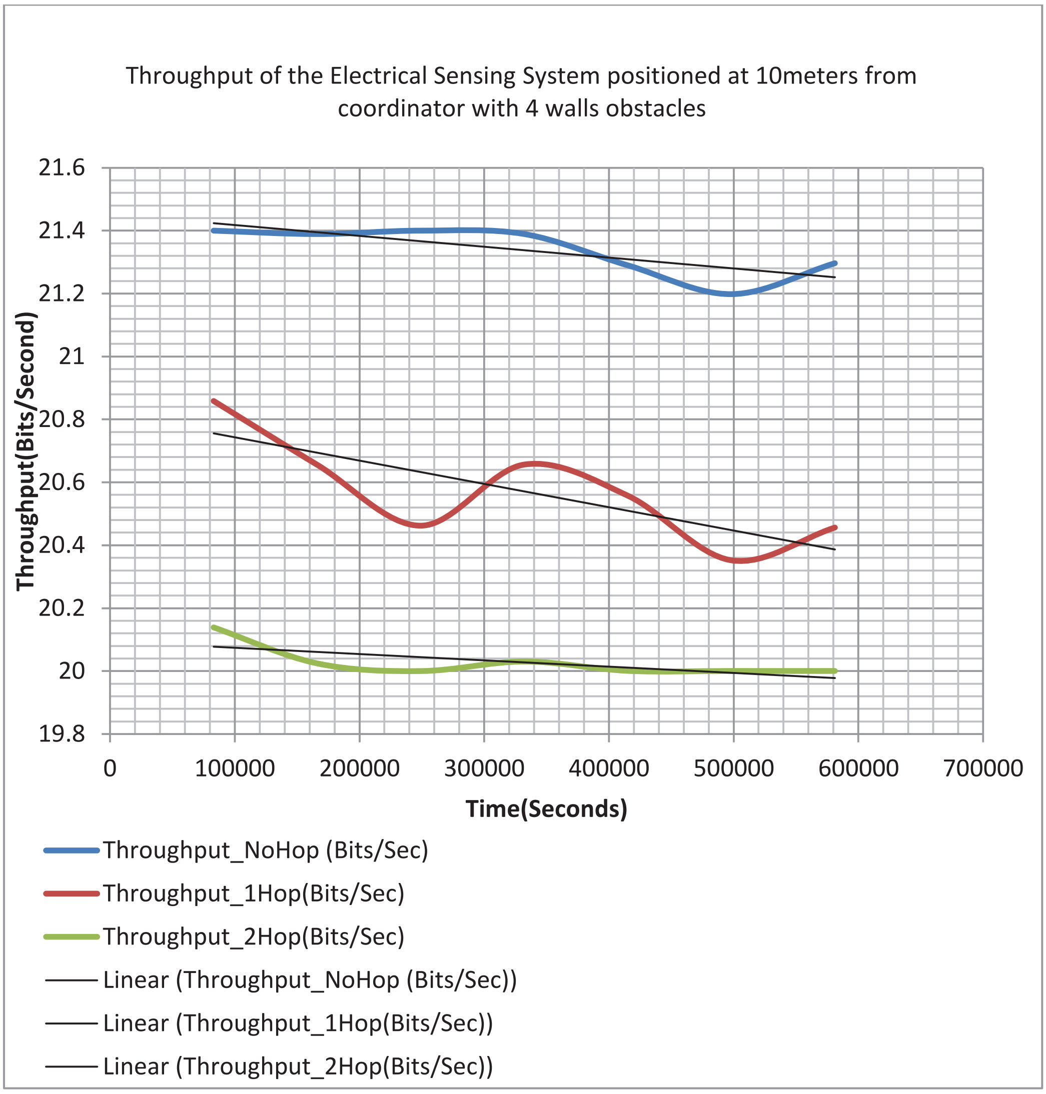


Figure 3-20 Throughput of the electrical sensing system positioned at 10meters from the Base Station with Four Walls Obstacles

The total number of bits in each electrical sensing system is 224 bits and the interval to send the packets was set at 10 sec, theoretically, the throughput of each electrical sensing system is to be 22.4 bits/sec. However, the typical (average) throughput of the electrical sensing system is 21.8 bits/sec (97.4%). The likelihood of the slight drop in the throughput may be interfering with the supplementary networks such as Wi-Fi existing in the home. It was observed that the throughput of the electrical sensing system was a linearly decreasing trend when the number of hops is increased in the network. However, as the numbers of packets sent from the sensing system were enough in number (based on the sampling rates) there was no loss of data in terms of event identification.

3.12.5 DATABASE STATISTICS

In the beginning, the system was trailed for duration of four weeks at four different subject houses. From March-2013, the system is continuously monitoring one subject with some technical exceptions as presented in the limitation section 3.14. It is observed that on average 23 queries are executed per second, 1,405 queries per minute and 84326 queries per hour on the database. The maximum percentage of queries executed on the database is of insert queries. The insert queries are related to the insertion of sensor data into the sensor database from wireless sensing systems. Fig.3-21 to Fig.3-25 shows the snapshots of the sensor database runtime information on different dates. The snapshots are taken while the system is continuously running for more than a month. It was observed that the sensor data acquisition program is robust in continuously running without any exceptions for longer period of time.Table.3-6 shows the top four percentages of the queries on the sensor database.

Table 3-6 Top 4 queries execution on the sensor database

Type of the Query	Percentages	Type of the Sensing System	# Samples inserted per Second
Insert	76%	Electrical Sensing unit (3Nos)	3*4 = 12
		PIR sensing unit (5Nos)	5*1 = 5
		Temperature Sensing unit (1Nos)	1*3 = 3
		Solar_Panel unit(3Nos)	3*1 = 3
		Total	== 23
Change_db	23%	Change_db operation is for the backup of the database	
Select	0.5%	Select operation is for retrieving the data from the database tables and displaying on the webpages	
Set option	0.5%	Set operation is for the setting the schedules on the tables	

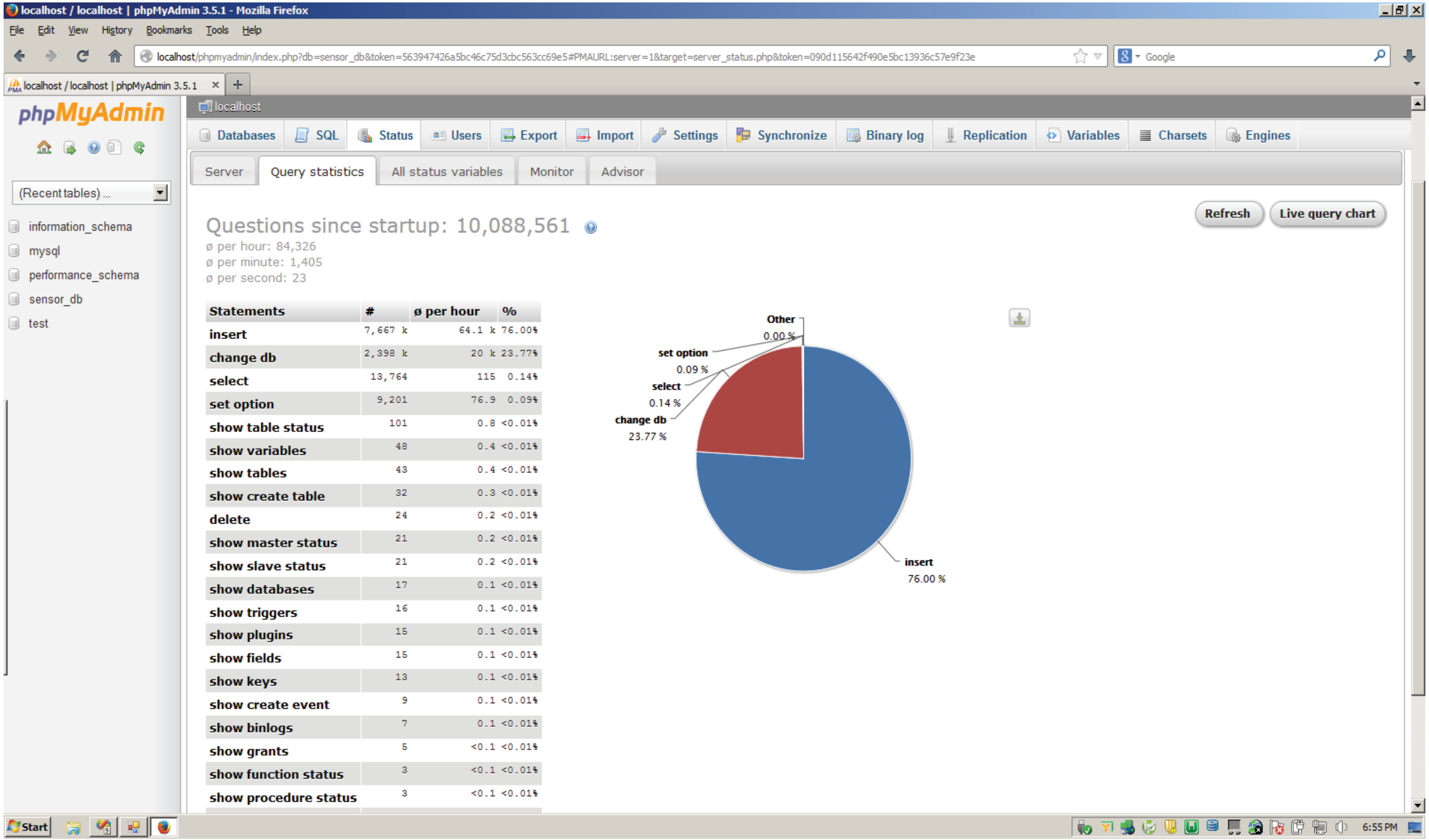


Figure 3-21 Sensor database queries executed during the run-time of the HMS on fifth day

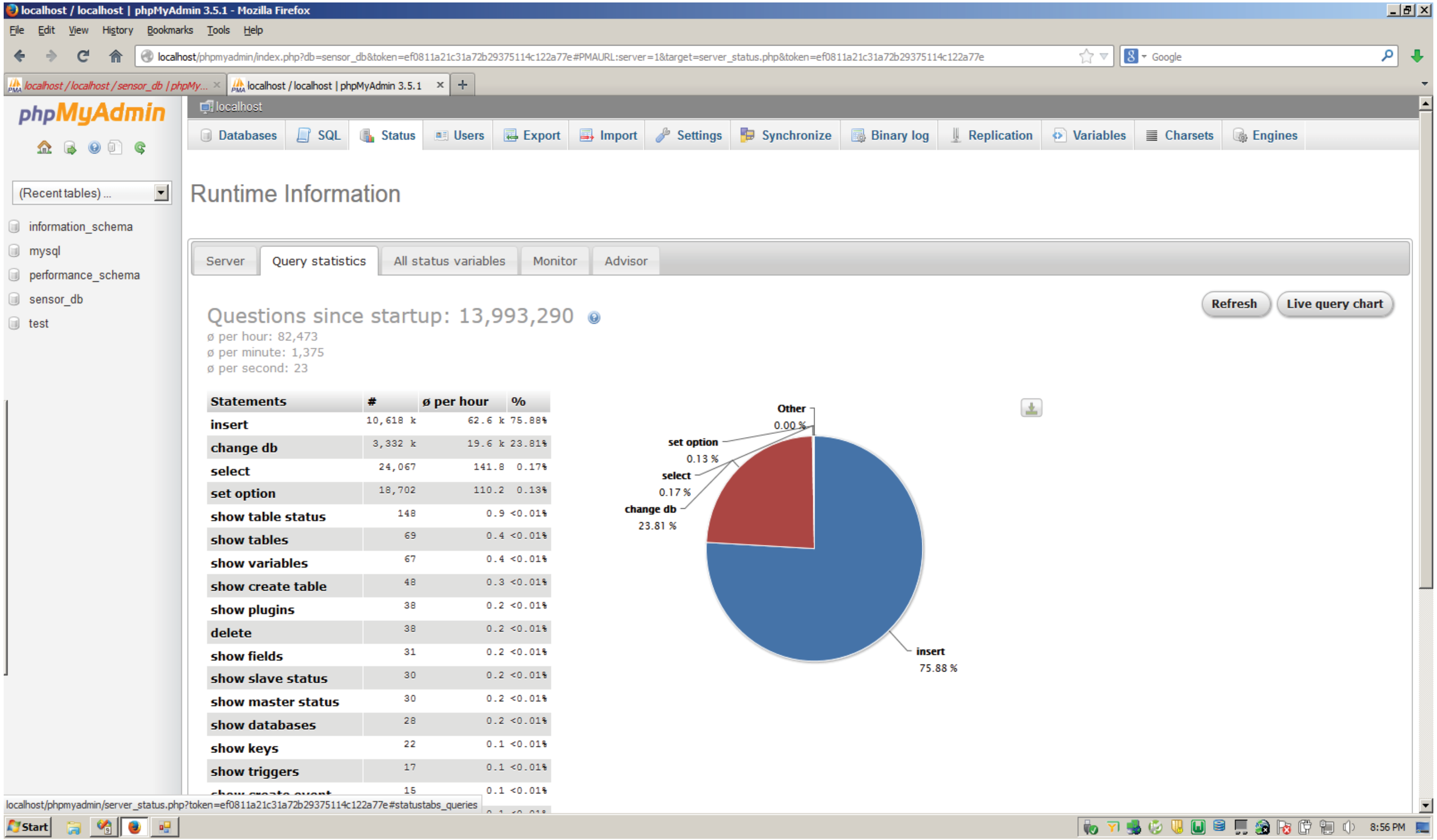


Figure 3-22 Sensor database queries executed during the run-time of the HMS on eighth day

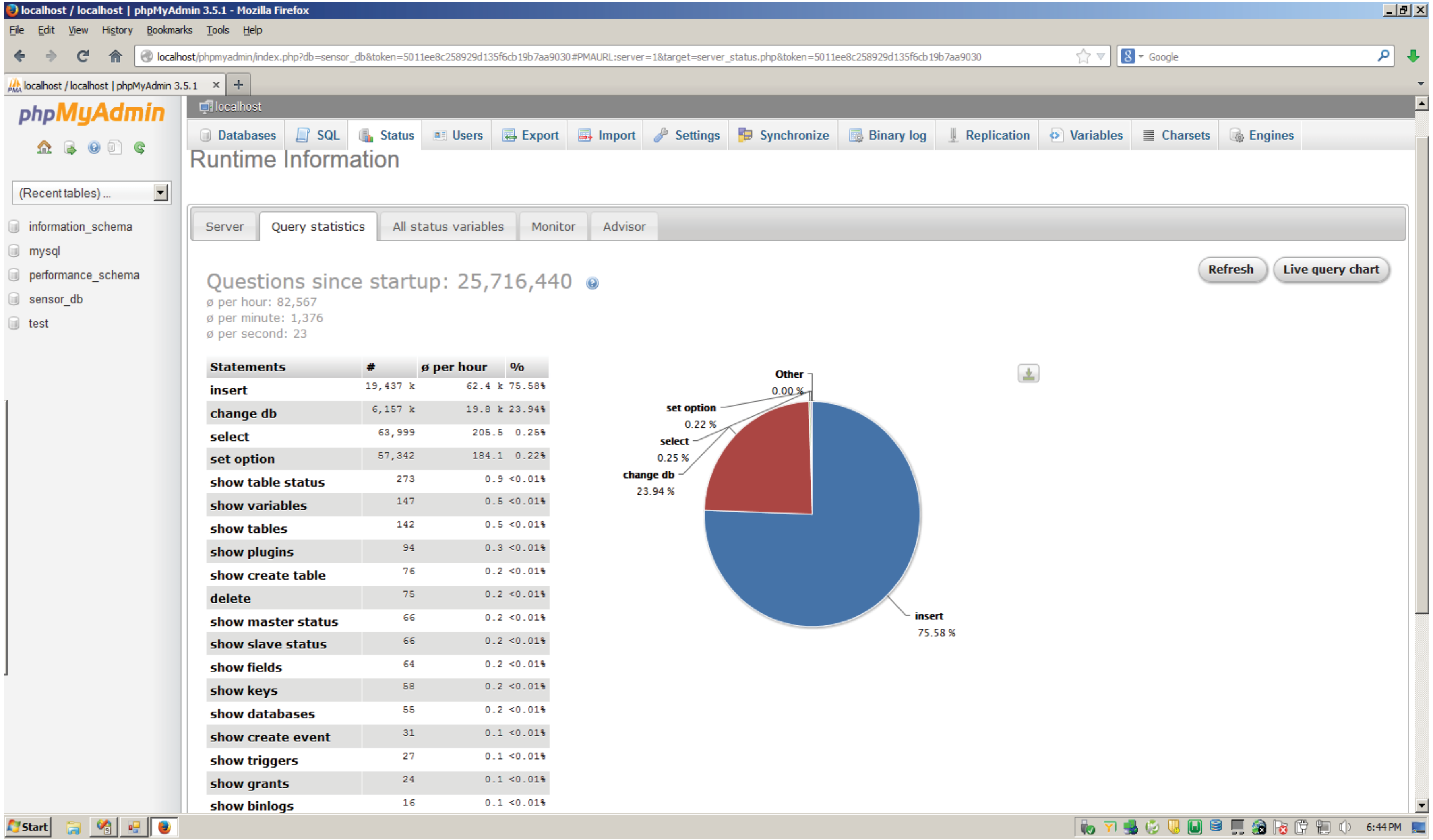


Figure 3-23 Sensor database queries executed during the run-time of the HMS on thirteenth day

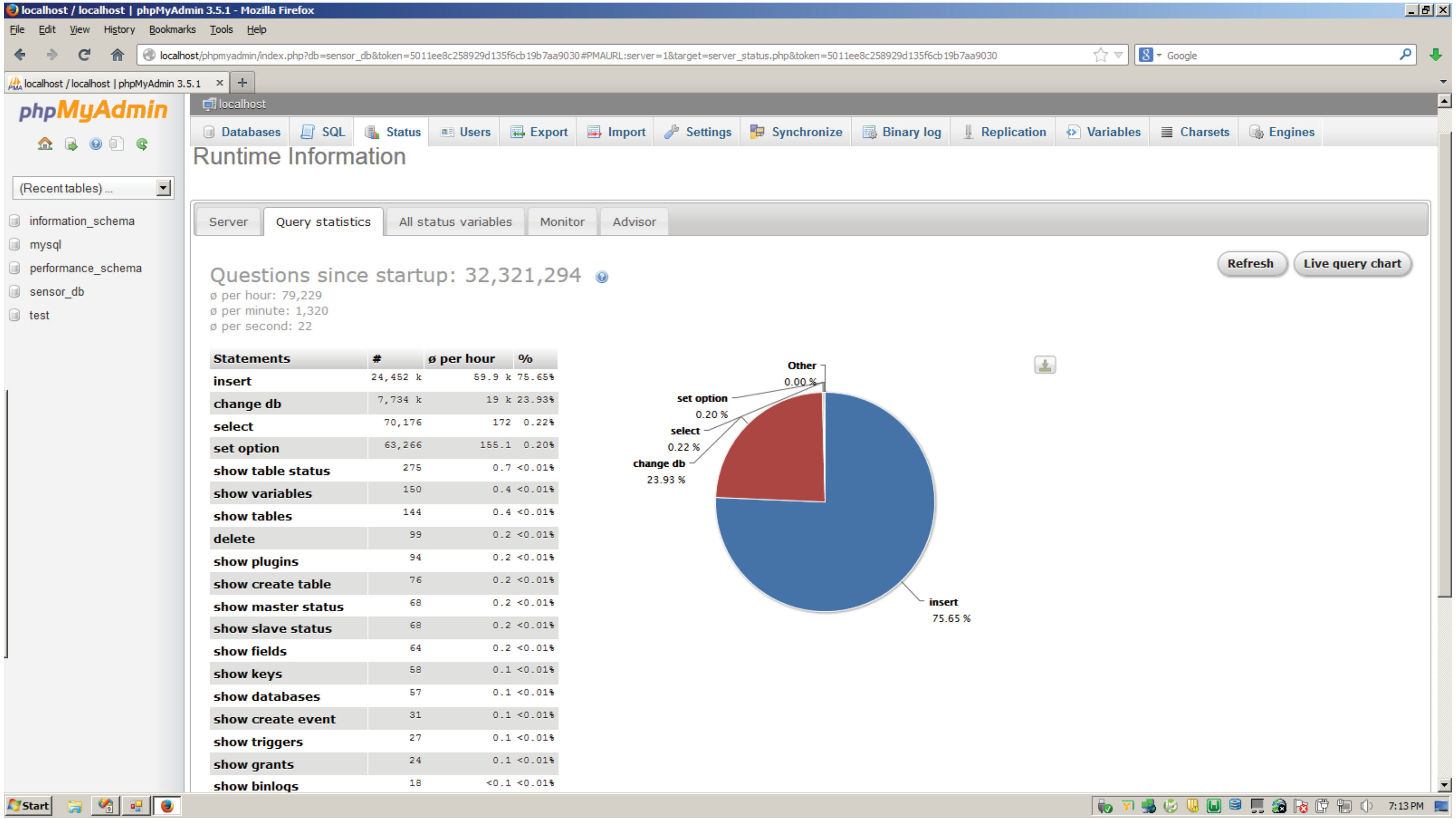
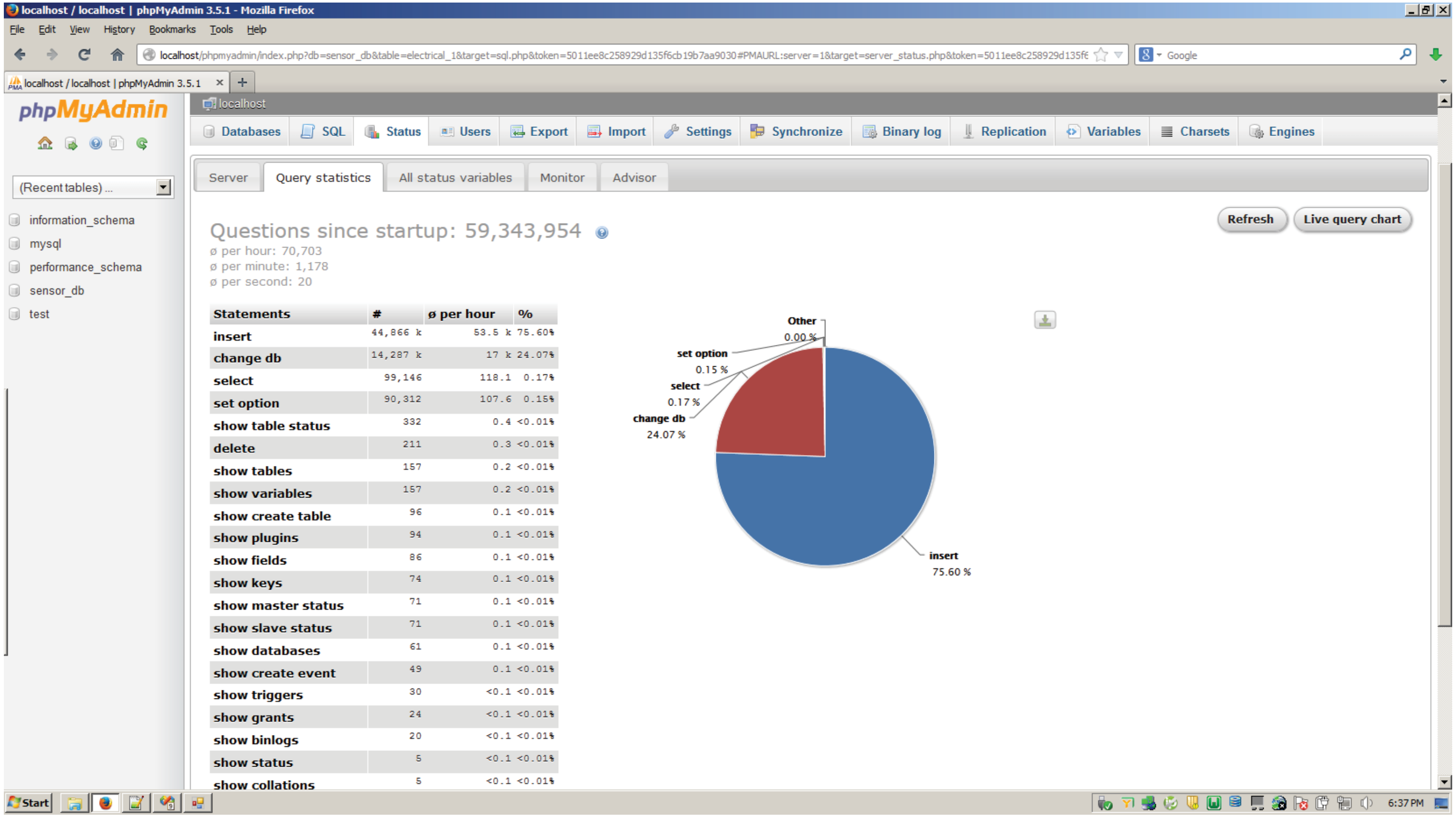


Figure 3-24 Sensor database queries executed during the run-time of the HMS on sixteenth day



Statements	#	ø per hour	%
insert	44,866 k	53.5 k	75.60%
change db	14,287 k	17 k	24.07%
select	99,146	118.1	0.17%
set option	90,312	107.6	0.15%
show table status	332	0.4	<0.01%
delete	211	0.3	<0.01%
show tables	157	0.2	<0.01%
show variables	157	0.2	<0.01%
show create table	96	0.1	<0.01%
show plugins	94	0.1	<0.01%
show fields	86	0.1	<0.01%
show keys	74	0.1	<0.01%
show master status	71	0.1	<0.01%
show slave status	71	0.1	<0.01%
show databases	61	0.1	<0.01%
show create event	49	0.1	<0.01%
show triggers	30	<0.1	<0.01%
show grants	24	<0.1	<0.01%
show binlogs	20	<0.1	<0.01%
show status	5	<0.1	<0.01%
show collations	5	<0.1	<0.01%

Figure 3-25 Sensor database queries executed during the run-time of the HMS on thirty-fifth day

It is observed from Fig.3-21 to Fig.3-24 that the numbers of queries executed on the database are consistent for the one month observation on the database. The sensor database performs appropriate scheduling and triggering process so that the fusion of data and storage operations simultaneously works efficiently. This implies that the sensor data collection is reliable and the data acquisition program is robust and efficiently executing. Fig.3-26 show the offline analysis of the percentage usage of household appliances. Fig.3-27. Show the comparison of bed usages based on the force sensing system data.

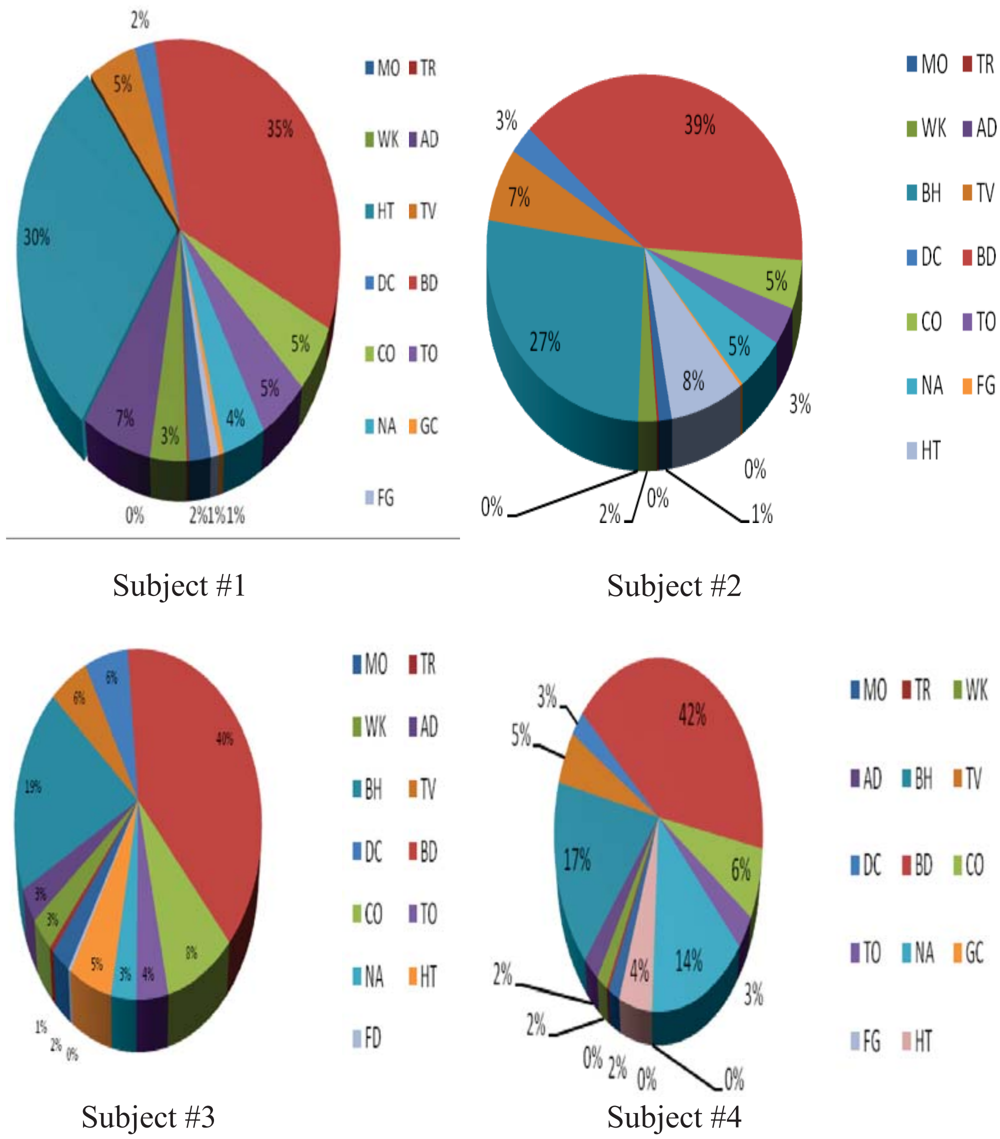


Figure 3-26 Percentage usage of Household appliances and the Elderly Activity Behaviour[3]

[3] BD: Bed; CO: Couch; FG: Fridge; DC: Dining Chair; TO: Toilet; AD: Audio; HT: Room Heater, TR: Toaster; NA: No Appliance.

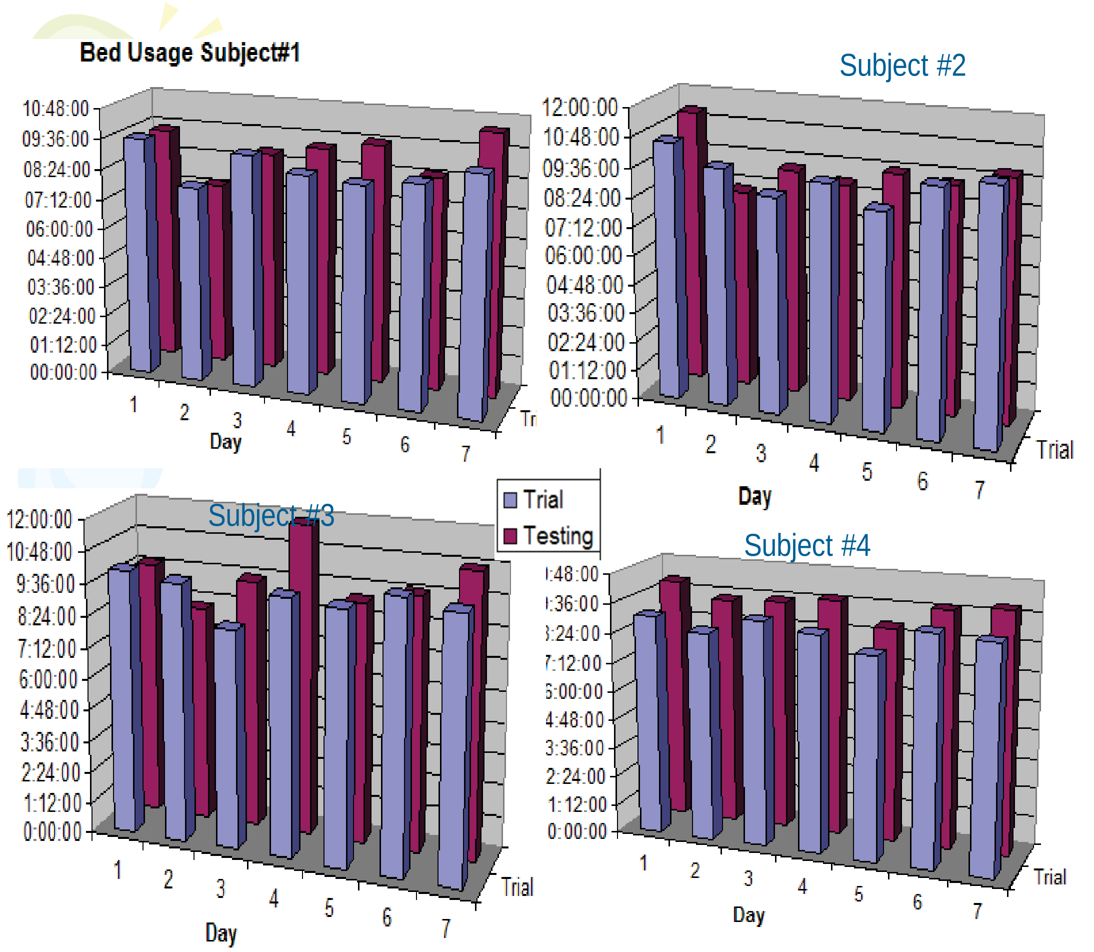


Figure 3-27 Comparison of Bed Usages based on Force Sensing System Data at Different Elderly Houses

3.13 Troubleshooting with XBee Modules

In most of the instances the XBee module did not open the coordinator module configuration in XCTU software when the system ran for more than 90 days. A significant number of XBee modules have been wasted due to this. While neighbouring pins were used to access signals, in some instances the influence of signals to the neighbouring signals was observed. In some situations it was difficult to read digital input data. It was not completely clear whether the problem was in reading the data at the input stage, or the problem was in the communication or in the receiving stage. Though this type of problem was not very common it happened when the system was running for long durations. The sampling rate was set at a minimum of 20ms. The rate corresponded to a sampling frequency of 50 Hz. This is quite low for many applications. Even with the sample rate of 50 Hz the data communication did not take place properly when a few sensor nodes were added in the system.

The selection of baud rate was another issue. Though there are many available baud rates for selection a low rate of 9600 bps worked very well. Usually in a smart home environment with heterogeneous sensing units for different home monitoring reasoning tasks, optimal sampling rates are required for proper data transmission. Throughput is decreased with increase in obstacles between the coordinator and the router devices. This may be due to collision of packet transmission. Sometimes packets which are required of high priority are not being received (Ex. Emergency push button signal packets). The XBee of push button is configured with digital input. It requires multiple times pressing the button to reach the coordinator. (Note: Emergency push button is part of the multiple sensing devices used in the home monitoring system). Sensing devices with digital I/O configuration require multiple channel allocation. Sometimes, the data acquisition system will be able to recognize the digital signal only from the pins configured from different channels. Proper exception handling mechanisms are required for the sensor data acquisition system. The reason for this is that extractions of bytes from the packets do not have corresponding data. If a single radio module is used to configure consecutive channels for two different devices to be interconnected then the ADC values are swapped (interchanged) when continuously collecting the data for long durations of time. Frequent firmware updates are required in order to module work effectively.

3.14 Limitations of the Wireless Sensing Systems

- Sensing systems do not have any computational resources (i.e., no-microcontrollers).
- The XBee radio component is the most energy-consuming. It operates the functions of sending messages, receiving messages, and attending to the transmission requests from other sensing systems. The wireless sensing system data transmission mechanisms are taken care of by the standard XBee protocol architecture.
- Due to drift with time, there is need of a dynamic threshold of the output of the force sensor

3.15 Chapter Summary

This chapter presents the intricacies of the real-time heterogeneous sensor fusion for home monitoring systems. The design and development of the sensing systems, the set-up of the wireless communication topology and the configuration of Analog/Digital sensor data and the Input / Output data transmission were described. The wireless sensor fusion of the in-house designed and developed sensing systems with the optimal sampling rates of the sensor data were exemplified. The numbers of sensing systems required for monitoring the basic ADLs of an elderly person were identified based on the investigation.

The results of the QoS parameters related to the wireless sensor network such as reliability and throughput of the in-house developed sensing systems were presented. The real-time collection of sensor data and the storage mechanism for various data analytics were described. The developed home monitoring system using WSN is robust, flexible and efficient and monitors the elderly person activities at home in real-time. The reliability of the sensor data transmission is measured as 98.2% and the throughput to be 97.4%. The present hardware and software setup has enabled the home monitoring system to provide a framework for the IoT paradigm.

The following chapters describe the sensor data analytics for the effective elderly well-being condition monitoring, based on the present chapter hardware and software set-up convolutions.

Chapter 4. Sensor Data Analytics for Wellness Determination of an Elderly Person

The sensing systems designed for home monitoring to recognize behavior of the elderly person living alone require efficient sensor data analytics. This implies that software methods require efficient design and development for processing the stream of sensor data. Novel methods presented in this research provide a mechanism to recognize the elderly person's behavior in near-real time processing.

The wellness determination of an elderly person is obtained by following two data mining approaches on the real-time fusion of sensor data: i) model driven and ii) data driven methodologies. The processing of sensor data streams is done at the base station (data sink). The effective execution of the novel methods is realized by responding to the queries and procedures formulated to run simultaneously with the fusion of heterogeneous sensor data.

The target of the model driven data mining methodology is conceptually to process queries on all data discerned by the fusion of WSN. The method basically works on assumption models that encapsulate the interrelations that are present in the WSN data. It can also be noted that sensor readings portray such interrelations in a broad set of domains and applications.

In general, the procedures of the model driven methods are based on the prior information of the application. During the early training stages of the model, all the sensed data are gathered from the sensor nodes, so as to guide the probabilistic models that are stacked up in the sink. After that, these models are utilized to assess the sensed values, and they furthermore present probabilistic assurance on the accuracy of the guess estimates. If the guarantee given by the models for these data does not convince the exact requirements of the application, then extra authentic data values from the sensors will be considered. This help to enhance the models to the extent that the probabilistic guarantees assure the application requirements.

The model driven techniques can lead to important energy savings for the data acquisition task. Nevertheless, by the nature of their methodologies, they can only give probabilistic guarantees on the exactness of the data that the sink gathers, and, therefore, no total bound on the estimates of error. The model driven data acquisition methods work well for some applications such as environmental monitoring parameters (humidity and temperature readings for Heating, Ventilation and Air Conditioning (HVAC)) systems. However, there are certain applications, which require high accuracy assurances such as scientific domains that need exactness. In many scientific applications, it might also be the situation that the domain professionals do not previously have a model of the data allocation they are using as samples using the WSN, but are instead concerned in gathering accurate measurements so as to develop a model. Certainly, WSNs provide an exclusive prospect to scientists to monitor particular phenomena and develop models for them at a size and level of intricacy that was not known earlier.

In the data driven data mining method, the assumption is made that the application being executed at the base station permits for a minor acceptance in the correctness of the described data sets. In distinction through the idyllic needs of the base station attaining correct values, the exactness of these applications is not affected as long as the reported values match closely with the past ones, and inaccurate values occur only occasionally. However, in the medical care applications with regard to monitoring the well-being function of older people, a major focus will be on monitoring the physical and psychological aspects of the lifestyle of elderly people. A "Quality lifestyle" is a period that is generally considered as a measure of daily living condition [153]. Every single element of daily living functionality needs to be evaluated regularly so that proper assistance can be provided.

In the present research study, a combination of model driven and data driven mining approaches is investigated for processing fusion of heterogeneous sensor data to recognize elderly behaviour in near-real time. The recognition tasks of complex behaviour of an elderly person performed by the home monitoring system using the above mentioned two approaches are realized as:

i) The first step towards the development of monitoring of well-being of an elderly person is to identify the day-to-day activities of the individual. The elderly person’s independent functioning can be assessed by looking into the ADLs recognition and its performance. The recognition of the ADLs is done by applying a model driven approach. The wellness determination process of the elderly in terms of domestic appliances usages is performed by following a data driven approach by implementing novel computational methods. The details of the application are given in chapter 5.

ii) The forecasting of the behavioural patterns of an elderly person from the sensory observations is done by following a data driven approach with modified time series analysis formulations. The details of the operation are provided in chapter 6.

iii) The process of matching the activity patterns of the sensors obtained as a time series sensor stream for effective recognitions of the mobility of a person is done with the conceptualization of data driven approach. The details of the execution are provided in chapter 7.

Fig.4.1 shows the overall schematic representation of sensor data analysis related to the wellness determination model of an elderly person in a smart home monitoring environment. The recognition of basic ADLs and determination of wellness of the elderly are described in the following chapters.

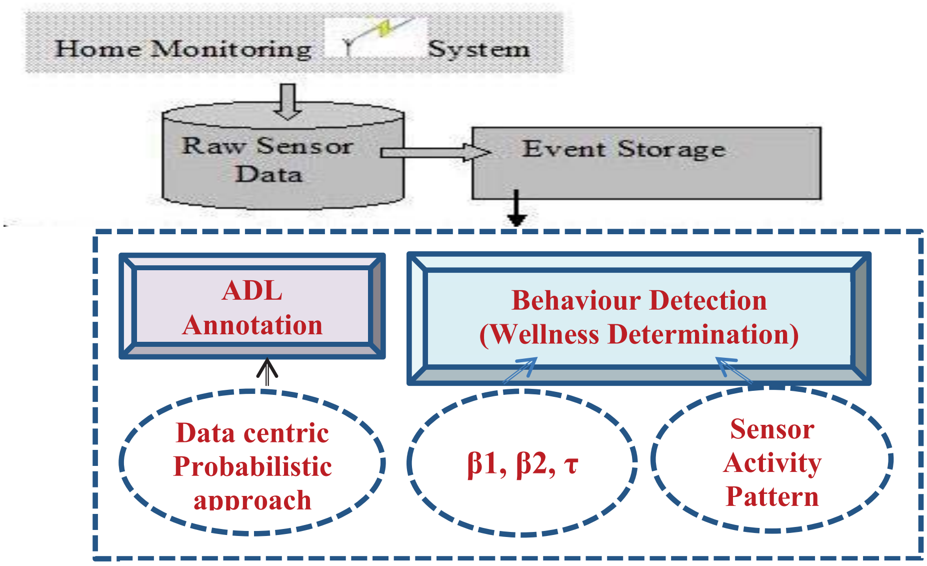


Figure 4-1 Block diagram of the elderly wellness determination process

Chapter 5. ADLs Recognition of an Elderly person and Wellness Determination

5.1 Introduction

The recognition of ADLs is not new to the AAL research field. In a survey for assistive technology it emerged that the recognition of ADLs is ranked highest by health caregivers in order to provide proper assistance to the elderly [154] [155]. With the increased requirement for activity recognition, the researchers looked at different methods for it. These methods are not similar due to the utilization of different kinds of sensor information for categorization.

The researchers have put forward different methods to shape and identify ADLs. Based on the ADLs performance the functional health quantification of a person can be known [156] [157]. However, conventional contextual recognition of ADLs research have some shortcomings such as an individual way to timely oriented activities, imprecision of identification and unawareness of a number of contexts parallel to indistinguishable activity or situation. The existing methods [158] [159] [160] assume that each person continuously acts on each single set of ADLs in a pre-defined approach in domestic surroundings having greater ease of supervision, which is contrary to the real circumstances. The ADLs executed under watchful surroundings may differ with individuals carrying out actions in a different manner. It makes the dependence on a catalogue of pre-defined actions irrelevant because of the difference in inter-contents. Further, a single activity can be executed in a different manner by a single individual, demanding different approaches to pact with intra-subject inconsistency.

The selective tracking of pre-defined actions will completely overlook key insights from other activities contributing towards the functional health of persons. For example: Hayes et al. [161], discovered a correlation between the disparity of entire activity level at home and placid cognitive impairment where the activity level was confined to pre-programmed actions and was associated with the entire activity level in supervised surroundings.

The tracing of a pre-described listing of actions requires ADLs labeling of a greater level of training information which must be offered to data mining algorithms. Every individual executes actions in a different manner due to varied cultural, mental or physical lifestyles. Sample data requires gathering and characterization for each person prior to the utilization of a learned model to constantly trace individual actions and functional safety. The gathering and labelling of sensor information in smart surroundings is a very tedious job.

The functional status of a person refers to an individual who can do certain tasks within his lifestyle [162] [163]. The basic self-care tasks (e.g. preparing food, eating, self-grooming etc.,) are especially essential, because they are classified as the basic ADLs. The ADLs recognition program collects data from the sensing systems in which each of the entity (domestic object) has related contextual information. It organizes the disorderly data from the lowermost level into informative messages of higher level by a systematic process to present the inhabitant(elderly person) with a range of ADLs information.

5.2 Design of ADLs Recognition System

The ADLs recognition system design has the basic component of the contextual information of the ADLs.

Sensor Event Level (0): This level contains a range of sensing systems located in the AAL environment. These are mainly used to generate fundamental data to upper level. It carries out the fusion of the heterogeneous sensor data related to the subject information and sends the data to the contextual recognition level for categorization.

Context Recognition Level (1): This level extracts the information from sensor data and, depending on the AAL set-up's principal values of location (S), time (T) and context (C), the situational information is derived for the identification of Basic ADLs.

ADLs Recognition Level (2): Labelling for the Basic-ADL's will be performed depending on the contextual information and the status of the sensor stream.

Fig.5-1, shows the recognition of ADLs, it comprises a Sensor Event Level, Context Recognition Level and ADL Recognition Level.

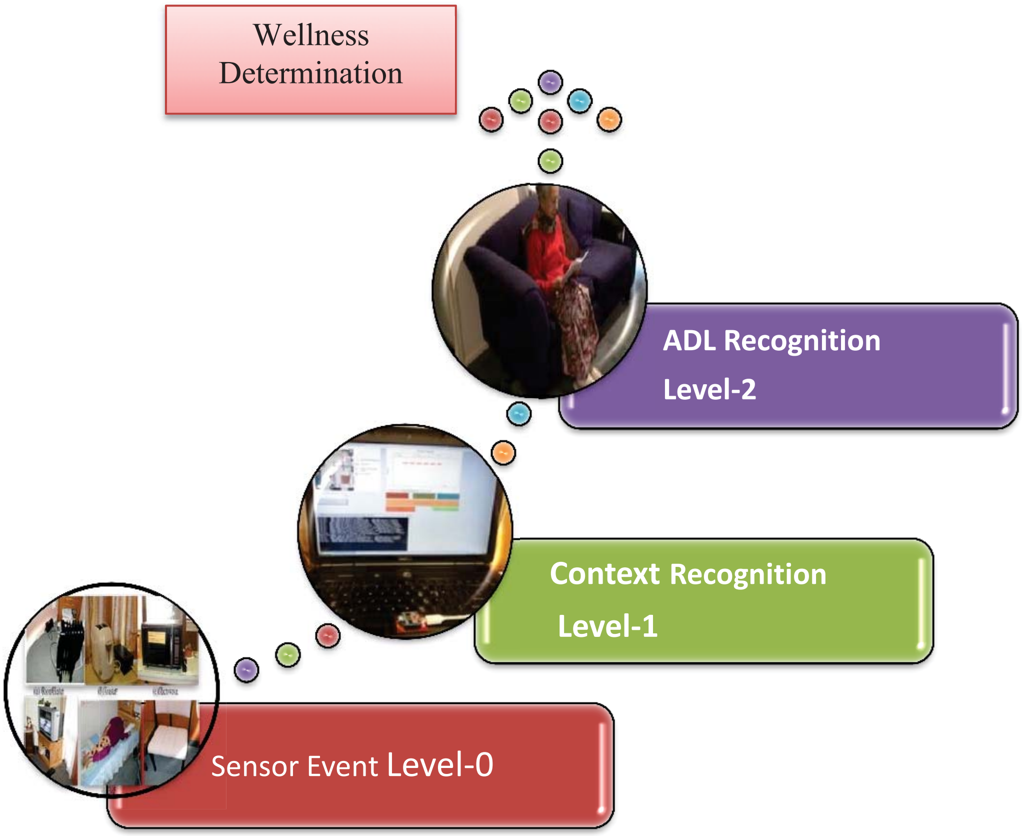


Figure 5-1 ADL recognition system structure

5.3 ADLs Annotation

Several investigators have published the outcomes of experiments where the contestants (elderly person) are needed to note every activity of their daily living. While it is not appropriate to ask the contestants for performing pre-defined activities, so that exact activity labels were recognized. For many situations, the proposed ideas of ADL annotation in smart home monitoring have practical challenges. Hand labelling from the sensor information is time consuming and hence may not be the most beneficial approach either.

In this research, the labelling for the elderly ADLs was done during the real-time fusion of usages of appliances with the help of 'sensor events'. Fig.5-2 shows the recognition of ADLs from a multi-level structure of sensor events processing.

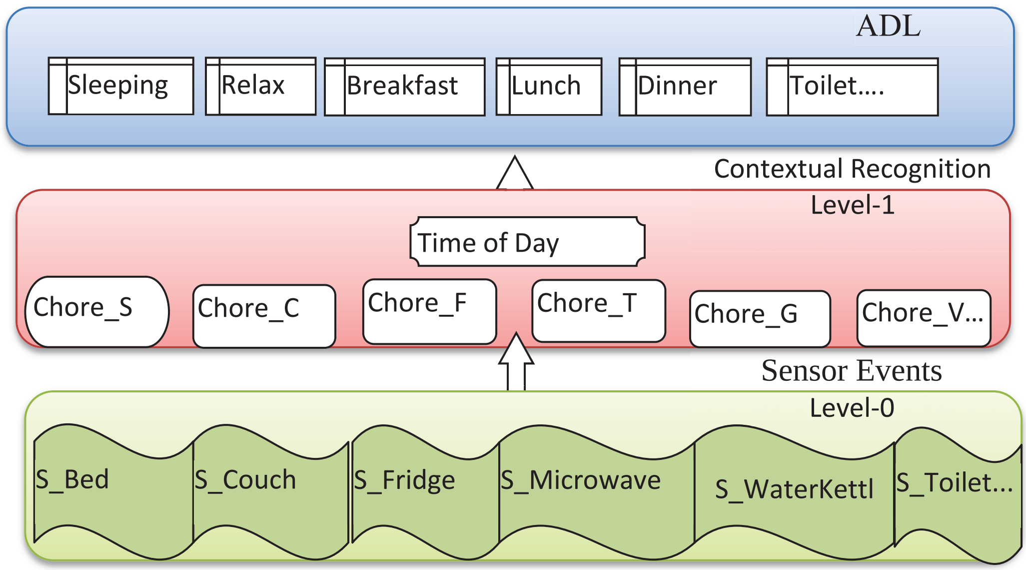


Figure 5-2 ADLs are recognized from a multi-level structure of sensor events processing

The lowest level of the multi-level structure of the ADLs recognition map consists of the sensor systems used to generate sensor events when they are activated in the home. The next level is chore identification. A chore is defined as an association of task (sub-activity) related to sensor event. This is to be monitored when the elderly person uses a household appliance for some purpose.

The process of chore identification is to map each sensor event to the possible tasks which are related with sensor event. At the higher levels, these are recognized as activities of the person being monitored. The number of levels above the chore level depends on the complexity of the activity recognition. The elderly person's basic ADLs such as Preparation of Food (PF), Dining (D), Sleeping (SL), Toileting (TO), Relaxing (RE), Self-Grooming (SG) are recognized by the HMS based on the real-time status of the sensors activation.

The spatio-temporal information (Sensor Identifier and Time of the Day) along with the sensor "ON" status will determine the corresponding ADLs. Thus, the regular domestic object usage activity is directly correlated to the basic ADLs. Fig.5-3 shows the direct correlation of household appliances usages with the ADLs.

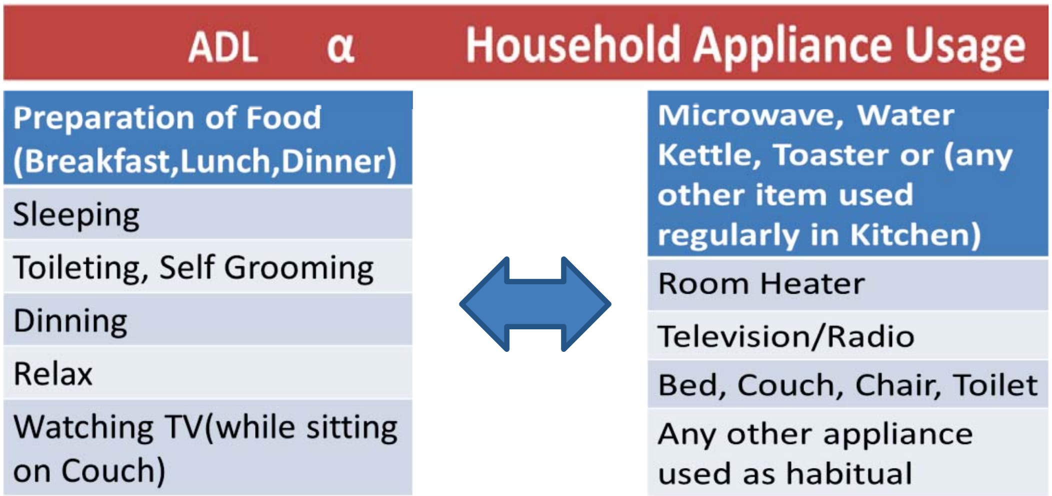


Figure 5-3 ADLs having direct relation with the household appliances usage

The Sub-Activities (Chores) like preparing Breakfast / Lunch / Dinner, Watching Television and Preparing Tea are recognized with the help of a probabilistic learning method of Naïve Bayes model along with an add-one Laplace smoothing technique. The objective of the sub-activities identification process is to identify (recognize) maximum probable activities from the sensor stream event letters.

5.3.1 ADL Sub-Activities (Chores) Identification

The Sub-Activities (Chores) like preparing Breakfast / Lunch / Dinner, Watching Television and Preparing Tea are as follows:

Step (a): *Ascertain different activities with unique letters such as Preparing Tea (PT) = A, Preparing Coffee (PC) = B, Preparing Toast (TS) = C.*

Step (b): *If the sensor for the Water Kettle is active then the following stream of letters A, B will be considered, indicating it may be used for preparing tea or preparing coffee. Similarly, if the sensor unit of the Fridge door open is active then the stream of letters A, B, C will be considered, and if a sensor unit of a teabag container is active then letter 'A' will be considered.*

Step (c): *If the inhabitant uses household appliances Water Kettle, Fridge, and Teabag container in any sequence then the letter stream generated will be either: A,A,B,C,A or A,B,C,A,B,A or A,A,B,A,B,C etc,.*

Step (d): *A Fragment of chore is identified by the parts of sensor events that correspond to a particular chore. However, this idea may sometimes generate sensor* *event chores that are not properly mapped. In order to have proper chore identification apply Eq.5-1. To eliminate zeroes for the probability of an unseen event, the add-one, Laplace smoothing concept is considered. Eq.5-1 describes the probability of the term (set of letters) belonging to a particular class of sub activity.*

$$P(t \mid c) = \frac{Nct + 1}{\sum_{t' \in V} (N_{ct'} + 1)} = \frac{Nct + 1}{\sum_{t' \in V} Nct' + K'} \tag{5-1}$$

Where t is a term containing a set of letters, c is a class of sub-activity (chore). N_{ct} *is the number of times a particular letter occurs in class 'c'. V is the set of letters. K'=|V| is the number of unique letters.*

From Fig.5-4 the maximum likelihood stream of "(A, B, A, B, C, A)" letters belong to the chore of preparing tea (C_PT). Similarly, other chores are identified. Once the individual chores are identified they are mapped to the next level along with the time of day to recognize the appropriate ADL.

Sensor Events (Any Order)	Stream of Letters "t"	Belonging to Class "c"	P(t | c)
Water Kettle, Fridge, Tea_Bag	A,B,A,B,C,A	P(A,B,A,B,C,A | Prep_Tea(A))	0.0109739
		P(A,B,A,B,C,A | Prep_Coffee(B))	0.0133333
		P(A,B,A,B,C,A | Prep_Toast (C))	0.0020576
Fridge , Toaster	A,B,C,C	P(A,B,C,C | Prep_Tea(A))	0.0185185
		P(A ,B ,C ,C | Prep_Coffee(B))	0.0185185
		P(A,B,C,C | Prep_Toast (C))	0.0277777
Coffee_Bag, Fridge, Water Kettle	B,A,B,C,A,B	P(B,A,B,C,A,B | Prep_Tea(A))	0.0019753
		P(B,A,B,C,A,B | Prep_Coffee(B))	0.0046296
		P(B,A,B,C,A,B | Prep_Toast (C))	0.0020576

Figure 5-4 Likelihood of the sensor event stream of letters belonging to a particular sub-activity class

The importance of a chore identification method is in the accuracy of the model to be built based on the activity annotation rather than accuracy of the activity annotation. Sensor fusion data was not segmented into separate sequences for each activity; rather it was processed as a continuous stream. Table 5-1 depicts the activities annotated during the run-time of the system.

Table 5-1Labelling process during run time of the system

Sensor-ID/ Status	Connected to Appliance	Type of Sensor	Time of Usage	Annotated Activity	Run Time Data
18(Active)	Bed	Force Sensor	09:00pmto 06:00am	Sleeping(SL)	2011-6-9 21:02:10 18 ON SL begin 2011-6-10 05:50:10 18 OFF SL end
11/12/13 (active)	Microwave Oven/ Water Kettle/ Toaster	Electrical sensor	6:00amto 10:00am	Breakfast(BF)	2011-6-5 06:16:42 11 ON BF begin 2011-6-5 06:21:35 11 OFF BF end
11/12/13 (active)	Microwave Oven/ Water Kettle/ Toaster	Electrical sensor	11:01amto 02:00pm	Lunch(LN)	2011-6-6 12:11:27 13 ON LN begin 2011-6-6 12:12:18 13 OFF LN end
11/12/13 (active)	Microwave Oven/ Water Kettle/ Toaster	Electrical sensor	07:00pmto 10:00pm	Dinner(DN)	2011-6-4 20:59:26 11 ON DN begin 2011-6-4 20:59:32 11 OFF DN end
17(active)	Dining Chair	Force sensor	Anytime	Dine(DI)	2011-6-11 14:43:02 17 ON DI begin 2011-6-11 14:43:05 17 OFF DI end
10(active)	Toilet	Force sensor	Anytime	Toileting(TO)	2011-6-7 02:15:30 10 ON TO begin 2011-6-7 02:16:07 10 OFF TO end
19(active)	Couch	Force sensor	Anytime	Relax(RE)	2011-6-8 05:20:45 19 ON RE begin 2011-6-8 05:35:30 19 OFF RE end

14(Active)	TV	Electrical sensor	14->19 or 19->14	Watching TV(WTV)	2011-6-6 17:20:35 14 ON TV begin 2011-6-6 17:20:45 19 ON WTV begin 2011-6-6 18:05:39 19 OFF WTV end 2011-6-6 18:06:05 14 OFF TV end
25(Active)	Fridge	Contact	25->12 or 12->25	Preparing Tea(PT)	2011-6-9 10:15:20 25 ON FR begin 2011-6-9 10:15:50 12 ON PT begin 2011-6-9 10:15:45 25 OFF FR end 2011-6-9 10:16:50 12 OFF PT end
26(Active)	Grooming Cabinet	Contact	Anytime	Self-Grooming (SG)	2011-6-8 09:20:10 26 ON SG begin 2011-6-8 09:22:40 26 OFF SG end

In the ADLs recognition process, the appropriate size of time slot is considered for labelling the activity based on the sensor id and time of the day. It provides sufficient information for data analysis. Even if the sensors are active for multiple times during a particular time slot, activity labeling is done according to the definition specified in the system. The model is experimented with different sizes of time slot for one hour, three hours, four hours and six hours duration. Activity recognition in terms of three hour and four hour time slot sizes gives more modelling accuracy for labelling the activity processing (i.e.,) In table.5-1 the sensors id 11, 12, 13 are used as kitchen appliances. If multiple times of sensor id 11, 12 or 13 are active during a four hour time slot the event is annotated with defined activity as preparing breakfast, lunch or dinner respectively. Obviously, an event like preparing breakfast, lunch or dinner do not happen at the same time every day, but it usually happens within specified time duration. Hence preparation of food between 6:00 am to 10 am has been considered as preparation of breakfast. So sensor events generated in the kitchen between 6:00 am to 10:00 am used labeling as "breakfast".

5.3.2 DELTA SMOOTHING FOR SUB-ACTIVITIES IDENTIFICATION

The Delta-Smoothing: 'δ' is the smoothing value to provide probability for an unseen sensor stream of letters. Eq.5-2 describes the probability of a term (set of letters) belonging to a particular class of sub-activity.

$$P(t/c) = \frac{Nct + \delta}{\sum_{t' \in V}(Nct' + \delta)} = \frac{Nct + \delta}{\sum_{t' \in V} Nct' + K'} \tag{5-2}$$

Where t is a term containing a set of letters,

c is a class of sub-activity,

N_{ct} is the number of times a particular letter occurs in activity class 'c'.

V is the set of letters. K'=|V| is the number of unique letters.

'δ' is the smoothing (discounting) value to provide probability for an unseen sensor stream of letters.

Fig 5-5 shows the likelihood of the sensor event stream of letters belonging to a particular sub-activity class.

Sensor Events (Any Order)	Stream Letters	Belonging to activity class 'C'	δ Smoothing	
			0.5 (a)	1 (b)
Water Kettle, Fridge, Tea_Bag	A,B,A,B,C,A	**P(A,B,A,B,C,A |Prep_Tea(A))**	**$0.421875/9^6$**	**$8/9^6$**
		P(A,B,A,B,C,A |Prep_Coffee(B))	$0.140625/9^6$	$4/9^6$
		P(A,B,A,B,C,A |Prep_Toast(C))	$0.046875/9^6$	$2/9^6$
Fridge, Toaster	A,B,C,C	P(A,B,C,C| Prep_Tea (A))	$0.1875/7^4$	$2/7^4$
		P(A,B,C,C| Prep_Coffee (B))	$0.1875/7^4$	$2/7^4$
		P(A,B,C,C| Prep_Toast (C))	**$0.5625/7^4$**	**$4/7^4$**
Coffee Bag, Fridge, Water_Kettle	B,A,B,C,A,B	P(B,A,B,C,A,B |Prep_Tea(A))	$0.140625/9^6$	$4/9^6$
		P(B,A,B,C,A,B |Prep_Coffee(B))	**$0.421875/9^6$**	**$8/9^6$**
		P(B,A,B,C,A,B |Prep_Toast(C))	$0.046875/9^6$	$2/9^6$

Figure 5-5 Likelihood of the sensor event stream of letters belonging to a particular sub-activity class[4]

In both the cases (δ=0.5 [164] and δ=1 [165]), the sub-activities (Preparing Tea, Preparing Toast and Preparing Coffee) were recognized correctly. However, in the present application add-one Laplace smoothing has significance in recognizing the pattern of stream letters from the sensor events correctly. This method is effective for recognizing the unseen sensor events.

5.4 Wellness Determination of an Elderly Person based on the usages of Household Appliances

The health-care providers assisting the elderly can have a comprehensive and longitudinal evaluation of the activities of an elderly person rather than a snap shot assessment obtained during an annual physical examination [166] [167]. "*An index or scale which measures a patient's degree of independence in bathing, dressing, using the toilet, eating and transferring (moving from a bed to a chair)*" [168] [169] [170] can support in determining the assistance to be provided to the elderly. Novel wellness functions were introduced to determine the wellness of the elderly person under the monitoring environment on real-time data collection. The two wellness functions β_1 and β_2 determine the wellness of an elderly person were based on the usage of house-hold appliances.

The first function (β_1) was determined from the non-usage or inactive duration of the appliances. The second function (β_2) was determined from the over-usage of a few specific appliances. Fig.5-6 shows the functional description of the Wellness functions.

[4] Add-delta=0.5 (Lidstone's & Jeffreys-Perks' Laws) Add-delta=1.0 (Laplace smoothing)

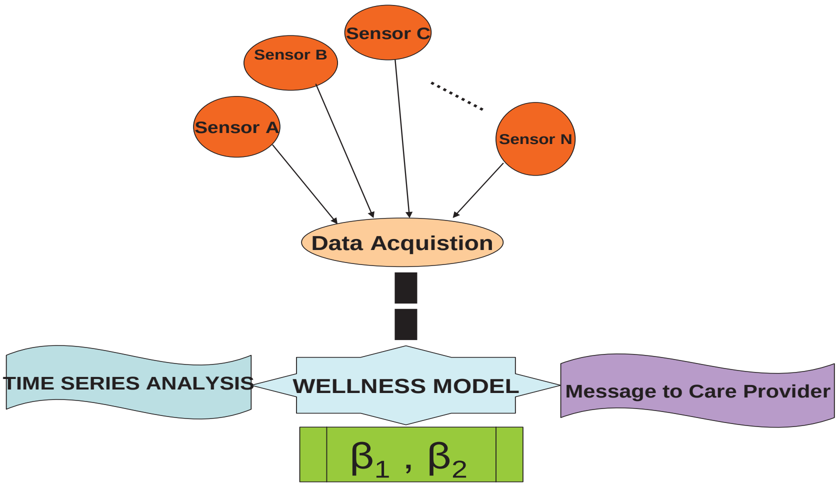


Figure 5-6 Functional description of Wellness Computation Functions

The wellness functions were calculated during the run-time of the system as a background process taking the ADLs durations from the respective files of the computer system. These indices were simultaneously recorded in the database for data processing and prediction of the behavior of the elderly person. The β_1 and β_2 are helpful in deriving the reliability of performing ADLs as regular or irregular over a long period of execution of the system.

In the initial stage of research (β_1 and β_2) were defined as ($\beta_{1,old}$ and $\beta_{2,old}$) to know the wellness level of the elderly in the monitoring state. Later (β_1 and β_2) were modified as ($\beta_{1,new}$ and $\beta_{2,new}$) to have a better understanding on the usage of household appliances and reducing the number of false messages of unusual behaviour.

5.4.1 WELLNESS FUNCTION #1

The wellness function #1, designated as ($\beta_{1,old}$) was defined by the following equation

$$\beta_{1,old} = 1 - \frac{t}{T} \tag{5-3}$$

Where $\beta_{1,old}$ =Wellness function of the elderly based on the measurement of inactive duration of appliances; t = Time of Inactive duration of all appliances (i.e.,) duration of time when no appliances were used; T= Maximum inactive duration during which no appliances were used, leading to an unusual situation.

If $\beta_{1,old}$ is equal to 1.0 indicates the elderly is in a healthy well-being situation. If $\beta_{1,old}$ is less than 1.0 the situation indicates some unusual situation. If $\beta_{1,old}$ goes below 0.5 then care is required.

5.4.2 WELLNESS FUNCTION #2

The wellness function #2, designated as ($\beta_{2,old}$) was defined by the following equation

$$\beta_{2,old} = 1 + \left(1 - \frac{Ta}{Tn}\right) \quad (5\text{-}4)$$

Where $\beta_{2,old}$ *= Wellness function of the elderly based on excess usage measurement of appliance;* T_a*= Actual usage duration of any appliance;* T_n *=Maximum usage duration use of appliances under normal situation.*

Under normal condition, $T_a < T_n$ and abnormality is not calculated. Only if $T_a > T_n$ then $\beta_{2,old}$ was calculated using the Eq.(5-4), while the value of $\beta_{2,old}$ is close to 1 to 0.8 it may be considered as normal situation. If $\beta_{2,old}$ goes less than 0.8, then it indicates the excess usage of the appliance corresponding to an unusual situation. In ideal case, $\beta_{1,old}$ and $\beta_{2,old}$ equals to 1 indicated the elderly activities were recurring with normal conditions every time. However, human behavior is not consistent; hence the optimum alarm level for $\beta_{1,old}$ and $\beta_{2,old}$ were determined so that false warning messages are minimized.

Based on the experiments conducted at different houses of a few elderly people there are instances of the maximum inactive and active duration of the appliances. Deriving $\beta_{1,old}$ and $\beta_{2,old}$ accordingly from the experiments at the elderly houses, warning messages were generated when $\beta_{1,old}$ goes below 0.5 and $\beta_{2,old}$ goes less than 0.8.

Maximum inactive duration and maximum usage duration of appliances can be obtained during the trial run period of the system. The period of trial run may be varied depending on the elderly person's activities of daily living conditions. Once the system learns the behaviour of the daily activities then the trial run execution phase will be shifted to test phase and optimal wellness indices can be determined.

5.4.3 NEED FOR DYNAMIC WELLNESS FUNCTIONS

The wellness functions as determined in the previous section 5.4.1 to 5.4.2 do not take into account the day of the week, weekly, monthly and seasonal variations and therefore it is prone to generate more false warning messages related to the domestic object usages. In order to determine the wellness functions in the best practical manner the β_1 and β_2 have been modified and seasonal variation has been included through time-series data processing techniques.

The first improved wellness function was related to the determining the index level of inactive usage of household objects so that it indicated there was no performance of basic daily activity. This leads to a vital indication for the healthcare provider about no performance of routine activity. Table.4.2 provides the details of the improved wellness functions.

5.4.4 IMPROVED WELLNESS FUNCTION #1

The modified wellness function #1, designated as ($\beta_{1,new}$) was defined by the following equation

$$\beta_{1,\text{new}} = e^{-t/T} \tag{5-5}$$

Where: $\beta_{1,New}$ *= Wellness index of the elderly person based on the measurement of inactive duration of household objects; t = Time of Inactive duration of all appliances (i.e.) duration time no objects are used; T = Maximum inactive duration when no objects were used in the past*

Fig.5-7 depicts the comparative advantage of the improved β1 wellness index in terms of considering appropriate time period to generate false positives warnings of irregular ADL.

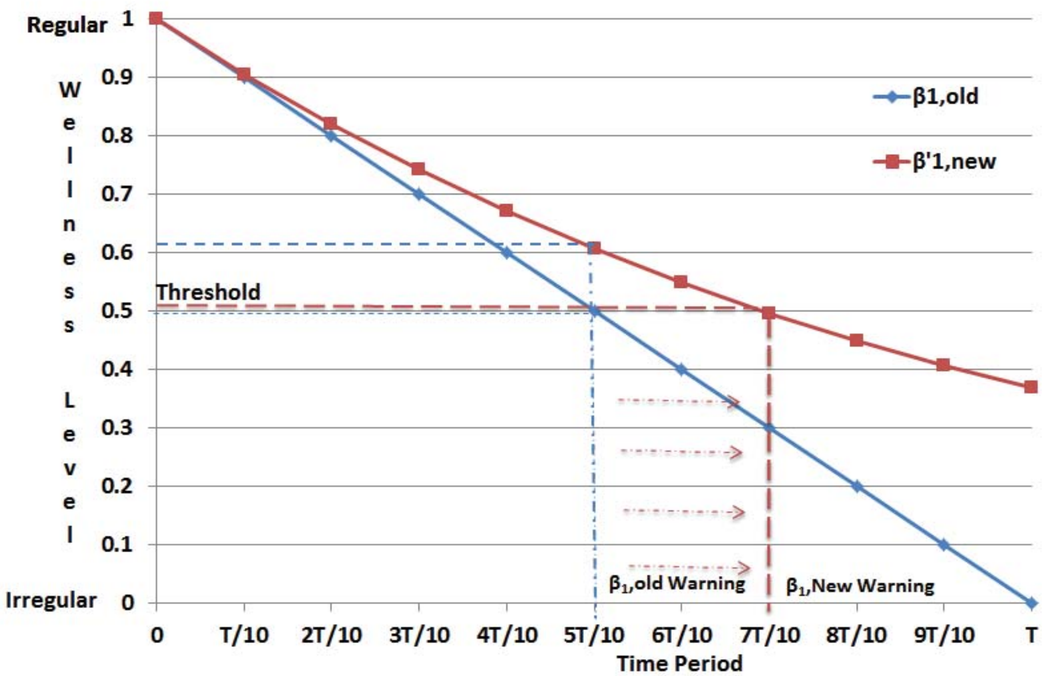


Figure 5-7Comparison of β1,old and β1,new wellness functions

The second improved wellness function was related to the determining the index level of excess usage of household object so that it indicated that there is unusual performance of a basic daily activity. This leads to a vital indication for the healthcare provider about the sudden change in a specific routine daily activity when compared to its past history.

5.4.5 Improved Wellness Function #2

The modified wellness function #2, designated as ($\beta_{2,new}$) was defined by the following equation

$$\beta_{2,\text{new}} = e^{\frac{Tn - Ta}{Tn}} \tag{5-6}$$

Where: β2, new = Wellness function of the elderly person based on excess usage measurement of household object; Ta= Actual (current) usage duration of the household object; Tn= Maximum usage duration use of household object in normal situation of the past.

Fig.5-8 depicts the advantage of the improved β2 wellness index in terms of considering an appropriate time period to generate false positives warning messages of irregular ADL.

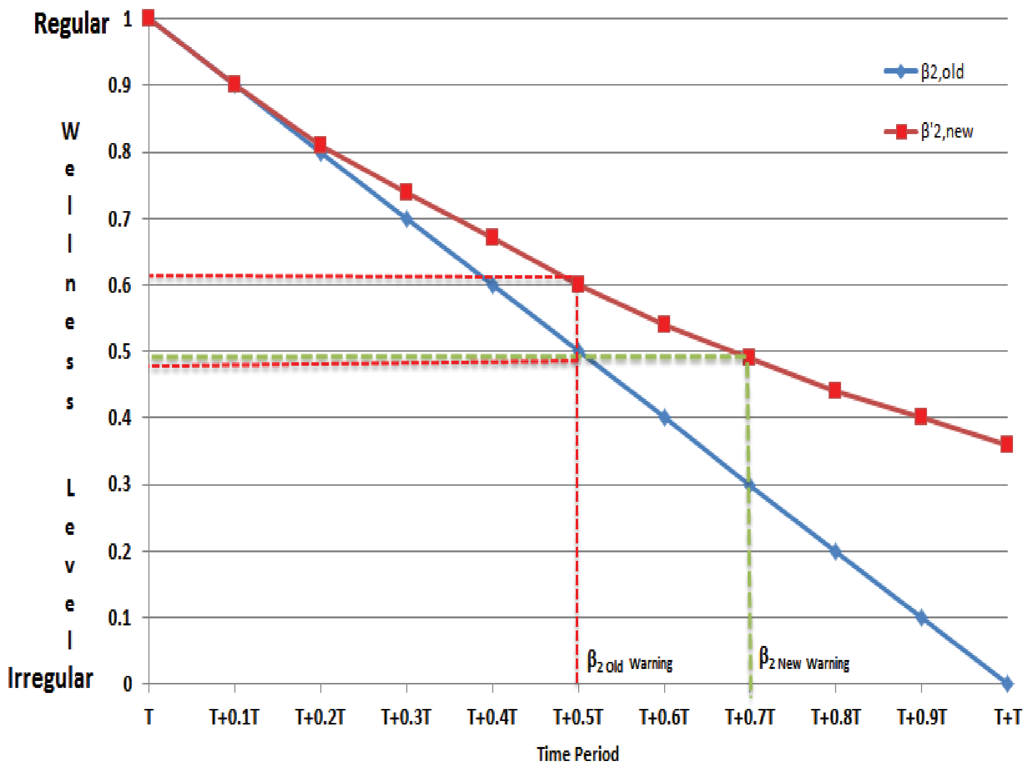


Figure 5-8 Comparison of β2,old and β2,new wellness functions

Advantages of Improved Wellness Functions:

- For linear wellness indices ($\beta_{1,old}$ and $\beta_{2,old}$) the threshold value were kept at 0.5 for generating irregular behaviour warning messages. Whereas, the improved wellness index $\beta_{1,new,}$ $\beta_{2,new}$ allowed more time to generate warning messages for the same threshold.
- It was determined that at 50% of the time period the new wellness functions indicated a wellness of 62%, better than 50% of the previous wellness indices.

5.4.6 MAXIMUM INACTIVE AND EXCESS ACTIVE USAGE DURATIONS (T, T_N)

The regular duration of household appliances usages with allowable residuals of certain objects can indicate the regular behaviour of the elderly person. However, changes in daily activities are inevitable and can be easily known with respect to the time. If there are any significant deviations to the regular usage duration then we can say that it is an irregular behaviour. The day- to-day lifestyle of elderly person changes slowly with ages subsequently, the lifestyle is also very dependent on weather (seasonal variation). Therefore, dynamic values of T in eq. and T_n in eq. are very much important in the determination of wellness functions.

In order to have an accurate maximum inactive (T) and maximum excess active object usage durations (T_n) with respect to weekly, monthly and seasonal variation in the wellness determination functions; the T and T_n were formulated with the help of time series principles. The following Eq.5-7 shows the dynamic T and T_n expressions:

$$T = \delta(C_{1t} - C_{1T-1} + (1-\delta)T_{t-1}$$

$$C_{1t} = \alpha(xt) + (1-\alpha)(C_{1t-1} + T_{t-1}) + S_t \qquad (5\text{-}7)$$

$$T_n = \delta(C_{2t} - C_{2t-1}) + (1-\delta)T_{nt-1}$$

$$C_{2t} = \alpha(x_t) + (1-\alpha)(C_{2t-1} + T_{nt-1}) + S_t$$

Where: T: Trend of the Maximum Inactive usage durations, Tn: Trend of the Maximum excess active usage durations, C1t, C2t: Seasonal trends; xt is the object usage observation at the current time, s is the number of periods in one cycle (week) (i.e.. s=7), α, δ are the smoothing parameters ranging from 0 to 1, selected by minimizing mean square errors. St is the seasonal term (for spring =1, summer=2, monsoon=3, autumn=4, winter=5, prevernal=6)

Starting values:
$C_{1t} = (1/s)\ (x_1+x_2+x_3+\ldots..x_s)$; $C_{2t} = (1/s)\ (x_1+x_2+x_3+\ldots..x_s)$;
$T_t = (1/s)\ ((x_{s+1}-x_1)/s+ (x_{s+2}-x_2)/s+\ldots.\ (x_{2s}-x_s)/s)$;
$T_{nt} = (1/s)\ ((x_{s+1}-x_1)/s+ (x_{s+2}-x_2)/s+\ldots.\ (x_{2s}-x_s)/s)$

5.5 Results and Analysis

The performance of the novel computing functions(β_1 *and* β_2) defined to measure the wellness of the elderly person living alone was evaluated by running the system at four different elderly houses, recording the data and analyzing the data through offline. The elderly houses were equipped with the wireless sensor network with the fabricated sensor units attached to various household appliances. Six electrical sensors were connected to appliances Microwave, Toaster, Water Kettle, Room Heater, TV and Audio. Four force sensors were connected to Bed, Couch, Dining chair and Toilet. One contact sensor was connected to the grooming table/Fridge. Sensor_id notations are as follows: MO = Microwave Oven, TR= Toaster, WK= Water Kettle, AD= Audio device, HT=Heater, TV=Television, DC=Dining Chair, BD=Bed, CO=Couch, TO= Toilet. Fig.5-9 shows the sensor activity status at various subjects (elderly people's) houses at a particular time instance.

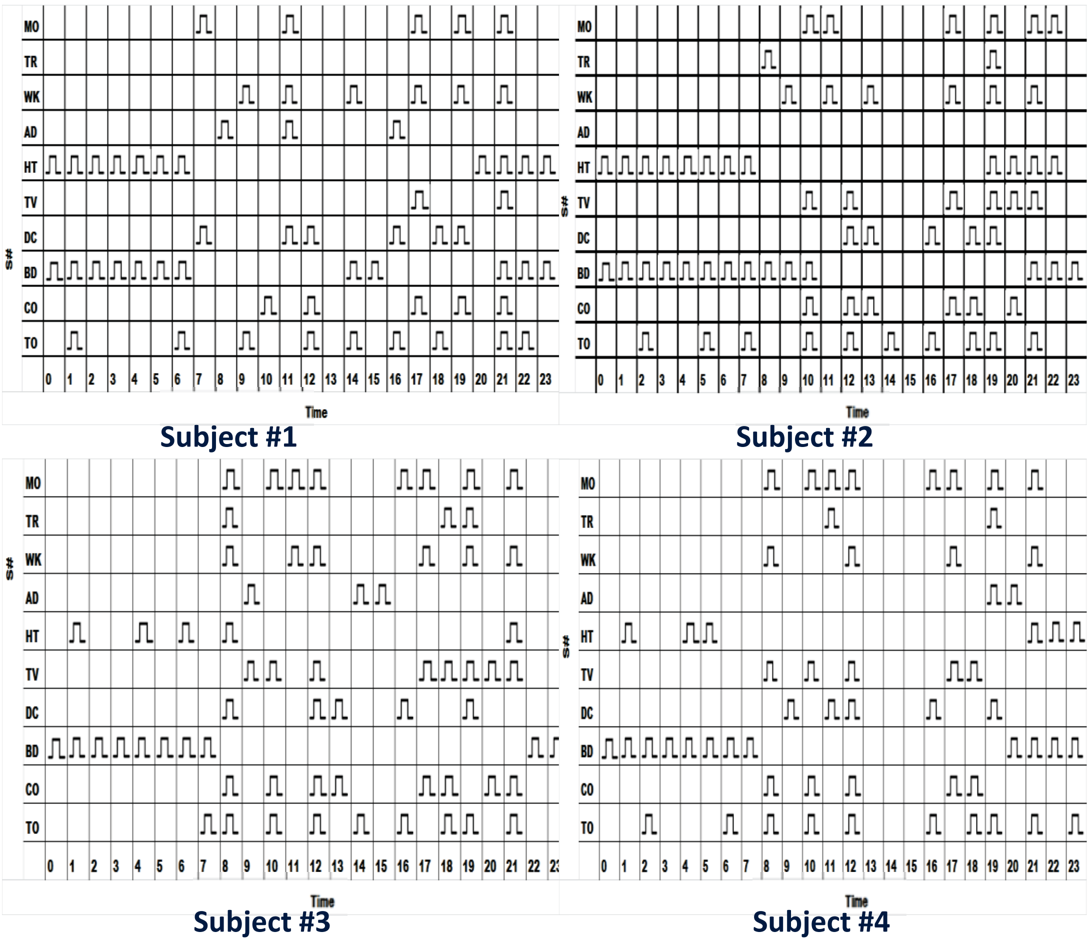
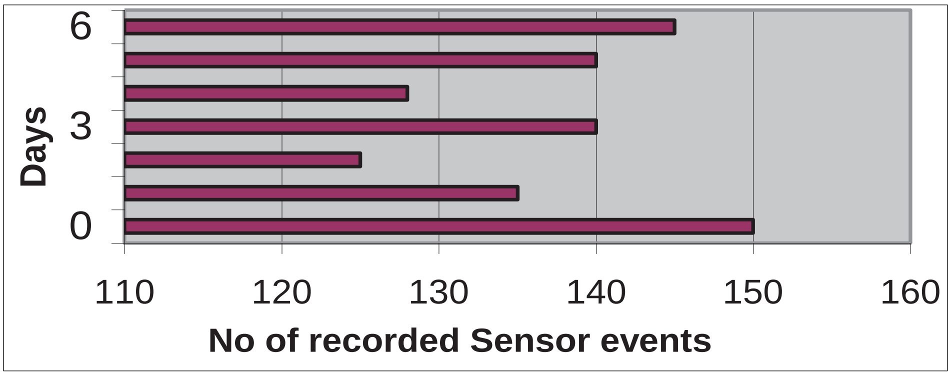
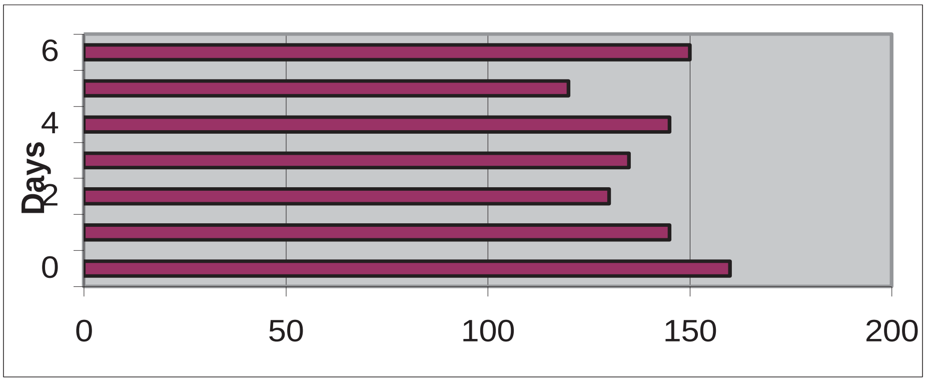


Figure 5-9 Sensor activity status at various subject locations

From Fig.5-10, it can be inferred that the number of recorded sensor events at different subject houses varies and this is helpful in the calculation of the activity recognition and wellness for day to day activities.



(a) Subject #1



(b) Subject #2

Figure 5-10 Number of sensor events at different subject houses

The wellness determination based on the functional measurement of daily activities through the use of sensing units. Fig.5-11 shows the sensing unit's active duration over time.

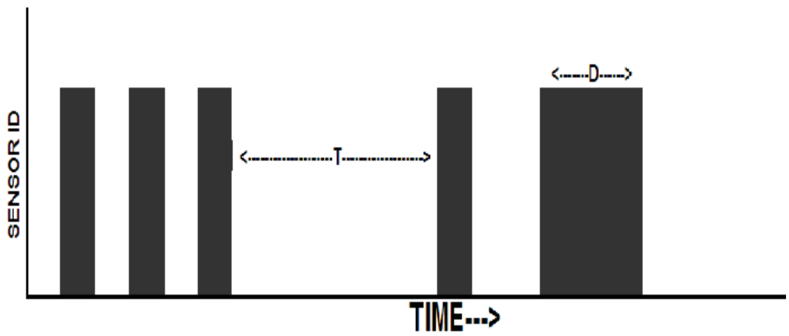


Figure 5-11 Sensing units connected to household appliances usages

Where T: Maximum duration usage (time duration) of sensing units for performing daily activities and D: Excess usage of an appliance connected to a sensing unit. "T" and "D" can be used for predicting the abnormal living condition or the unreliability of the system. If the maximum duration of "T" or "D" exceeds the normal living condition then the system is alerted to unusual behaviour of the elderly.

The “T” and “D” were determined for the 24-hour duration at the house of subject #1. T had 68 mins duration and D for individual sensing unit appliances. There are given in Table 5-2. Accordingly, “T” was determined for a one week trial run for subject#1 house and found to be 72 mins. If no sensing unit is in operation for more than the obtained T (time duration), then the system will indicate that there is abnormal living status of the elderly and appropriate care should be taken. Tables: 5-3, 5-4 and 5-5 shows the (β2,old) calculations of various elderly subjects during the testing week.

Table 5-2 ‘T’ values of various objects usages at sub#1 home for a week

Date/Appliance	Maximum Active Duration(hh: mm: ss)				
	Bed	Toilet	Chair	TV	Couch
05/06/2011(Sun)	9:35:40	0:12:20	0:17:45	1:10:50	0:57:45
06/06/2011(Mon)	7:50:10	0:10:35	0:15:35	0:45:20	1:45:50
07/06/2011(Tue)	9:20:10	0:14:45	0:25:28	2:15:10	2:30:10
08/06/2011(Wed)	8:45:50	0:13:55	0:10:20	1:45:50	0:55:20
09/06/2011(Thu)	8:35:25	0:12:20	0:19:45	1:55:30	2:20:10
10/06/2011(Fri)	8:50:25	0:15:45	0:20:35	1:30:20	1:30:45
11/06/2011(Sat)	9:25:15	0:10:55	0:28:30	1:40:10	2:10:35
Maximum	9:35:40	0:15:45	0:28:30	2:15:10	2:20:10

Table 5-3 (β2,old) values of various objects usages at sub#1 home

Date/Appliance	Maximum Active Duration(hh: mm: ss)			
	Bed, $\beta_{2,old}$	Toilet, $\beta_{2,old}$	Chair, $\beta_{2,old}$	Couch, $\beta_{2,old}$
12/06/2011(Sun)	9:25:20, 1.01795	0:11:10, 1.291005	0:18:55, 1.336257	1:27:45, 1.3736
13/06/2011(Mon)	7:20:45, 1.234366	0:12:15, 1.222222	0:16:25, 1.423977	3:15:50, 0.602854
14/06/2011(Tue)	8:50:37, 1.078257	0:10:45, 1.31746	0:20:18, 1.287719	2:45:20, 0.82045
15/06/2011(Wed)	9:15:15, 1.035466	0:12:55, 1.179894	0:34:30, 0.789474	1:15:20, 1.46253
16/06/2011(Thu)	9:35:35, 1.000145	0:15:20, 1.026455	0:13:15, 1.535088	2:50:40, 0.78204
17/06/2011(Fri)	8:30:55, 1.112478	0:13:45, 1.126984	0:25:25, 1.145324	1:45:50, 1.24456
18/06/2011(Sat)	10:25:15, 0.913868	0:12:15, 1.222222	0:18:40, 1.384675	1:55:35, 1.175386

Table 5-4 ($\beta_{2,old}$) values of various objects usages at sub#2 home

Date/Appliance	Maximum Active Duration(hh: mm: ss)			
	Bed,	Toilet,	Chair,	Couch,
	$\beta_{2,old}$	$\beta_{2,old}$	$\beta_{2,old}$	$\beta_{2,old}$
03/07/2011(Sun)	10:15:10,	0:16:10,	0:20:15,	0:45:50,
	1.03179	1.13854	0.910314	1.6026
04/07/2011(Mon)	8:10:15,	0:14:15,	0:14:35,	1:10:15,
	1.2284	1.24512	1.233184	1.3909
05/07/2011(Tue)	9:15:10,	0:12:25,	0:16:18,	0:55:10,
	1.12623	1.35169	1.125561	1.52168
06/07/2011(Wed)	8:55:30,	0:09:45,	0:28:20,	0:35:15,
	1.15718	1.51155	0.47982	1.69436
07/07/2011(Thu)	9:35:35,	0:13:30,	0:12:15,	1:45:10,
	1.09409	1.2984	1.340807	1.60838
08/07/2011(Fri)	9:20:45,	0:12:15,	0:35:45,	0:58:20,
	1.11744	1.35169	0.10314	1.49422
09/07/2011(Sat)	9:55:20,	0:15:35,	0:19:30,	1:05:15,
	1.06301	1.19183	0.964126	1.43425

Table 5-5 ($\beta_{2,old}$) values of various objects usages at sub#3 home

Date/Appliance	Maximum Active Duration(hh: mm: ss)			
	Bed,	Toilet,	Chair,	Couch,
	β_2	β_2	β_2	β_2
31/07/2011(Sun)	10:02:35	0:28:36	0:24:45	1:10:45
	0.932694	0.525773	1.27737	1.294264
01/08/2011(Mon)	9:24:56	0:19:25	0:16:20	0:45:28
	0.99938	0.999141	1.523114	1.546467
02/08/2011(Tue)	9:30:12	0:22:30	0:22:45	0:50:28
	0.990052	0.840206	1.335766	1.496592
03/08/2011(Wed)	9:45:20	0:18:45	0:18:50	1:25:30
	0.963247	1.033505	1.450122	1.147132
04/08/2011(Thu)	8:50:10	0:16:30	0:25:45	0:35:45
	1.060959	1.149485	1.248175	1.643392
05/08/2011(Fri)	9:45:20	0:26:45	0:27:30	1:15:10
	0.963247	0.621134	1.19708	1.250208
06/08/2011(Sat)	9:55:36	0:17:30	0:32:38	1:20:50
	0.945063	1.097938	1.047202	1.193682

Fig.5-12 shows the $\beta_{1,old}$ at four different elderly houses. It was observed that the β_1 for the subject #2 on a particular day has gone below 0.5. In reality, it was been the elderly person went outside the house for quite a long duration without deactivating the monitoring system.

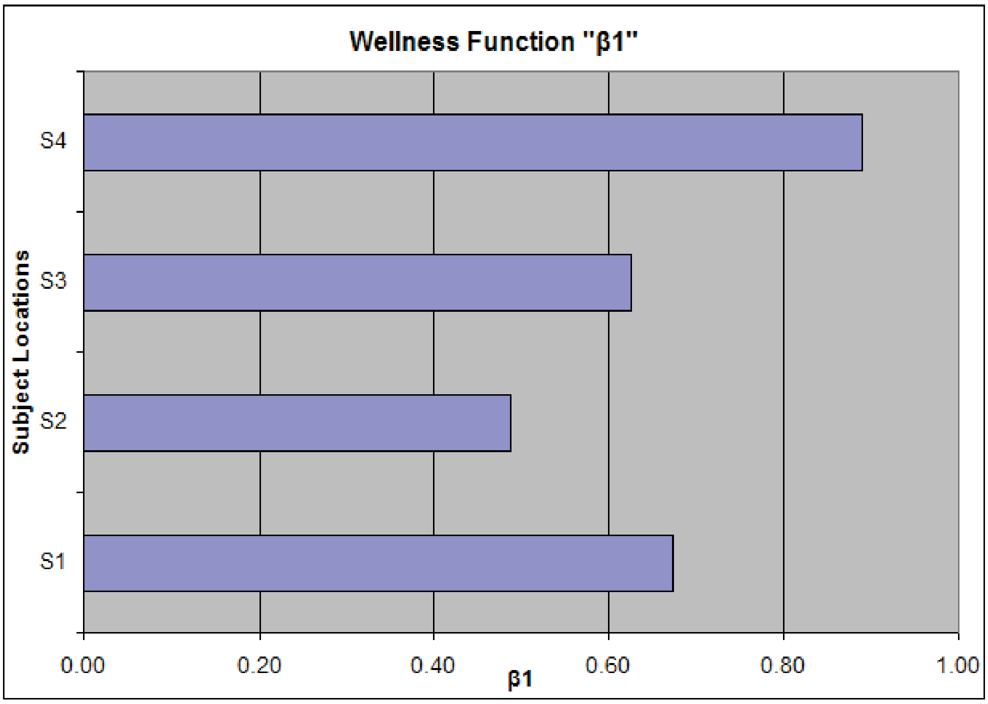


Figure 5-12 β1,old at four different elderly houses

Fig.5-13 shows the graphical representation of the (β2, old) calculations of various elderly subjects.

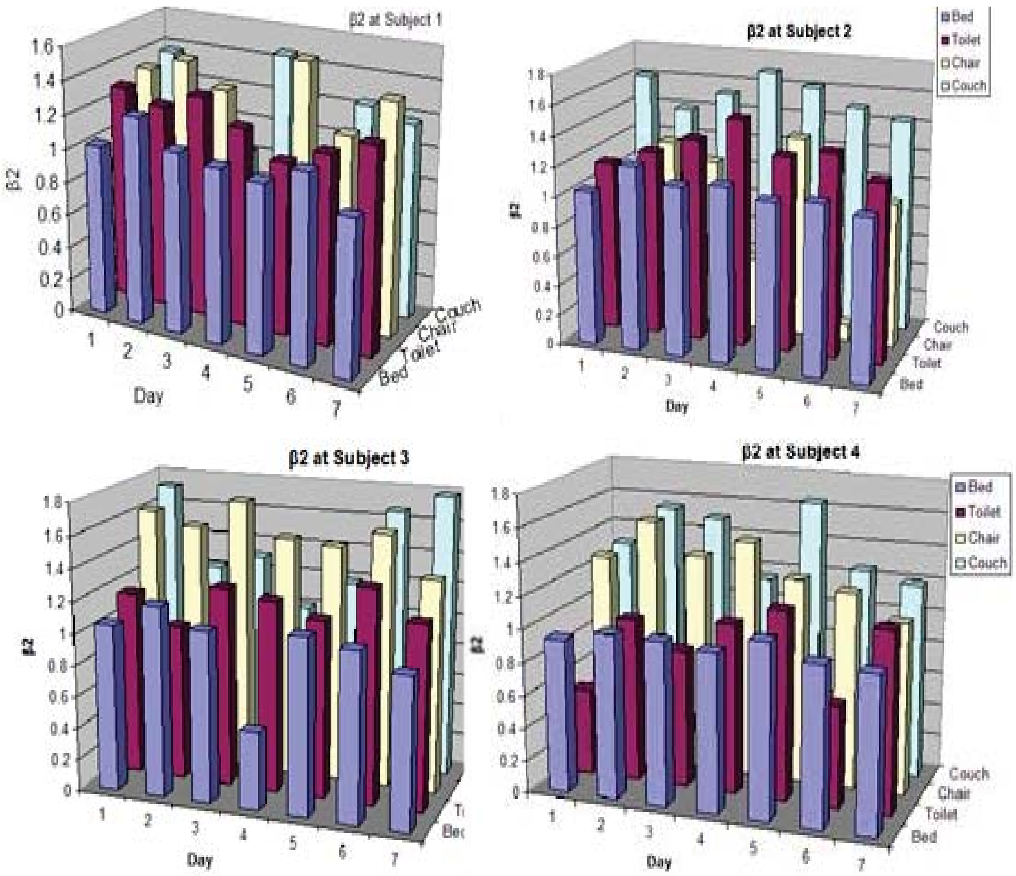


Figure 5-13 Graphical representation of β2,old Values at different elderly houses

It was observed from tables 5-3, 5-4, 5-5 that there are instances (values denoted in bold) of excess usage of the appliances by the elderly during one week of the testing phase. The subject #1 has one instance of over-usage of couch and they are verified with the ground truth of the respective subjects. It can be inferred from the results that the results of wellness functions are able to determine how well (regular) the elderly is performing their daily activities in using their household appliances.

In Fig. 5-13 it is seen that β2 for subject #2 has gone to a very low value for the use of chair. It was observed that on that particular day, the elderly had a visitor and had lunch sitting on the chair for a long duration. For the subject #3, it was observed that the elderly slept quite a long time as she was not feeling well. These observations tell clearly about the wellness determination of the system. The alarm can be set depending on values of β1 and β2. These should be diverse for different elderly people. While the alarm is set, the system will generate a sound to inform the elderly that a message is going to be sent to the care provider. The elderly will have approximately one minute to de activate the alarm. The developed home monitoring sensing systems were initially trial tested at four different elderly homes and then in use continuously at elderly person subject#1 from March 2013. There is no specific reason for choosing four, the elders had volunteered for testing the system.

For the process of understanding the functionalities and the importance of improved wellness functions, we have analysed the 90 days of sensor data collected from elderly subject #1. There were 14 warning messages for the methods of old wellness functions. These included excess usage of Bed(6), excess usage of dining chair(4), excess usage of couch(2) and no usage of appliances(2).

The reason for generating warning messages related to no usage of appliances ($\beta_{1,\ old}$) is that the elderly was on the lawn(outside the house) for 1Hr 14mins on 28-Mar-2013 and on another occasion went out shopping for 1Hr 38mins on 06-Apr-2013. For both instances, the home monitoring system was not switched off, hence no object used warning messages have generated. Whereas, ($\beta_{1,\ new}$) has generated only one warning messages.

The second wellness function ($\beta_{2,\ old}$) of Bed, D.Chair and Couch usages generated 12 messages. But ($\beta_{2,\ new}$) was able to restrict the generation of warning messages to Bed (3), D.Chair(1) and Couch (1). The reduction of warning messages was due to the fact that the maximum usage durations were updated with the time series processing and the time durations to be considered for threshold limit was increased in the improved wellness functions.

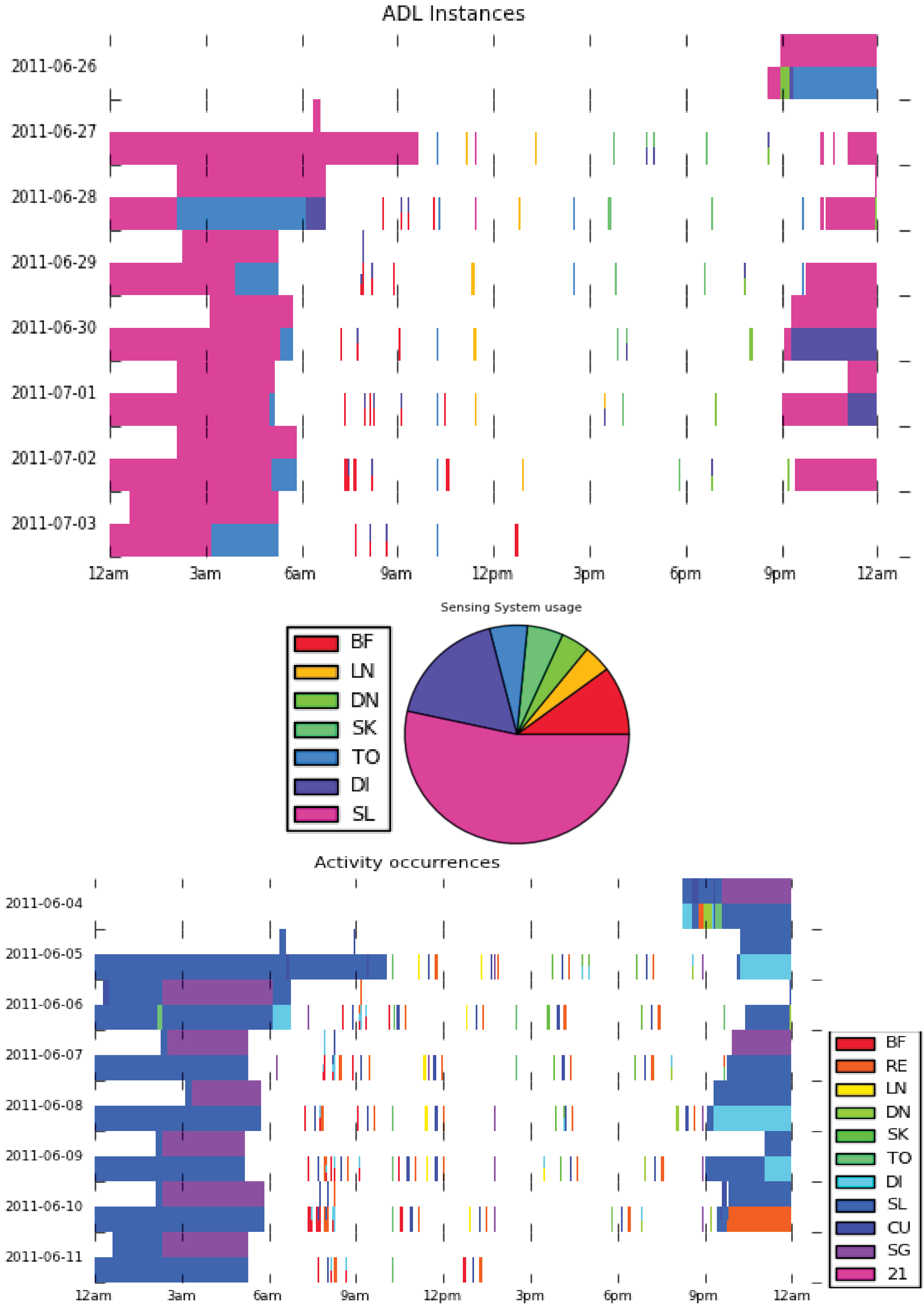
Thus, there was an improvement of 42.8% in reducing the false positives by the newly defined wellness functions. The improved wellness functions (β1,new and β2,new) calculations at a particular instance of time at different elderly subject's houses are shown in table 5-6.

Table 5-6 Improved Wellness Functions Calculations

Subject	**Sensor_ID**	**ADL**	**Max-Active Duration**	**Min-Duration (Sec)**	**Actual Duration (Sec)**	$\beta_{1,\,old}$	$\beta_{2,\,old*}$	**ADL Message based on Old indices**	$\beta_{1,\,new}$	$\beta_{2,\,new*}$	**ADL Message based on New indices**
#1	Bed	Sleeping	28456	20405	22505	0.71	NA	Regular	0.72	NA	Regular
	Chair	Dining	1208	845	1150			Regular			Regular
	Toilet	Toilet	1444	1028	1353			Regular			Regular
	Couch	Relax	1457	840	1104			Regular			Regular
#2	Bed	Sleeping	30258	23450	27268	0.82		Regular			Regular
	Chair	Dining	14545	10425	21817		0.51	Irregular	0.83	0.60	Regular
	Toilet	Toilet	1838	1426	1718		NA	Regular		NA	Regular
	Couch	Relax	2018	1487	1645			Regular			Regular
#3	Bed	Sleeping	27545	21408	26258	0.60		Regular	0.68		Regular
	Chair	Dining	16250	12350	15145			Regular			Regular
	Toilet	Toilet	1628	1245	1465			Regular			Regular
	Couch	Relax	1845	1423	1628			Regular			Regular
#4	Bed	Sleeping	28235	22035	43701	0.75	0.45	Irregular	0.76	0.57	Irregular
	Chair	Dining	1340	950	1205		NA	Regular		NA	Regular
	Toilet	Toilet	1123	885	1060			Regular			Regular
	Couch	Relax	1630	1245	1420			Regular			Regular

NA: No Abnormality
β2, old* and β2, new* are calculated only when actual duration is greater than maximum duration

The ADLs annotation process has helped the monitoring system to recognize the various behaviours of the elderly at different instances of time. This process was done based on the collection of sensor identity from the sensor fusion of various sensing units connected to different household appliances. Fig 5-14 gives the graphical ADL representation of two elderly subjects



Subject #2

Figure 5-14 ADLs instances at two different subject locations during the trial run of the HMS

5.6 Chapter Summary

In this research, wellness is about well-being of elderly people in performing their daily activities effectively at their home. The present chapter provides a novel framework for a wellness determination process as it verifies the behaviour of elderly people at different stages of daily living (usage of appliances, activity recognition and forecast levels) in a smart home monitoring environment. This will help in not generating frequent false unusual ADLs alarms.

The developed system including sensing and intelligent behaviour detection subsystems was developed in-house and used to recognize basic ADLs from the data analysis of sensor streams. The developed prototype is suitable for easy installation and maintenance in an existing elderly person's house.

The systems were stable in executing multiple tasks concurrently, such as data collection and provided a framework to analyze sensor data in near real-time. If the system executes continuously for a longer time, an optimal, maximum utilization of the appliances used by the elderly are obtained. Thus, cumulative data for time series analysis will enable better prediction of the abnormal behaviour of the elderly.

The wellness determination process helps the healthcare providers to see the performance of the elderly person's daily activities. Data relating to the wellness indices and behavior recognition can guide the healthcare professionals to find out the starting variations of elderly activities quantitatively. This will enable health professionals to provide precise elderly assistance.

The determination of elderly wellness model parameters like an excess usage of appliances, no-usage of appliances (β_1, β_2), and irregular behaviour detection through the usage duration of activities based on smart home object usages are formulated so that near real-time determination of wellness can be done. The developed system can be easily augmented with other co-systems such as physiological parameter monitoring sub-systems. This will supplement information about health parameters like body temperature and heart rate, so that elderly health perception and daily activity behaviour recognition together can be assessed to determine the wellness of the elderly.

Chapter 6. Forecasting the Behaviour of an Elderly Person Using WSN Data

6.1 Introduction

The forecasting process in a smart home setting equipped with WSN is a learning task. A major task for the intelligent home monitoring system is to have the ability to perceive, understand and realize the new situations. This will support an interpretation of sensory information in order to represent, understand the environment and perform correctly, based on the prior knowledge when there is a situational change. For the execution of these tasks, a variety of methods such as Analysis of Knowledge Discovery and Soft Computing Techniques were introduced.

The major task of the analysis of knowledge discovery in an AAL set up is an attempt to learn the daily activity patterns from a large data set to realize a new situation for predicting the abnormal behavior of the elderly person. Some of the existing methods are context-aware case-based reasoning [171]. Formulating the description logic based on the trial system may not be apt, as human behavior is complex. Also, the specified ontology concepts and their corresponding rules may not match in a real situation over a long run of the system execution. Aggregating sensor observations along a time line requires complex procedures to be incorporated for effective activity recognition. There are methods for recognizing sequential, interleaved and concurrent activities using an emerging patterns approach. The idea is to differentiate daily activities accurately. But, the quantitative wellbeing assessments of the inhabitant in terms of forecasting events in a smart home that are related to the daily activities have not been greatly explored.

A study on an inhabited intelligent environment performed a test bed mechanism for prediction in various phases for learning, controlling and adaption. Different techniques of clustering and fuzzy functions were implemented for the collected information on the observation of interactions by the inhabitant. Several methods including neural networks and heuristic functions were used to extract patterns for predictive models [172]. However, these techniques need alternating solutions (i.e., the activities learning model need regular updates) if the execution environment was changed and there can be issues of data inadequacy for adapting to a new system. In order to overcome the deficiencies of the analysis of knowledge discovery and soft computing techniques [173] [60] [174] [175], Time Series Data

Mining (TSDM) approach can be applied for forecasting the behavior of a person. TSDM can interpret the temporal patterns exhibiting the behavior of the person from the continuous sensor stream.

6.2 Time Series Modeling and Forecasting

"Time" is a fundamental element in our daily life and will provide us with a vital source of information for a smart home monitoring system. Moreover, livelihood activities are cyclic, and evaluation of daily activities will indicate performance behaviour of an elderly person. Hence, monitoring daily usage of household appliances (i.e.,) object monitoring in a smart home will help us to recognize the habitual nature of the person and thereby we can know how "well" the elderly person is able to perform his/her essential daily activities.

The changes in normal daily activities can be determined with respect to the time. Regular usage duration with allowable residuals of activities can indicate the regular behaviour of the elderly person. If there are any changes to the normal activity durations (i.e.,) deviation from the allowable duration range then an irregular activity is detected. Therefore, a system in terms of time series analysis for forecasting the usage duration of objects in a smart home monitoring environment was devised. The modified TSDM concepts were applied to the observed series of daily activity durations to explore the temporal patterns existing in the activity durations. These patterns were formed into appropriate groups based on wellness parameters.

The wellness determination model acclimates and transforms data mining concepts to analyze time series data. Precisely, it notifies the hidden temporal patterns persisting in the time series data and predicts appropriate events. Conventional time series analysis approaches are restricted by the constraints of stationary series values and normality of the residuals. Also, obsolete time series analysis methods are unable to ascertain complex (nonlinear and irregular) characteristics of the human behaviour. The TSDM overcame the above limitations of conventional time series analysis techniques in analyzing the complex behaviour such as sleeping, toilet, dining chair usage patterns (which are completely non-stationary) of an elderly person. Our wellness determination process involving time series data mining can resolve the behaviour of a person as regular or irregular behaviour. Fig.6-1 shows the functional structure of the TSDM approach in this research task.

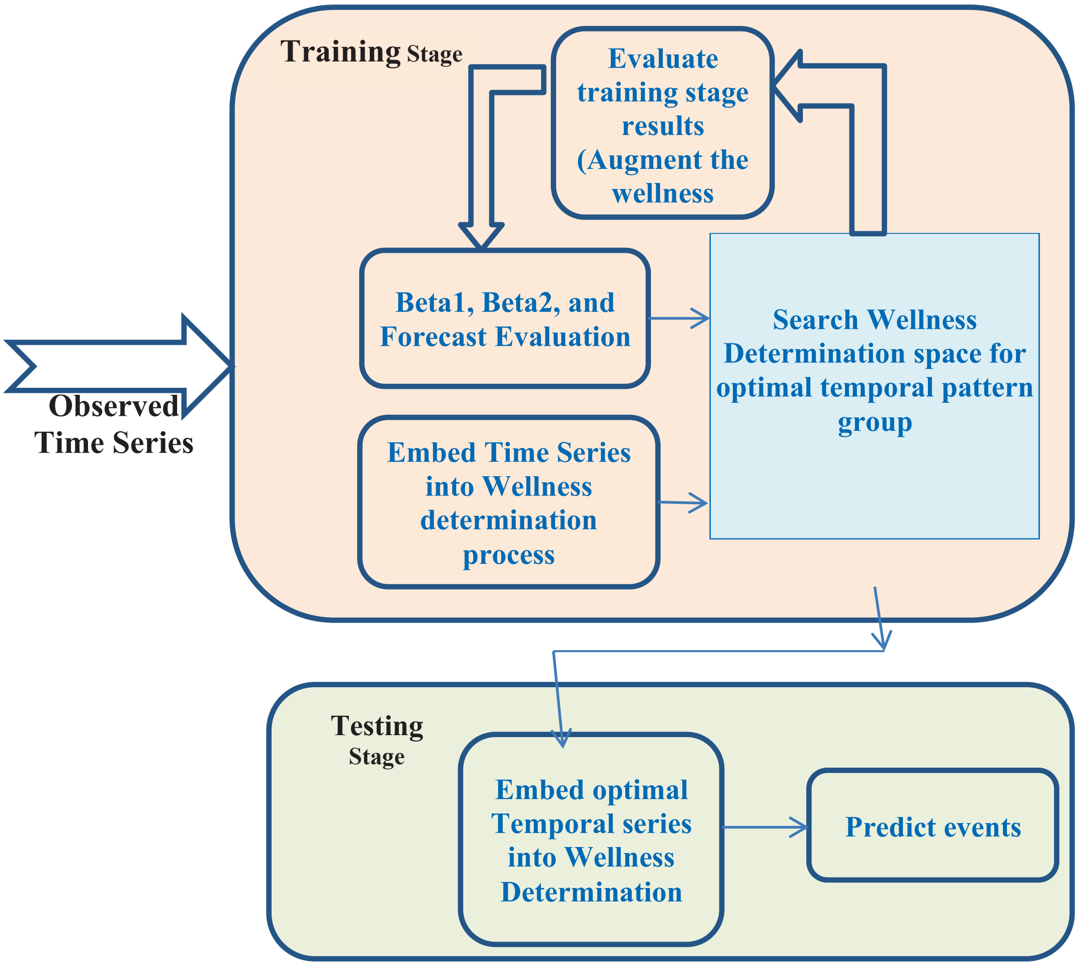


Figure 6-1 Functional blocks of Time Series Data Mining (TSDM)

The steps in the Training Stage were as follows:

Initial values such as activity durations are fed into the system with the data provided by the elderly person. The data are collected and trained to get the updated wellness parameters.

1. Evaluation of the basic wellness parameters.

a. Computing the wellness indices.

b. Forecasting formulation, including the independent variables over which the value of the wellness function will be optimized and the constraints on the wellness function

2. Determine the trend of the time series activity durations (with minimum of eight weeks training) and the length of the temporal pattern.

3. Based on step1 computation, transform the observed time series into the optimal temporal pattern group of daily activities with appropriate statistical characteristics groups.

4. Associate each cluster with an appropriate time index (such as weekdays and weekends in the training stage and augment the wellness indices.

5. In the training stage, search for the optimal temporal pattern group, which best characterizes the events (especially irregular events).

6. Training stage results will be updated continuously based on the elderly person's interactions with household appliances.

The steps in the Testing Stage were as follows:

Data was analyzed from day 1, and the optimal temporal groups of the wellness model were obtained after eight weeks of training

1. Embed the testing optimal temporal group into the testing stage.

2. Use the optimal temporal pattern group for predicting events.

3. Update the testing stage results continuously based on the optimal temporal pattern groups of training stage variations.

6.3 Seasonal Decomposition

Based on the time series of past data, "Seasonal (cyclic) Decomposition" [176] was considered for predicting the near future values. It was used primarily as a preliminary tool when attempting to analyze trend. It was also suitable for exhibiting seasonal pattern which may be existing in the series and useful for forecasting process. Trend component was estimated by using the principle of moving average. The initial Exponential Moving Average considered in the analysis was given by the Eq.6-1

$$MA_{t+1} = \alpha X_t + (1-\alpha)\, MA_t \qquad (6\text{-}1)$$

Where
MA_{t+1}-Moving average prediction;
MA_t - Previous Moving average;
α -- Smoothing Constant; X_t -- Observed quantity at time 't'

The smoothing constant ('α'), was derived from the number of sensor observations from the start of the system to the recently observed value. The basic features like trend and seasonality described a time series by its degree. After estimating the internal components like trend and seasonality of a time series, errors estimation were extracted by de-trending process. Smoothed Trend Curve (STC) for various household usage durations was derived by applying Eq (6-1).

The seasonal decomposition is apt for data revealing a cyclical pattern as well as a trend. In the present research task, a one week activity duration series was considered as one cycle or season to identify the weekly activity pattern of the elderly person. It also categorized the periodic components in the historical data and used them in a forecasting model.

6.4 Deriving Trend using Modified Double Exponential Smoothing Process

To handle data exhibiting seasonality effectively, an applied double exponential smoothing strategy Brockwell et al. [176] recursively as given in Eq.6-2 was used to determine the tendency of the activity. The advantage of this strategy was to minimize the mean deviation and capture the local (latest seasonal) trend of the series.

$$\tau = T = \delta(L_t - L_{t-1}) + (1-\delta)T_{t-1}$$

$$L_t = \alpha(x_t - S_{t-s}) + (1-\alpha)(L_{t-1} + T_{t-1}) \qquad (6\text{-}2)$$

$$S_t = \gamma(x_t - L_t) + (1-\gamma)S_{t-s}$$

Where:
T_t: trend (or slope) of the entire duration, L_t: local level seasonal slope, S_t: change in seasonal factor, x_t is the observation at the current time, s is the number of periods in one cycle (i.e., s=7 in our case), α, δ, γ are the smoothing parameters ranging from 0 to 1, selected by minimizing mean square errors.
Starting values are: L_t= (1/s) ($x_1+x_2+x_3+\ldots..x_s$);T_t=(1/s)((x_{s+1}-x_1)/s+ (x_{s+2}-x_2)/s+…. (x_{2s}-x_s)/s);S_t= x_k -L_s, where k=1, 2….s.

A Forecast of the activity duration is extrapolated by using the seasonal pattern Eq.(6-3)

F_{t+m}=L_t+T_{tm}+S_{t-s+m} *m' is the required forecast period* (6-3)

6.5 Behaviour Detection

In this process, a mechanism was proposed for determining elderly behavior. The behavior of the elderly person was categorized as regular or irregular based on the following conditions. The duration of the current activity was checked with the range of forecast. The forecast was estimated using Eq.6-3. A 95% confidence level was assumed in the forecasting. The allowable range of duration of any regular activity was given by Eq.6-4. If the actual duration was out of the range as given in Eq.6-4, an irregularity flag was set.

$$\text{Duration of regular activity} = \text{Forecast duration} \pm 2^*\text{standard deviation} \qquad (6\text{-}4)$$

6.6 Results and Analysis

A trial system was run in a smart home for collection of sensors' data. It was attempted to learn the daily activity pattern from the collected data then the learning pattern were considered to forecast the elderly person behaviour. The collected sensor data was stored in the appropriate files of the computer, and the sequences of steps as mentioned in sections 6.2 to 6.4 were implemented.

In the forecasting process, the most appropriate fitted curve is computed by adding smoothed trend curve and seasonally adjusted factors as given in section 6.3. For illustration, the non-electrical appliances usage durations and their corresponding trends were considered in the forecasting process. This will elucidate the exact behavior of the elderly person in utilizing the household appliances. Some of the electrical appliances such as water kettle, microwave, and laundry machines are preprogramed and auto control hence they may not aptly provide the forecasting process. The non-electrical appliances usage duration and their corresponding trend are plotted. Fig.6-2 shows bed usage activity durations and its corresponding trend for eight weeks at an elderly person house where they live alone.

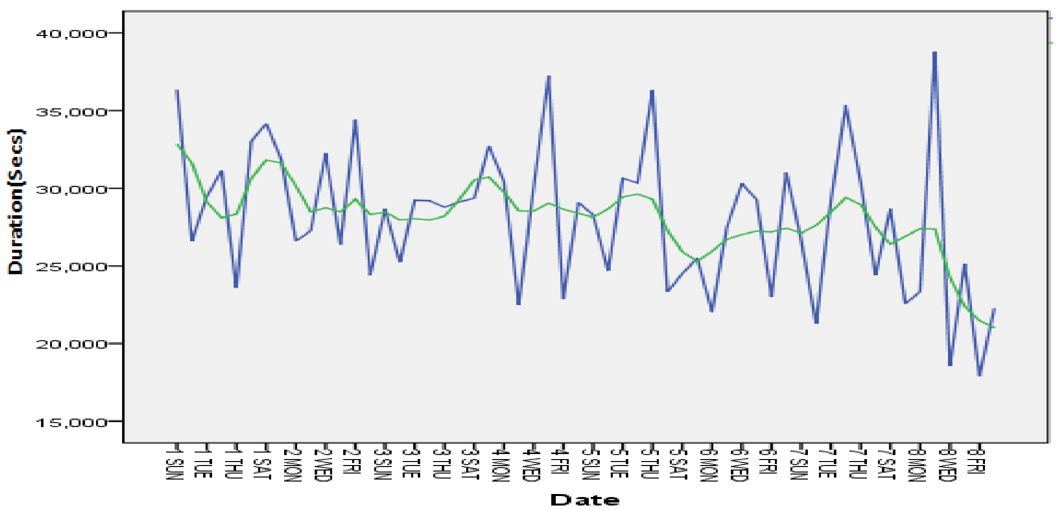


Figure 6-2 Subject #1: Bed usage durations and its trend[5]

[5] (Green color: Trend, Blue color: Actual Observations)

Fig.6-3 shows the toilet usage activity durations and its corresponding trend for eleven weeks at an elderly person house where they live alone.

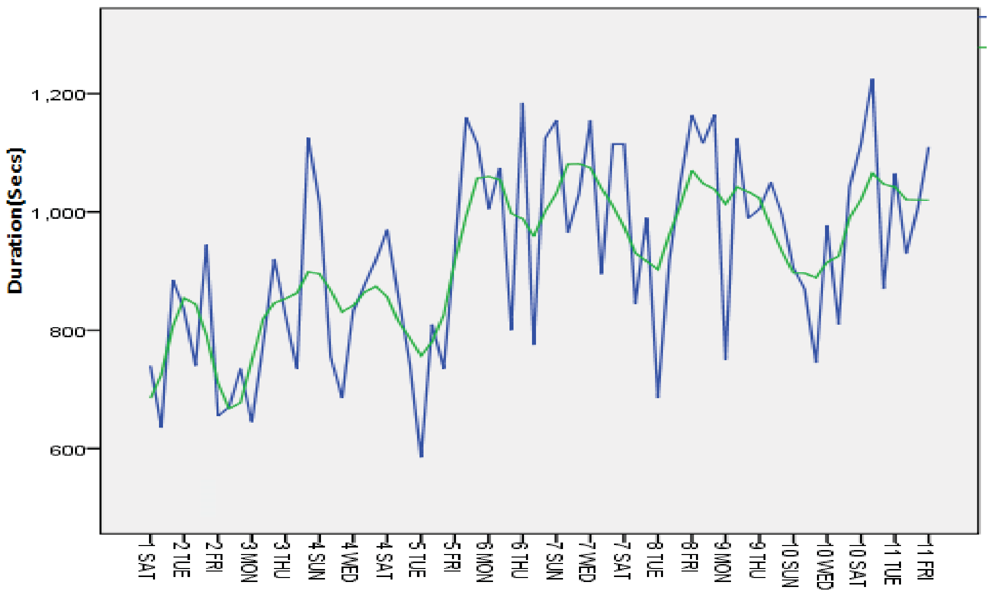


Figure 6-3 Subject #1: Toilet usage durations and its trend

Fig.6-4 shows the Dining chair usage activity durations and its corresponding trend for eleven weeks at an elderly person house where they live alone.

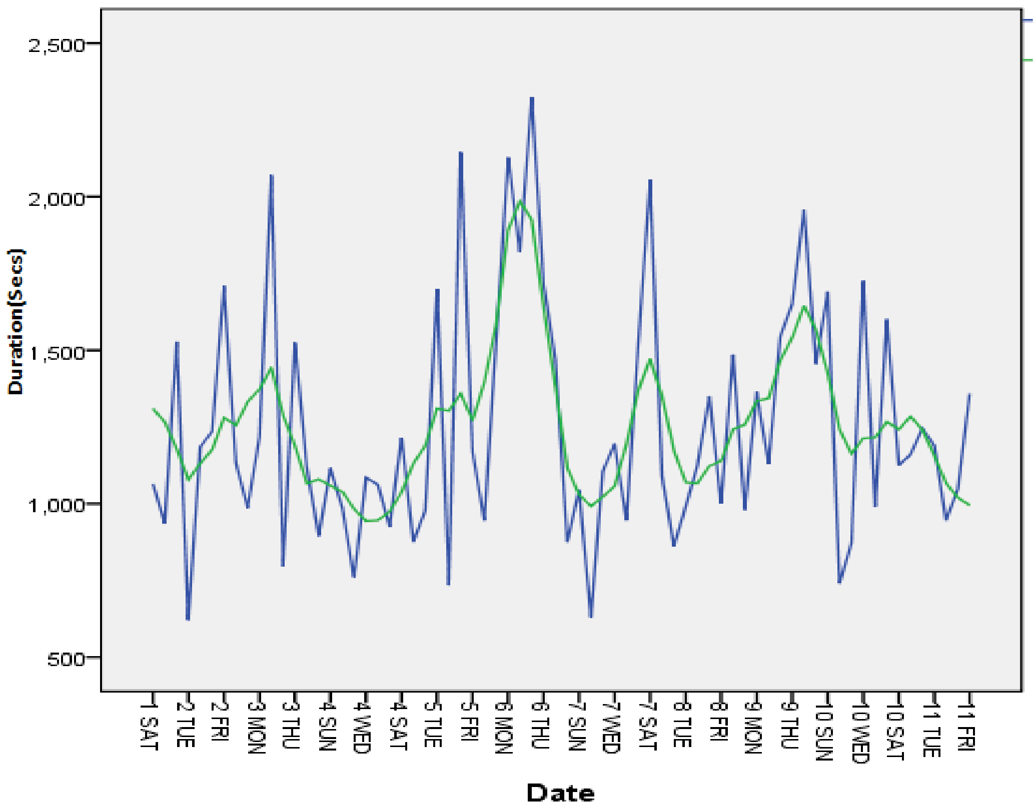
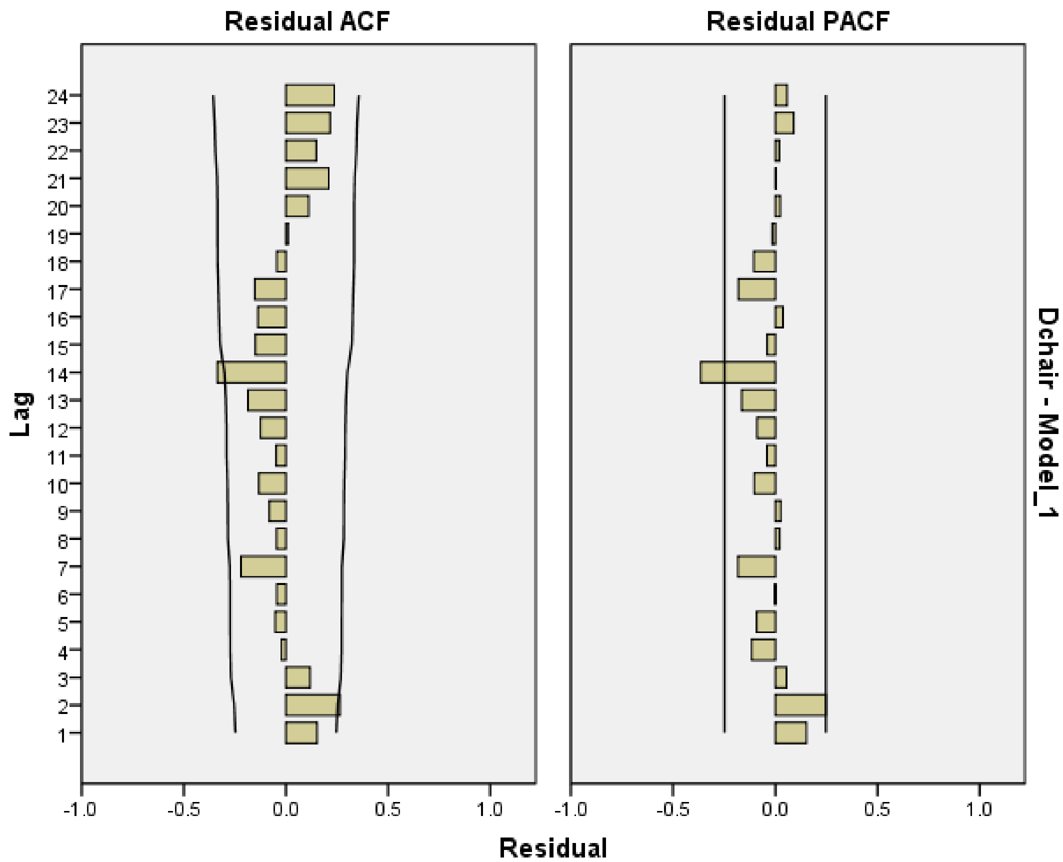


Figure 6-4 Subject #1.Dining chair usage durations and its trend

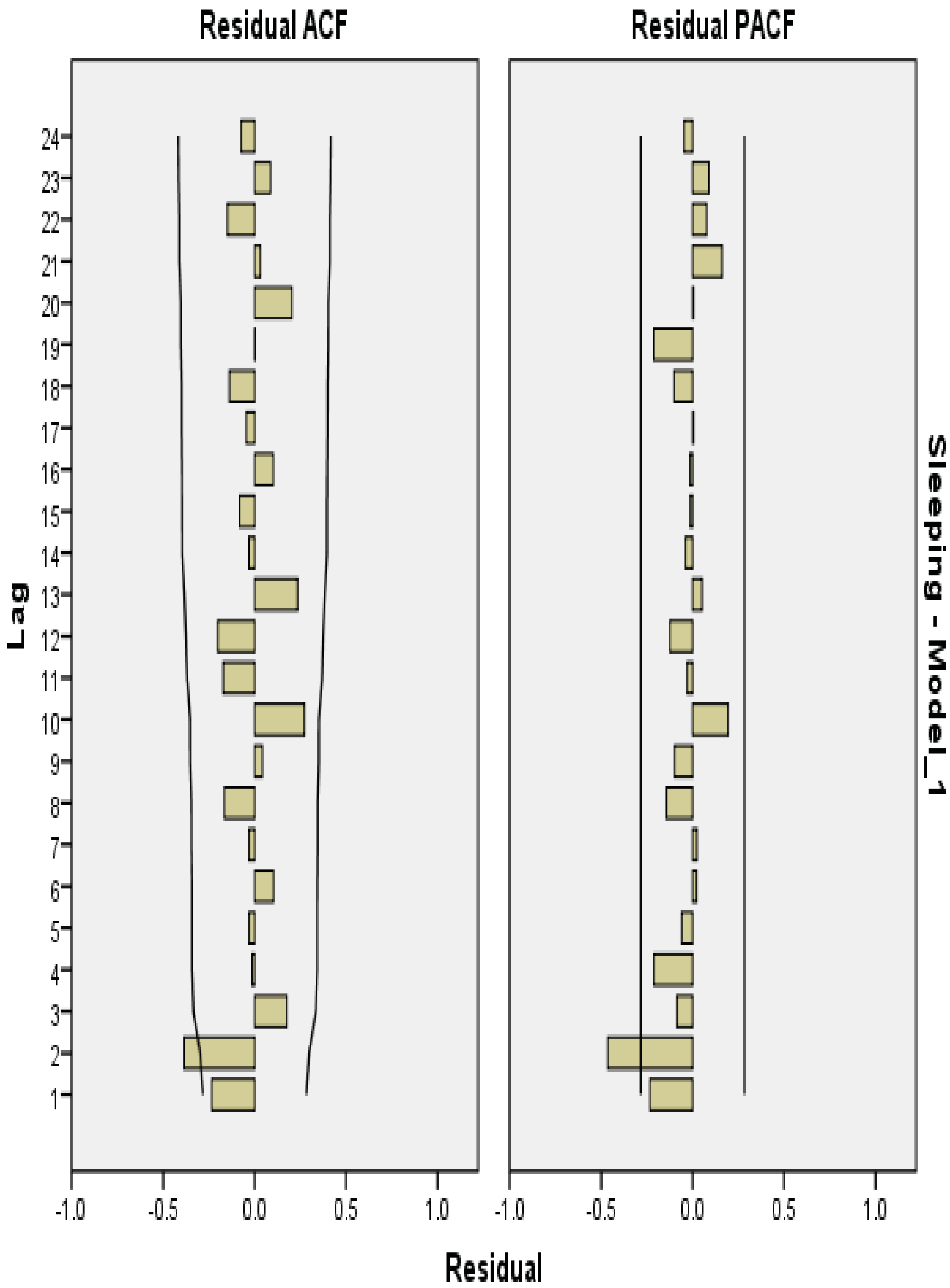
From Fig. 6-2, 6-3, 6-4, it was observed that the ADL (Sleeping, Toiling, Eating activities) time series was not stationary. It is obvious that human behavior is complex and the activity durations may not be constant. In order to have a reasonable ninth week forecast value from the past sensor activity durations, Seasonal-Auto Integration with Moving Average(S-ARIMA) was investigated and it was observed that this method was apt for forecasting and measuring wellness. The values of the S-ARIMA process such as trend, seasonal adjusted factor and residuals of the regression parameters were derived by using the Autocorrelation (ACF) and Partial Autocorrelation (PACF) functions of the time series. Fig.6-5 and Fig.6-6 shows the residual autocorrelations and partial autocorrelation function of time series of the sensing durations for Dining Chair sensing system and Bed Sensing system.



Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		MAPE	Statistics	DF	Sig.	
Dchair-Model_1	0	33.218	32.598	17	.013	0

Figure 6-5 Residual autocorrelations and partial autocorrelation function of time series of the sensing durations for Dining Chair usage durations.



Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		MAPE	Statistics	DF	Sig.	
Sleeping-Model_1	0	16.503	30.675	16	.015	0

Figure 6-6 Residual autocorrelations and partial autocorrelation function of time series of the sensing durations for Bed usage durations

The implemented process in the system is S-ARIMA (ps, ds, qs) (Ps, Ds, Qs)

Where ps: is order of process AR, Ps: is order of seasonal process AR, qs: is the order of process MA, Qs: is the order of MA, ds: is the order of difference, Ds: is the order of seasonal difference.

On the basis of a residual ACF spike at lag 1 and declining toward zero and a residual PACF spike at lag 1 that is also declining toward zero from lag 2, this guided us to select the SARIMA (1, 1, 0) $(1, 1, 0)_7$ model for forecasting process. Following the additive method for the forecasting process, the most appropriate fitted curve was computed by adding smoothed trend curve and seasonally adjusted factors i.e. Forecast=Trend + SAF.

The Seasonally Adjusted Factor (SAF) resulted from the decomposition process considering one week as one season (cycle). Considering a 95% confidence interval, the residuals prevailing in the prediction curve are computed by twice the standard deviation. Table.6-1 show the forecast range values for the ninth week based on eight week sleeping durations and comparing these with the actual values. Except in two instances, the remaining five days bed usage durations have matched correctly. Accordingly, the fitted curve and the forecast for the bed usage duration are shown in Fig.6-7.

Table 6-1Prediction of 9th week Bed, Toilet and Dining Chair usage durations based on SARIMA process

9th Week Duration(hh:mm:ss)								
Bed Usage			Toilet Usage			Dining Chair		
Forecast		Actual	Forecast		Actual	Forecast		Actual
Max	Min		Max	Min		Max	Min	
8:22:11	4:42:11	8:16:17	0:11:32	0:07:45	0:10:51	0:31:29	0:26:20	0:28:45
9:24:57	5:44:57	4:38:13	0:10:21	0:06:15	0:09:10	0:28:45	0:24:10	0:25:24
8:47:36	5:07:36	8:17:46	0:11:25	0:07:20	0:08:55	0:29:10	0:25:38	0:27:49
8:00:02	4:20:02	7:38:17	0:11:50	0:07:35	0:07:10	0:28:10	0:24:48	0:24:20
8:34:19	4:54:19	7:51:38	0:10:48	0:06:45	0:09:54	0:27:35	0:23:45	0:26:36
8:07:15	4:27:15	8:15:01	0:12:10	0:08:28	0:10:25	0:29:20	0:24:46	0:28:20
7:43:36	4:03:36	7:40:32	0:11:50	0:07:26	0:10:45	0:30:10	0:26:50	0:27:10

Two instances were rightly identified as irregular usage of the bed as the elderly person has woke up early at one instance and slept for a longer duration in the second instance. The significance levels of the residuals were less than 2%. The suitability of the predicted curve with respect to observation sequence is also verified by implementing a One-Sample Kolmogorov-Smirnov Test (KS-test) [176] for normal distribution of the errors existing in the predicted curve. Fig.6-8 indicates the errors of predicted fitting as a normal distribution.

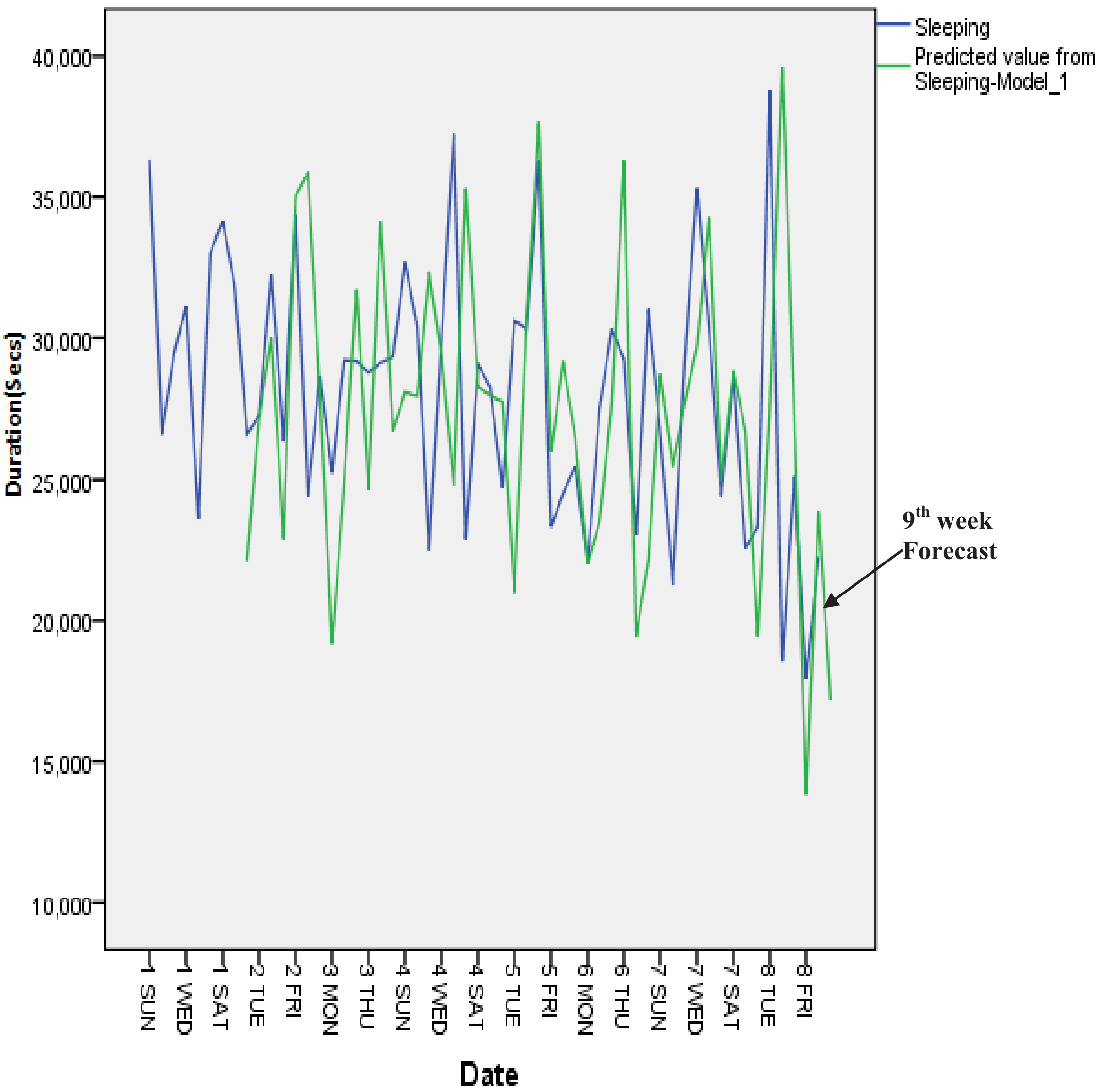
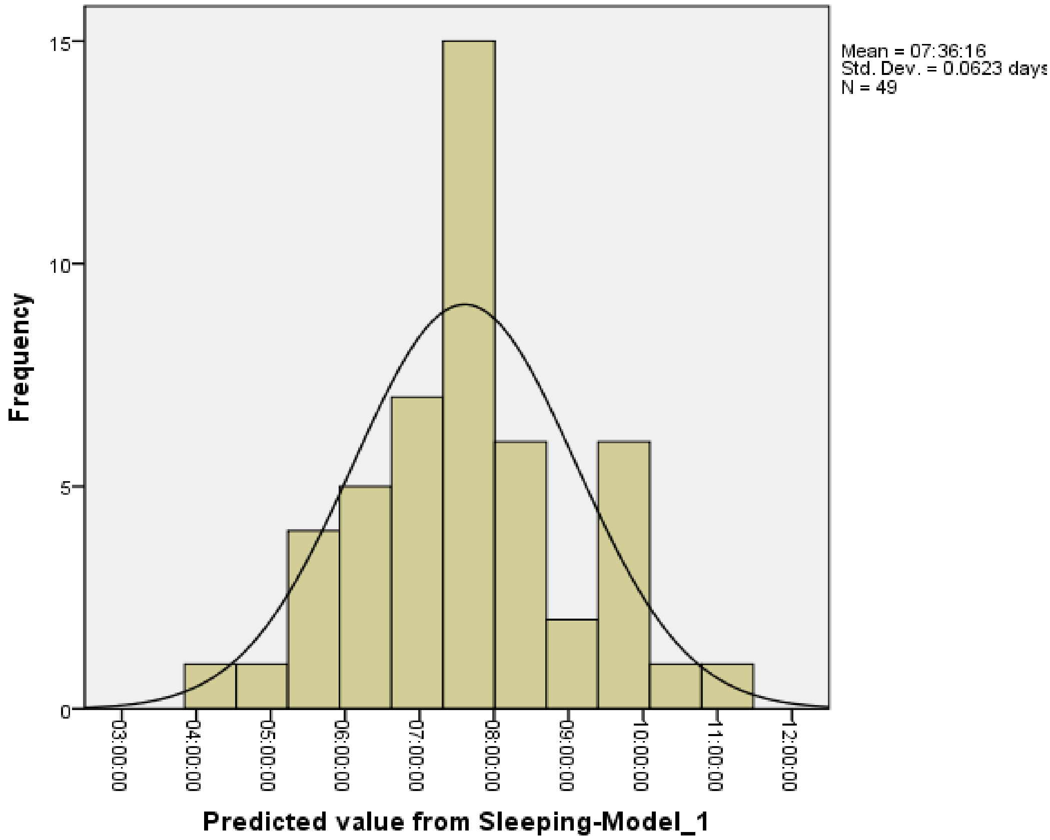


Figure 6-7 Eight week sleeping observations and Ninth week predicted sleeping durations[6].

[6] (Green color: Fitted and Forecast, Blue color: Actual Observations)



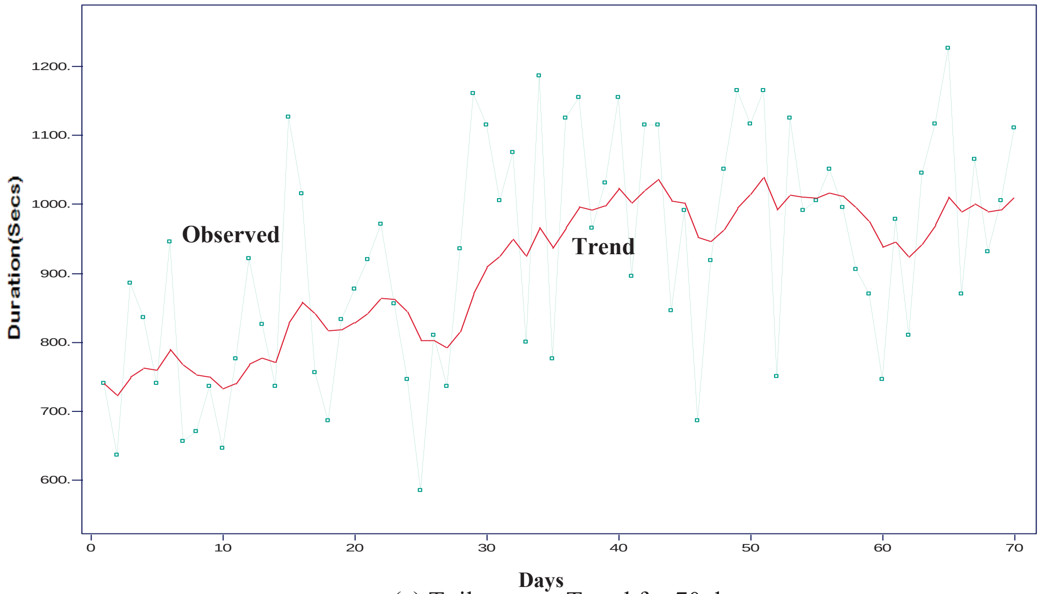
One-Sample Kolmogorov-Smirnov Test

		Predicted value from Sleeping-Model_1
N		49
Normal Parameters[a,b]	Mean	07:36:16
	Std. Deviation	01:29:39.474
Most Extreme Differences	Absolute	.089
	Positive	.089
	Negative	-.065
Kolmogorov-Smirnov Z		.620
Asymp. Sig. (2-tailed)		.837

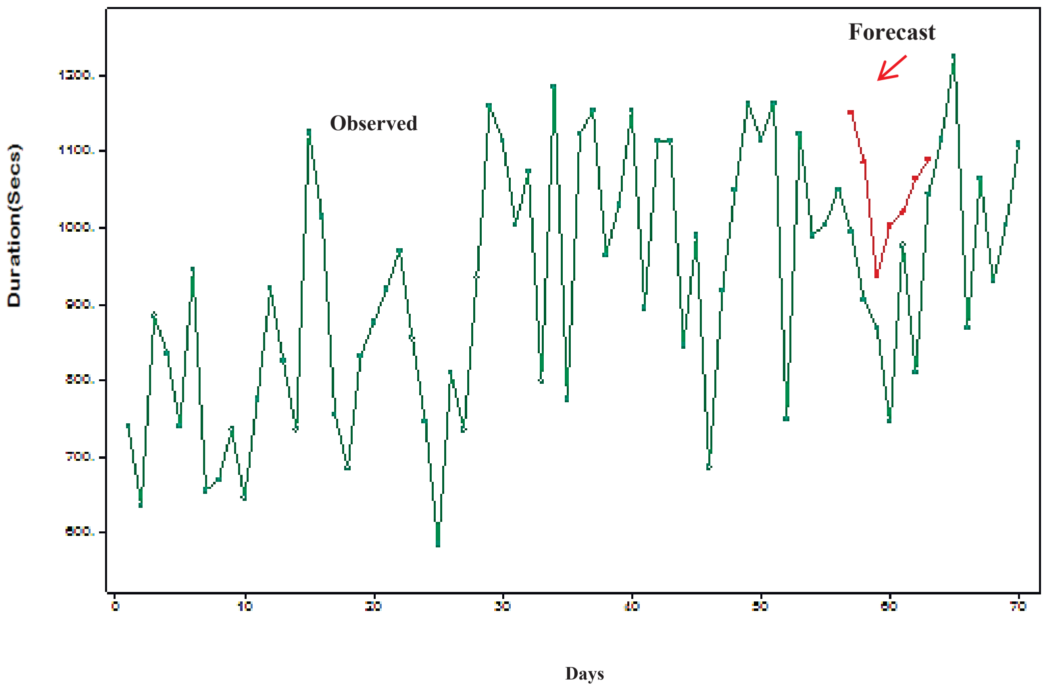
a. Test distribution is Normal.
b. Calculated from data.

Figure 6-8 K-S test result for Normal distribution of predicted sleeping durations

Based on the eight week appliance usages, corresponding trend, seasonal adjusted and fitted curve values as mentioned in sections 6.1 to 6.4 were computed. Ninth and Tenth week prediction of various appliances usages were derived and compared with the actual durations. Following are the illustrations about toilet and chair usages respectively. Fig.6-9 (a, b, c) is about the usage of toilet, its corresponding trend and 9th and 10th week predictions of an elderly at a subject house.

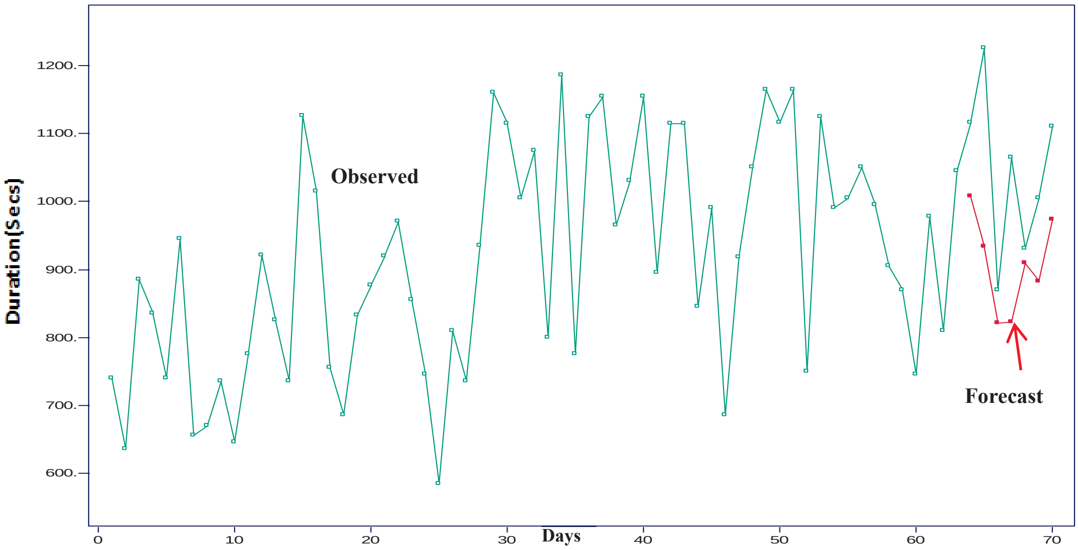


(a) Toilet usage Trend for 70 days



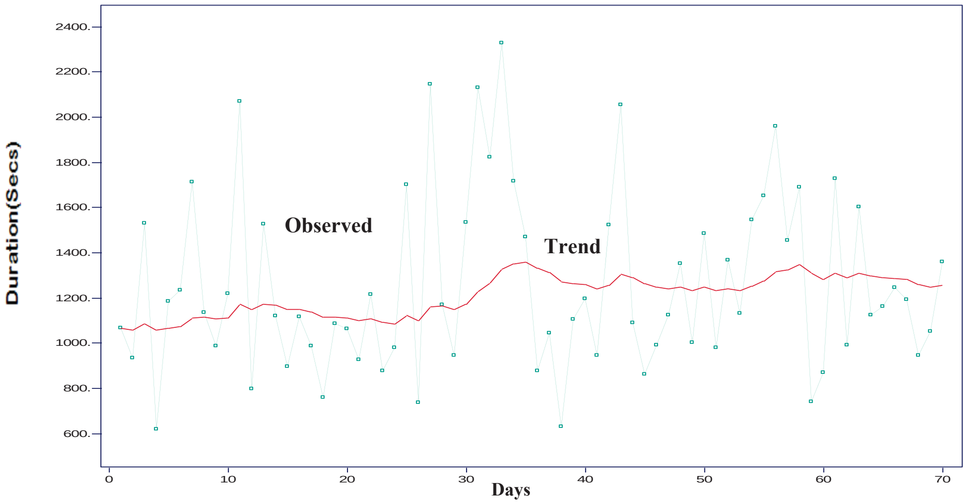
(b) Toilet usage trend and Ninth week forecast pattern

[7]



(c) Toilet usage (Tenth week forecast pattern) for 70 days

Figure 6-9 Toilet usage trend and tenth week forecast pattern



(a) Dining Chair Usage Trend

Fig.6-10 depicts the usage of dining chair by an elderly for a period of ten weeks. Its corresponding trend, forecast for ninth week and tenth week are shown in Fig.6-10 (b,c).

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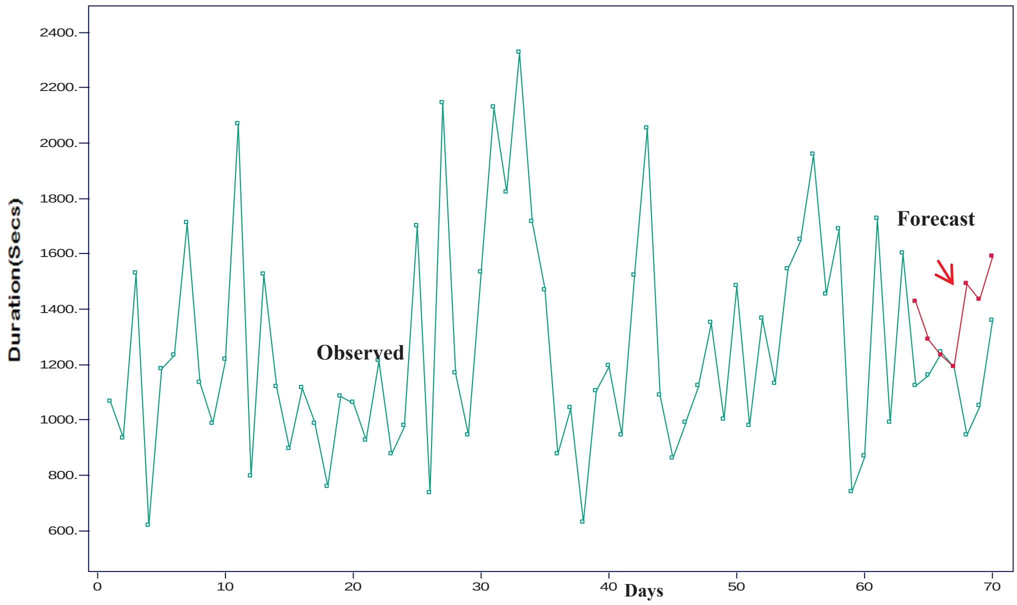
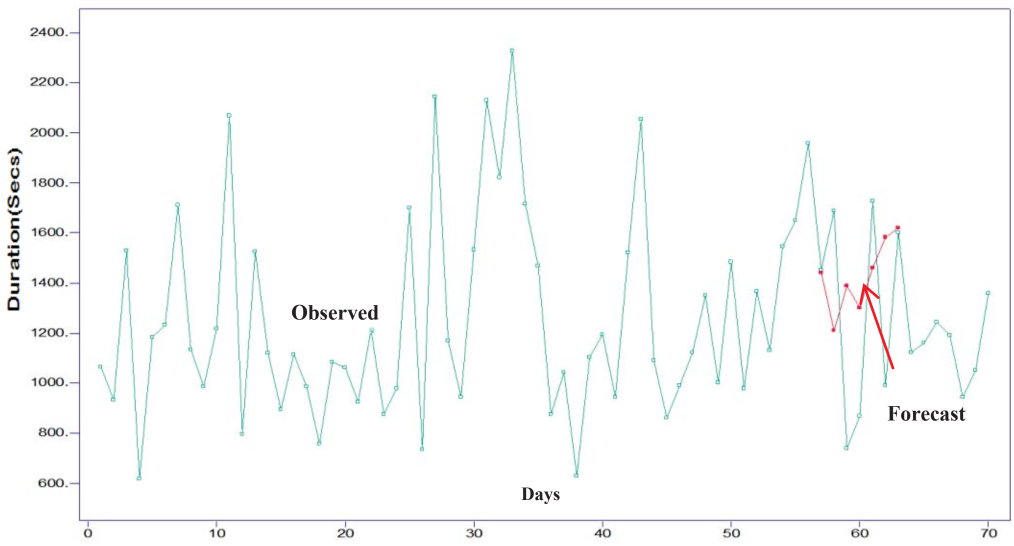
[7] (ALPHA = .140, THETA = .090, GAMMA = .350)



(b) Dining chair Usage and Tenth Week Forecast pattern



(c)

Figure 6-10 Dining chair usage and Ninth Week Forecast pattern

A snapshot of the 9th week (Friday), estimated values based on the recorded eight weeks is given in table.6-2. Considering statistical inference of 95% confidence interval, the residuals in the fitted (predicted) curve were computed by twice the standard deviation. Accordingly, the forecast ranges with maximum and minimum durations were computed according to Eq.6-4. A forecast of an appliance is derived by applying Eq.6-3 as discussed in sections 6.4 and 6.5.

Table 6-2 Wellness function indices of household appliances and forecast of the ADLs

SUB	Activity	Sensor_ID	β_1	β_2	Forecasting for 9th Week-(Friday)					Actual-Duration (Sec)	Status
					Max-Time (Sec)	Min-Time (Sec)	α	δ	Γ		
#1	Sleeping	Bed	0.715	0.829	28456	20405	0.120	0.170	0.650	22505	Regular
	Dining	Chair		0.865	1208	845	.0200	.1100	.2100	1150	Regular
	Toilet	Toilet		0.785	1444	1028	.1400	.0900	.3500	1353	Regular
	Relax	Couch		0.889	1457	840	0.150	0.130	0.540	1104	Regular
	Watching TV	TV		0.915	2806	2205	0.030	0.140	0.100	2608	Regular
#2	Sleeping	Bed	0.829	0.727	30258	23450	0.200	0.180	0.480	27268	Regular
	Dining	Chair		0.504	14545	10425	0.140	0.170	0.300	15580	Irregular
	Toilet	Toilet		0.576	1838	1426	0.160	0.130	0.200	1718	Regular
	Relax	Couch		0.614	2018	1487	0.150	0.040	0.250	1645	Regular
	Watching TV	TV		0.813	3804	2807	0.020	0.050	0.060	3045	Regular
#3	Sleeping	Bed	0.604	0.816	27545	21408	0.030	0.560	0.605	26258	Regular
	Dining	Chair		0.713	16250	12350	0.400	0.600	0.010	15145	Regular
	Toilet	Toilet		0.883	1628	1245	0.300	0.450	0.500	1465	Regular
	Relax	Couch		0.615	1845	1423	0.205	0.300	0.150	1628	Regular
	Watching TV	TV		0.715	4055	3605	0.100	0.650	0.750	3810	Regular
#4	Sleeping	Bed	0.758	0.445	28235	22035	0.205	0.600	0.700	29701	Irregular
	Dining	Chair		0.914	1340	950	0.400	0.250	0.010	1205	Regular
	Toilet	Toilet		0.818	1123	885	0.100	0.200	0.650	1060	Regular
	Relax	Couch		0.756	1630	1245	0.300	0.200	0.250	1420	Regular
	Watching TV	TV		0.828	4838	4210	0.040	0.100	0.200	4506	Regular

It was observed that two instances of irregularity at different subject houses were rightly predicted. These were related to the over-usage of the appliances. In reality, the subject was using a chair for a longer time because he was sitting and talking with a guest on that day. In another instance, the duration of bed-use shows an over-usage, because it was occupied by the elderly person for a long duration as he was unwell. The forecasting procedure has indicated the active durations of the bed and chair were outside the forecast ranges. Accordingly, the behavioral detection process set the status of the corresponding activities as irregular.

6.7 Chapter Summary

In this chapter, the main objective of the data analysis by time series was to find a model which was able to forecast the statistical characteristics of the series, as the model will allow us to predict next values of the series from its past data. This is important as the behaviour of the elderly person changes with time and the changes should be taken into consideration in the model. The following steps were performed in the analysis of data using the time series method: Time series of past data, a suitable method for parameters estimation, the best fitting model for diagnosis and forecasting of new values.

The measurement of daily activities was done through usage of household appliances' sensor data. Predicting the behavior of an elderly person was based on past sensor activity durations. A Combination of sensing system with time series data processing capability will allow us to measure how well an elderly person is able to perform their daily activities in real time. So far, the forecasting process was able to rightly measure the wellness indices related to use of non-electrical appliances. Hence, some of the basic elderly person's daily activities such as sleeping, toileting, dining and relaxing were rightly assessed by the wellness measurement system. Since, most of the electrical appliances usage durations are predefined; validation for activities such as preparing food was limited.

Forecasting the usage duration of objects in smart home by time series modeling can precisely predict how long a particular appliance can be used by the elderly person. This model was helpful in reducing the number of false alarms to be generated. This will enable us to have supplementary information in the data analysis for effective longitudinal forecasting of the sensing durations.

This implies that, over a long period, the forecasting method can optimize the defined wellness indices in the TSDM, thus supporting the behaviour detection more accurately. Also, it was observed that forecast process and wellness functions were not estimated accurately in the initial trial period (i.e., up to eight weeks). Data was not analyzed with the wellness determination process of less than seven weeks. It was inferred that better estimation of wellness functions with time series modeling can be performed with a minimum of 50 observations of activity durations. Hence, the forecasting process was accurate after eight weeks of monitoring. As data is accumulated over a longer period, the determination of wellness function indices and forecast process will be more effective and accurate. If the variations in the activity durations are large, then it is obvious that the standard deviation of the fitted curve and forecast range values will also be large. This was observed in forecasting sleeping duration.

Additionally, the sequence pattern of the sensors with temporal constraint was analyzed by a Sensors Activity Pattern (SAP) technique. The sequence of sensor stream on the basis of the day and time of the day are considered in analyzing the pattern. The next chapter discusses the SAP technique in revealing the sequence usage of sensors for detecting behavior of an elderly person and reducing the false warning messages related to irregular behaviour.

Chapter 7. Sensor Activity Pattern (SAP) Matching Process and Outlier Detection

7.1 Introduction

The AAL technology in the home environment is fitted with motion sensors to trace the movements of the residents in the home. The smart home technology is acceptable to the people only if it is operational with a low-profile [60] (i.e.,) the sensor environments should be capable to take care of the privacy-aware conditions of residents [177].

There are diverse approaches for tracking people in smart home technologies such as carried devices/tags [178], video (camera) biometrics [178], and Entity detection with space and time considerations [178]. In general, the base station of the centralized system reports the present position of the wearable device. This can be done through Personal Digital Assistants, mobile phones, custom built RF devices [178]. While these kinds of systems work, they do require every individual in the home environment to hold their personal devices at all times. It is easy for the residents to forget their device, or the batteries of the electronic gadgets run down. Most of the tracking algorithms are based on the use of Bayesian Updating Graphs (BUG), Markov Models, Graph and Rule based Entity Detector [179]. The existing tracking algorithms either use expensive and invasive sensors (e.g. a camera system) or depend on assumed movement models or test bed scenarios [178]. Moreover, a large number of sensors deployed in the house to track the person will be costly and their acceptability to the elderly person will be an issue. In many AAL environments, this is an unfeasible solution, given the manpower to maintain it. In general, the monitoring environment such as hospitals and full time residential care facilities are more likely to make use of large sensor systems [178].

However, in private homes, it becomes less feasible solution for tracking the inhabitants using the above mentioned approaches. For video biometrics, one or more cameras are placed around the monitored space [180]. These cameras capture the images of residents for tracking and processing [180] [181]. The purpose is to interpret the video images to identify individuals, detect ADLs and give more contexts to item interaction. While these methods are good at some tasks, the use of cameras is a very challenging factor of acceptance for the residents relating to their privacy.

Monitoring inhabitants continuously using video images at homes will be extremely unacceptable. Tracking people in smart home environments has many advantages, such as: data delivery to mobile users [182], mobile and social localization [183] and smart wireless healthcare. Inhabitants in smart home environments can be monitored unobtrusively, non-invasively and taking care of privacy issues effortlessly using low profile sensing systems as discussed and presented in section 3.3.4.

The purpose of monitoring the movements of an elderly person inside their house is to explore the elderly person's movement's context for timely tracking of their respective ADLs. The monitoring process of household appliances does not fully provide the physical activity information about the elderly person for all the twenty four hours. If a person is using a habitual object such as a sewing machine, continuous involvement of the person is required with the domestic object and, therefore, provides much better information for the wellness determination process. If a person uses a domestic object such as a microwave oven, it is essential that a person need to act with the object physically from the start of the usage. But then, it is not important for a person to stay continuously with the object. Also, during the time when no appliances are used, it is extremely difficult to tell about wellness of a person. That is one of the reasons of generating many false warning messages. Even though the person is at home, if he/she does not use any domestic appliances such as bed, couch, chair etc. all the time, it is important to know the whereabouts of the person inside the house for the wellness determination process.

A typical scenario in the smart home environment can be viewed as monitoring various household appliances for recognition of ADLs to know the wellbeing of the inhabitant. It was observed that in the case of an elderly person, the usage of the domestic objects is recurring and at fixed intervals of time. However, their usage durations and their frequency are varied at different contexts. Fig.7-1 shows the sensor activations of various domestic objects at different times in twenty four hour period.

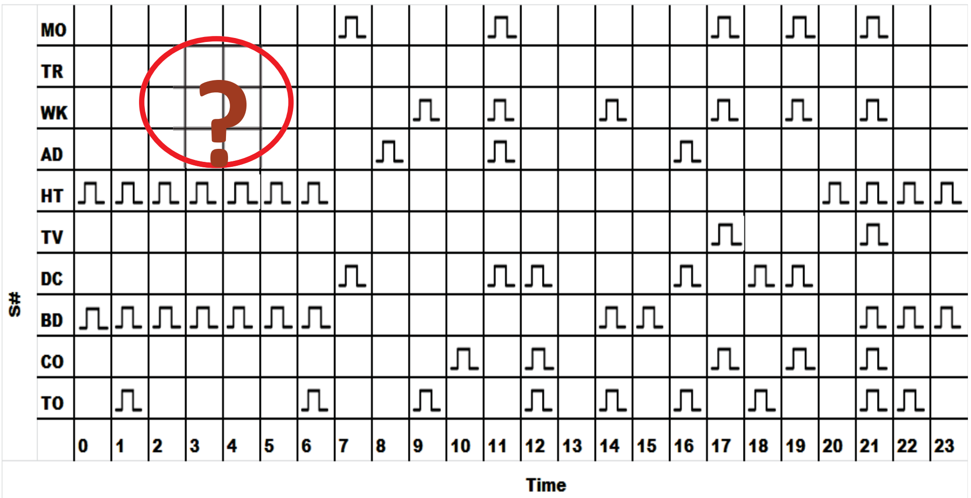


Figure 7-1 Domestic object sensor activities at different times in a day at an elderly person house[8]

Another interesting observation from Fig.7-1 is that, at some time periods there was no usage of domestic objects. In Fig.7-1, ("?") shows the time period in which there was no usage of domestic objects, and we do not know what was the activity of the elderly during that empty time slot (i.e., when there is no household object usage). In order to investigate the behaviour of an elderly person in depth and breadth for 24 hour period apart from household objects monitoring, monitoring the movements of an elderly person can provide proper inference for the recognition of the ADLs assessment.

A novel approach termed as Sensor Activity Pattern (SAP) for scalable tracking path of an elderly person with a limited number of sensors was designed and developed. The objective of this method was to provide a quality assistive technology and at the same time provide an effective quantitative measurement for the wellness of an elderly person in relation to their daily activities performance. For this, a limited number of movements sensing systems (PIRs) in an unobtrusive manner were used in this research to know the location of the elderly person and at the same time they could support wellness determination indices.

The fabricated PIR sensing units were placed at the focal points inside the house to track the movements of an elderly. The elderly movements were recorded in the home monitoring system with attributes Date, Time and Location (based on Sensor Identifier). The presence of an elderly person (at the instant of time) was known with the help of the real-time "ON" status of the respective PIR sensors located at important places of the house.

[8] (MO: Microwave Oven; TR: Toaster; WK: Water Kettle, AD: Audio, HT: Heater; TV: Television; DC: Dining Chair; BD: Bed; CO: Couch, TO: Toilet)

7.2 Sensor Activity Pattern (SAP) Algorithm

The SAP matching process is principally mining the sequential pattern of the real-time sensor stream. It is basically a novel depth-first strategy that integrates depth-first traversal of the search space with effective pruning mechanisms. The pruning mechanism is applied based on a support function which is dynamically adaptable with the occurrence of the sensor stream in order to reduce the search space in the depth first traversal.

7.2.1 Notations and Definitions of the SAP Algorithm

A sequence $S = \langle S_1, S_2, S_3, \ldots \ldots S_L \rangle$ is an ordered list of PIR Sensor Identifiers(SID) for $1 \leq L \leq F$, where 'F' is a constant representing the number of focal points under the monitoring environment (i.e., 'F' is the number of PIR motion sensors required for tracking the movements of the elderly person and may vary for different home environments). In the present HMS set-up, seven PIR sensors were placed at different important places of the elderly home. A PIR sequential Database is a set of sequences denoted as (PD). The length of a sequence $|S|$ is defined to be the number of SIDs in S. The number of sequences in PD is denoted as $|PD|$.

A sequence s= $\langle s_1, s_2, s_3, \ldots \ldots s_l \rangle$ is called a sub-sequence of sensor identifier's $\acute{S} = \langle \acute{S_1}, \acute{S_2}, \acute{S_3}, \ldots \ldots \acute{S_m} \rangle$, if $l \leq m$. A sequential database $\acute{PD}$ is generated from PD by deleting insufficient support sequences of PD. The insufficient sequences term is related to the sequences that do not have sufficient support in the database. The support sequence of the sequential database $\acute{PD}$ derived from the PD is defined as

$$\sigma_{\acute{PD}}(s) = {|\acute{PD}_S|}/{PD}, \text{ where:} \acute{PD}_S = \{s_i |\ s \subseteq s_i \wedge s_i \in \acute{PD}, i \in 1, 2, 3, \ldots l\} \qquad (7\text{-}1)$$

The SAP is the term referring to the sequence supported by many PIR sequences in the PD. The Expected Database (EDB) of an SAP has restricted sequences of PD that Support SAP. A SAP of length 'l' is frequent if the sub sequences are frequent. If SAP of length l is infrequent, then any lengthier SAP that includes sequences will not be frequent and therefore exclude such SAP for further processing. A node 'n' in the SAP tree is the time instance (Hour) of the Day. σ^{-1} is the least length 'l' that SAP must have to support condition to be called as frequent. Table 6.1 provides the details of the SAP algorithm.

Table 7-1 Sensor Activity Pattern (SAP) Algorithm

Objective: *What are the possible sets of sequences of PIR (motion) Sensor Identifiers at a particular time of the day?*

Input: File containing data with ON status of the PIR sensors and time stamped event. (Initial Data Base contains all the active PIR sensors information located at focal points of the house. As the Sensor Activity Pattern Pruning process is running continuously, optimal sequences of active PIR (i.e., frequent sequence patterns of PIR sensors on a particular Day of the Week and at a particular instance of Time) will be evolved with better support value for sequence patterns).

Output: Possible active PIR motion Sensor Identifier sequences at a particular instance of time.

Algorithm:

Sensor Activity Pattern–Pruning (node n= $\langle s_1, s_2, s_3, \ldots\ldots s_l \rangle$, S_n)

(1) EDB = $\emptyset$,Support=0
(2) For each ($i \in S_n$)
(3)   If ($(s_1, s_2, s_3, \ldots\ldots s_l, \{i\})$ is frequent)
(4)   EDB = EDB $\cup$ $\{i\}$
(5) For each ($i \in$ EDB)
(6) Sensor Activity Pattern-Pruning($(s_1, s_2, s_3, \ldots\ldots s_l, \{i\}$, EDB, all elements in EDB greater than 'i' and satisfies ***Support(EDB)*** **// Generating EDB at node i that satisfies Support for the SAP**
(7) ***Support (EDB)***: Each Sequence in $\acute{PD}$ has SAP as its prefix. If SAP is not frequent, and in order for the SAP to propagate to frequent then it should have a length at-least σ^{-1}(SAP).

The property of the support function enables the SAP process to have less computational space. Ex: Let a sequence 'S' is represented at node 'n' of the EDB. The largest SAP that S can support is of the length$|S| + |SAP|$. If $|S|+|SAP| < \sigma_{PD}^{-1}$ (SAP), then S is too small to support frequent patterns that have SAP prefix. This property will be able to prune the space computation in terms of searching the possible patterns of the sequential database. Each sequence in the tree can be considered as a sensor sequence extended. A sensor sequence extended is generated by adding new sensor_id at the end of the parent sequence in the tree. The SAP process uses the $|S|+|SAP| < \sigma_{PD}^{-1}$ (SAP) pruning principle to reduce the search space for generating frequent sets of patterns. If there are no frequent sets of patterns then the search space of the possible sequences of the sensor stream in the tree sequence will be less. Thus, the SAP process will be able to predict the possible sequence of sensor ids on a particular day at a particular time period. Fig.7-2 shows the pictorial representation of the SAP process tree.

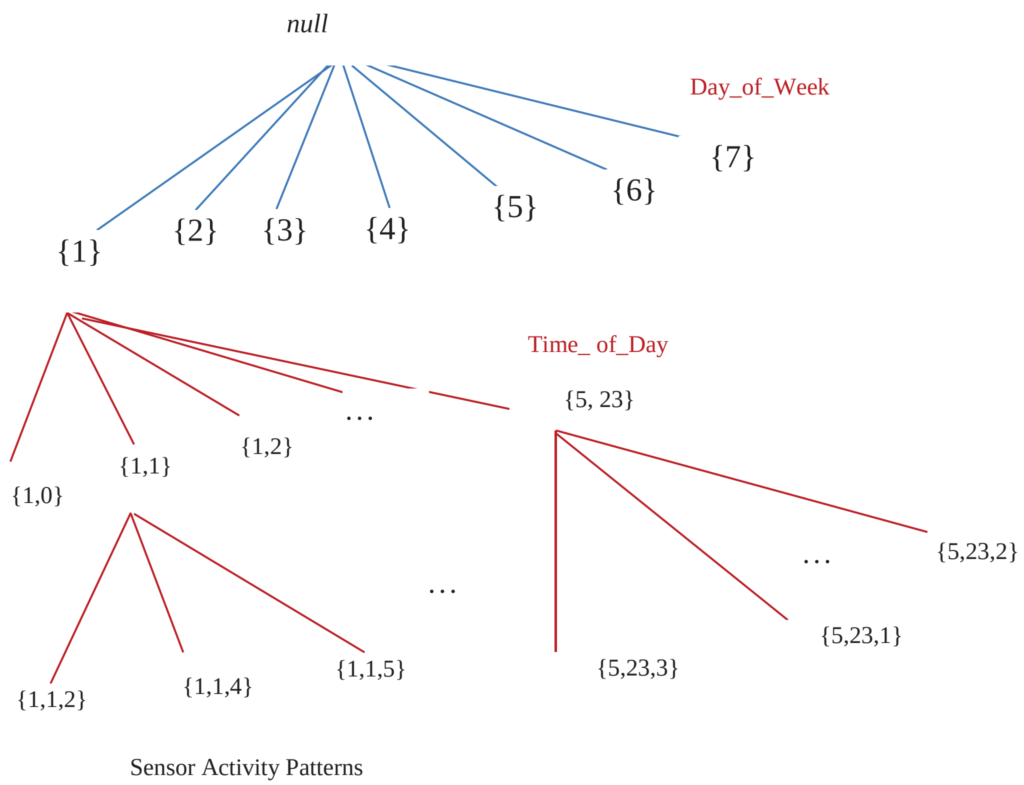


Figure 7-2 Sensor Activity Pattern Tree

7.3 Results and Analysis

The objective of the SAP method was to track the movements of an elderly person and infer the top sequence of PIR sensing systems at a particular time (hour of the day). It was beneficial to use a restricted number of movement sensors to determine the physical location of the person at real-time. Fig.7-3 shows the placement of PIR sensing systems at the focal points inside the house. It also shows other different sensing systems for monitoring of different domestic objects and effective reasoning of the well-being assessment. Seven fabricated PIR sensing units are placed at the focal points inside the house to track the movements of an elderly person . Fig.7-4 shows the movements of a subject inside the house as seen on a webpage.

Figure 7-3 Placement of the PIR sensing systems inside the home

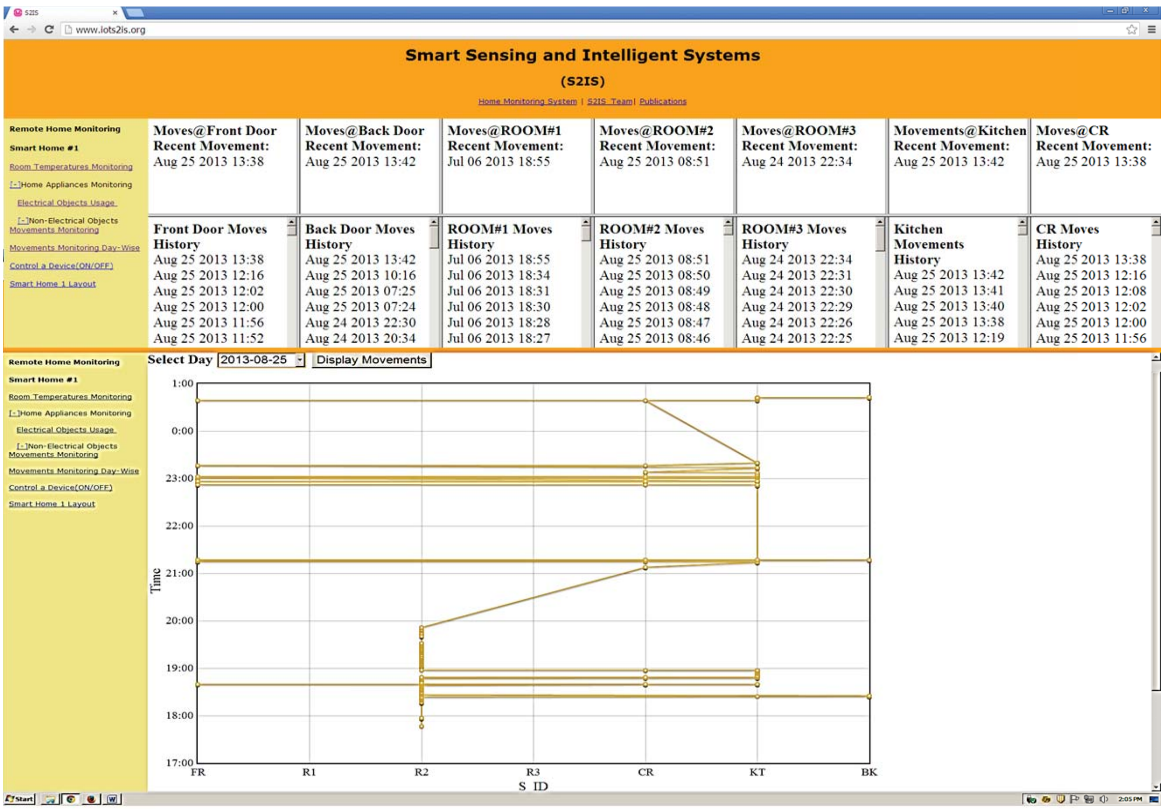
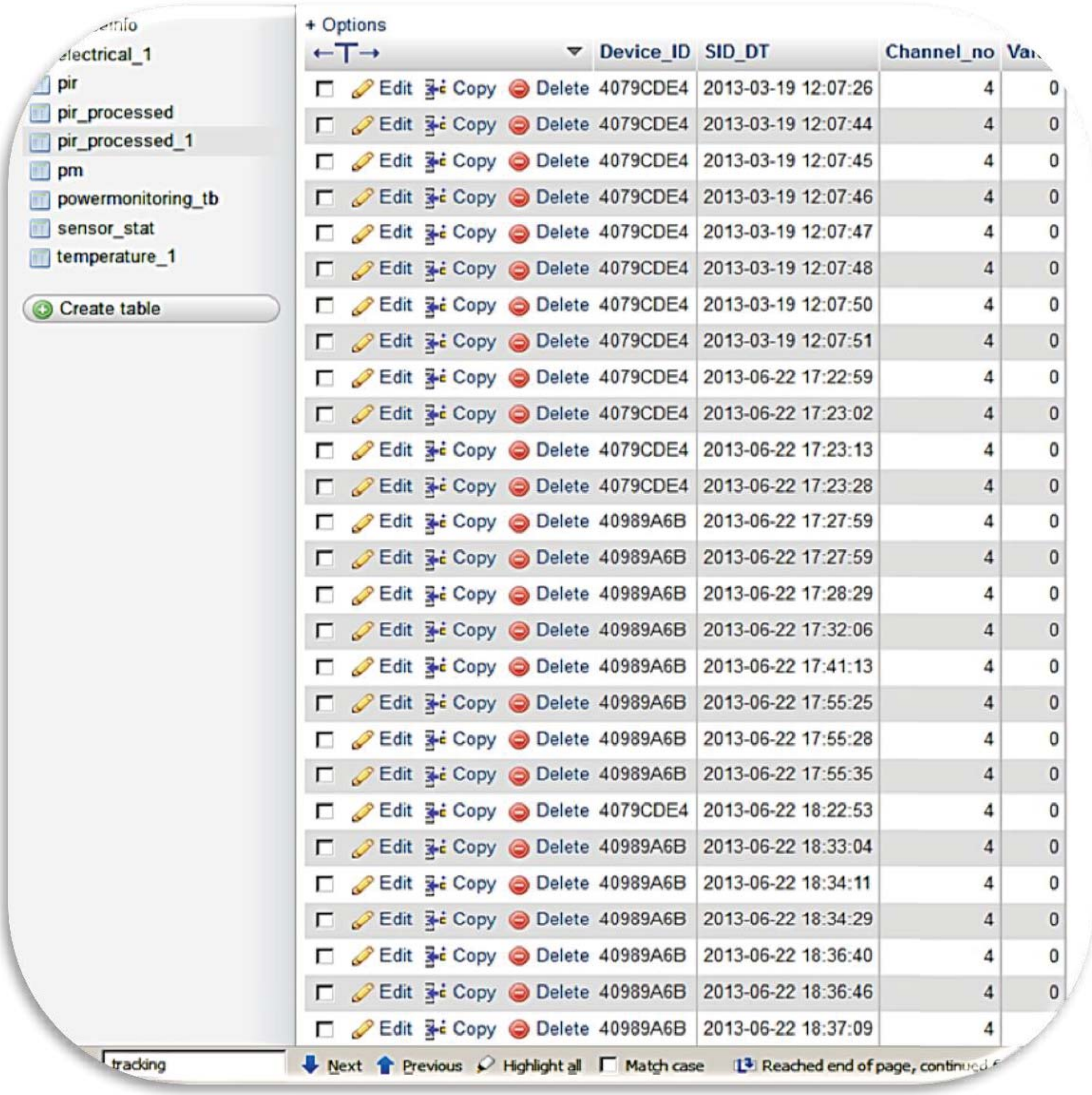


Figure 7-4 Movements of a subject on a particular day as shown on the webpage

Fig.7-5 shows the snapshot of the collected PIR sensor data in a database file of the HMS.



Device_ID	SID_DT	Channel_no	Va
4079CDE4	2013-03-19 12:07:26	4	0
4079CDE4	2013-03-19 12:07:44	4	0
4079CDE4	2013-03-19 12:07:45	4	0
4079CDE4	2013-03-19 12:07:46	4	0
4079CDE4	2013-03-19 12:07:47	4	0
4079CDE4	2013-03-19 12:07:48	4	0
4079CDE4	2013-03-19 12:07:50	4	0
4079CDE4	2013-03-19 12:07:51	4	0
4079CDE4	2013-06-22 17:22:59	4	0
4079CDE4	2013-06-22 17:23:02	4	0
4079CDE4	2013-06-22 17:23:13	4	0
4079CDE4	2013-06-22 17:23:28	4	0
40989A6B	2013-06-22 17:27:59	4	0
40989A6B	2013-06-22 17:27:59	4	0
40989A6B	2013-06-22 17:28:29	4	0
40989A6B	2013-06-22 17:32:06	4	0
40989A6B	2013-06-22 17:41:13	4	0
40989A6B	2013-06-22 17:55:25	4	0
40989A6B	2013-06-22 17:55:28	4	0
40989A6B	2013-06-22 17:55:35	4	0
4079CDE4	2013-06-22 18:22:53	4	0
40989A6B	2013-06-22 18:33:04	4	0
40989A6B	2013-06-22 18:34:11	4	0
40989A6B	2013-06-22 18:34:29	4	0
40989A6B	2013-06-22 18:36:40	4	0
40989A6B	2013-06-22 18:36:46	4	0
40989A6B	2013-06-22 18:37:09	4	

Figure 7-5 Database file of PIR sensing systems data

The PIR Sequence Database consists of the collected raw data of the PIR motion sensors. The attributes of the table are the sensor identifier, time stamp, channel number and status value. The raw PIR sensor data is processed at the coordinator workstation of the sensor network to have the input data file of SAP in the sequence form as (Day_of_Week, Time_of_Day, Sensor_Identifier). A "one minute" time window is considered as a set of sequence identifiers, so that the sensor identifiers within the same minute are considered to be of a particular "Sequence". Fig.7-6 shows the fragment of the PIR sensor sequences on a particular day and at a specific hour in a computer file for processing.

```
R2 #}R2 #}R2 #}R2 #}R2 #}R2 #}R2 #}R2 #}R2 #}R2 #}R2 #}KT

#}KT #}R2 #}R2 #}R2 #}R2 #}R2 #}R2 #}R2 #}R2 #}KT #}KT

#}FR KT #}KT #}KT #}KT #}KT #}KT #}</20>

KT #}KT #}KT #}KT #}KT #}CR FR KT #}R2 #}R2 #}</19>

CR #}CR R3 FR #}KT #}</15>

BK #}FR KT #}CR R3 FR #}R3 #}BK #}</14>

BK CR KT #}R2 #}R2 #}R2 #}KT #}R2 FR KT #}</08>
```

Figure 7-6 Fragment of the sequence of PIR sensors at a particular hour of the day

The PIR Sensor ID’s order within a minute is considered as a “Sequence” and has the delimiters as “#}” “</” Hour “>”. Ex: The meaning of a pattern sequence ***“FR CR KT #} BK #} KT CR R2 #} </06>”*** is given in Table.7-2.

Table 7-2 Sensor Sequence Pattern Meaning

PIR pattern sequence in a particular minute	Hour of the Day	Meaning of the Pattern
FR CR KT #}	06	Front Door to Centre of the House to Kitchen
BK #}	06	Movements at the Back Door
KT CR R2 #}	06	Kitchen to Centre of the house to Room2

Fig.7-7 and Fig.7-8 show the graph and grouped matrix of frequent patterns occurring between the PIR sensor-ID’s on a particular day (Tuesdays).

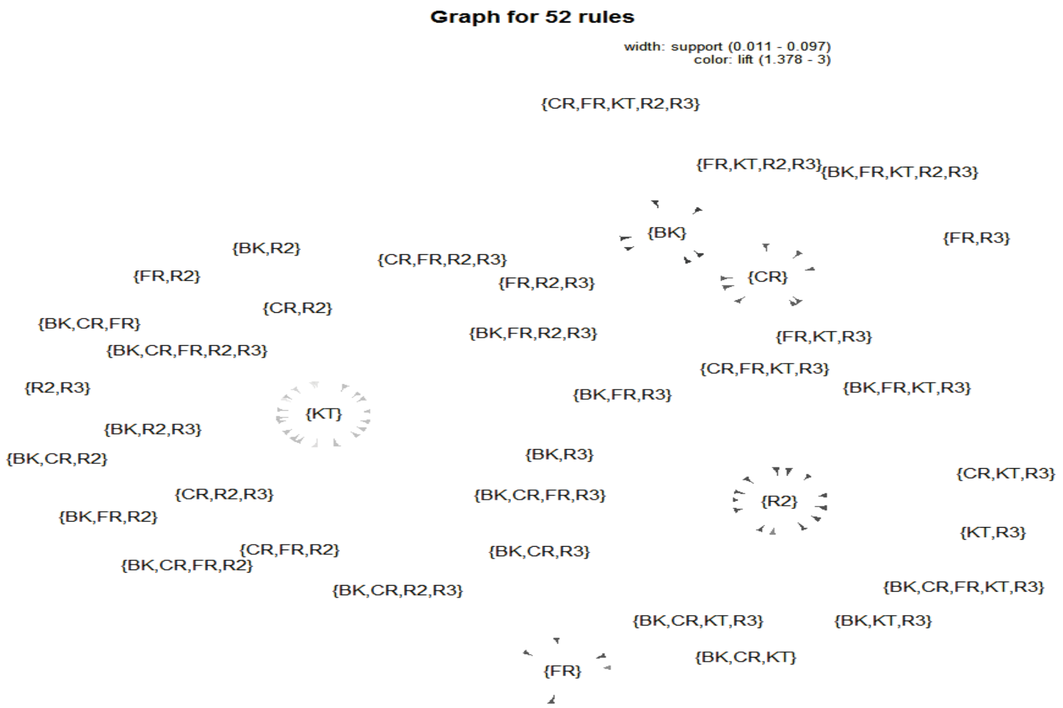


Figure 7-7 Frequent patterns (rules) of PIR Sensor ID’s on the Tuesdays movements in the form of graph representation and the concentration of sensor IDs

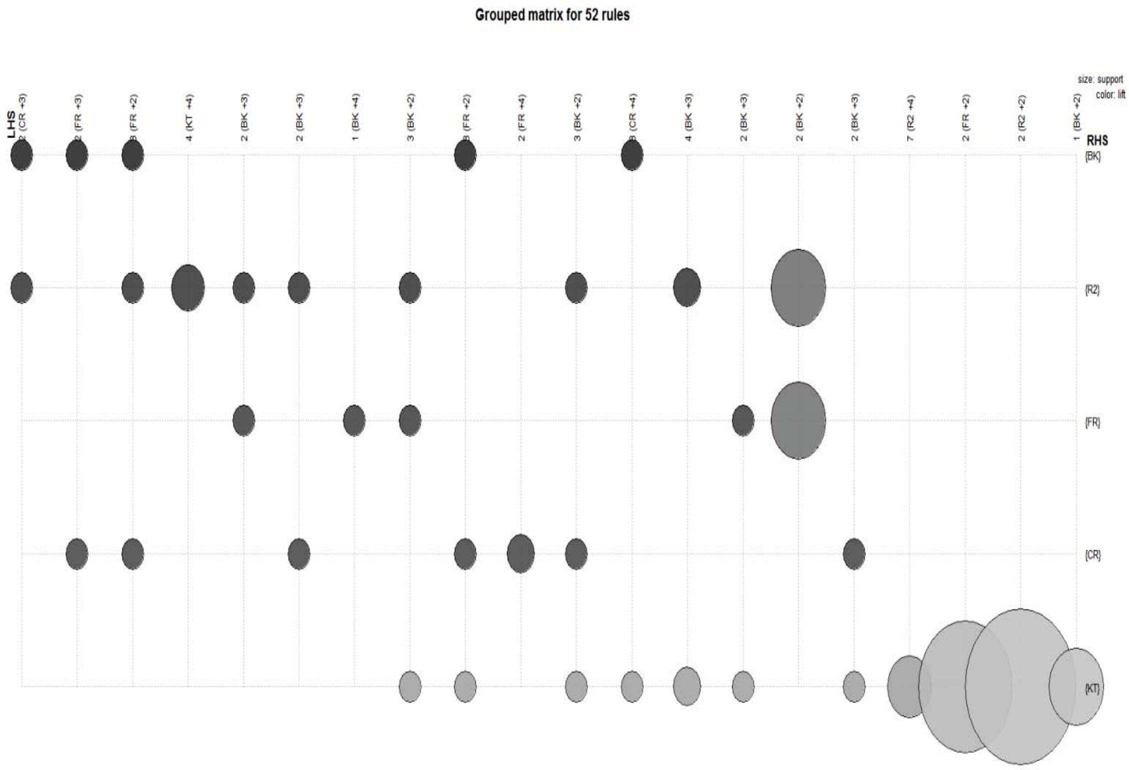


Figure 7-8 Frequent patterns (rules) of PIR Sensor ID’s based on the Tuesdays movements-Grouped matrix representation

The data considered for illustrating the SAP method is of an elderly person's movements at the subject house from 21-05-2013 to 06-08-2013(Only Tuesdays). With the support of 0.011 there were 52 rules generated from the set of the PIR database. The generated rules are based on the support description as discussed in Eq.7-1. The frequent pattern PIR sensor IDs concentrated at the focal points (i.e., at different positions in the home) are shown in both the graphs. In order to avoid the redundancy of the frequent patterns, the support functions as given in Eq.7-1 is tuned to have less numbers of frequent patterns.

Thus, it was observed that the data generated from the home environment was often dynamic, and the sequences of the sensor stream were changing over time. To adapt the discovered patterns to the changes, the most frequent patterns of PIR sensor activations of the elderly at an instance of time were maintained in PIR sequence database. From the procedure as mentioned in section7.2, the frequent patterns that are related to the focal point on each day of the week are depicted in the graphs. Fig.7-8 shows the different balloon sizes indicating cluster size (big size balloon indicates more frequent movements between the sensors at that particular time). From the generated frequent rules, optimal patterns are selected to know the status (position) of the elderly person at that instance of time which will support in the assessment of ADL recognition.

7.4 Sensor Activity for ADL Pattern Discovery

The likelihood of ADL patterns are generated from the sensor stream data by applying the SAP process. The temporal reasoning on the activity of the elderly person is considered in the SAP process. Based on the real-time sensor stream and the likelihood of ADL patterns, the behaviour of the elderly person is determined as regular or irregular. The SAP method uses a depth-first strategy that integrates depth-first traversal of the search space with effective pruning mechanisms. The pruning mechanism is the same as described for the PIR movement's recognition as presented in section 7.2. The pruning mechanism is applied in order to reduce the search space in the depth first traversal. The information required in the ADL behaviour determination process is: i) sensor stream data consisting of week days or weekends and time of the day. In this method, the time window of the day slots is considered as three hour duration. Fig.7-9 shows the temporal map for identifying the ADL behaviour of an elderly person during the particular time slot on a particular day.

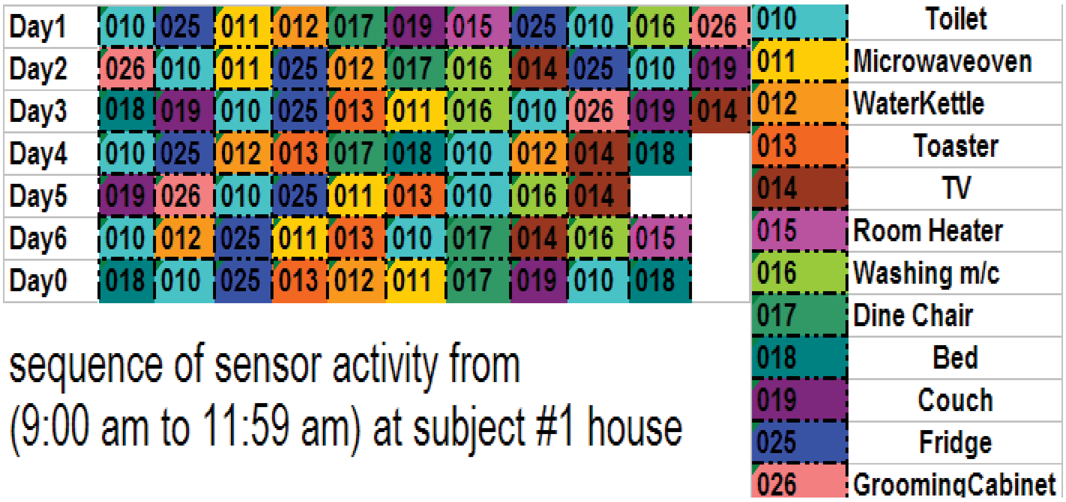


Figure 7-9 Sensor sequence at a time slot during different days of a week

A lexicographic tree sequence is constructed in depth first traversal. Each sequence in the tree can be considered as sensor sequence extended. A sensor sequence extended is generated by adding a new sensor_id at the end of the parent's sequence in the tree. Ex: If we are currently at the sensor node for sequence (10) and can reach sequences (10, 11), (10, 12), (10, 13). Then by pruning principle if (10, 13) is not frequent then (10, 11, 13), (10, 12, 13) all cannot be frequent or do not occur. Table. 7-3 shows the temporary I/O files snapshot of the household objects sensor sequences to recognize the ADL patterns.

Table 7-3 I/O files snapshot of the household objects sensor sequences to recognize the ADL patterns

Input File contents Sensor activity sequence during trial run			Output File contents from SPA process Sensors Likelihood sequence	
Day_of_Week	Time_Slot	Sensor_ID	Sensor_ID Sequence, Delimiter	Meaning (During (9-12)time slot and based on trial sensor activity sequence, probable usage of household appliances
1	1	10	…….	…….
1	1	25	10,18,25,26,-1	Toilet->Bed->Fridge->Grooming Cabinet
1	1	11	10,18,26,-1	Toilet->Bed
1	1	12	10,19,-5	Toilet->Couch
1	1	17	10,19,25,-5	Toilet->Couch->Fridge
1	1	19	10,19,25,26,-4	Toilet->Couch->Fridge->Grooming Cabinet
2	1	26	10,19,26,-4	Toilet->Couch->Grooming Cabinet
2	1	10	10,25,-7	Toilet->Fridge
2	1	11	10,25,26,-4	Toilet->Fridge->Grooming Cabinet

As shown in table.7-3, the SAP process can predict the possible sub-sequence of sensor ids at a particular time period and day of the week. A large set of sub-sequences can be avoided by the pruning process. A probable set of sensor id sequences obtained will be helpful to determine the performance of the elderly person in using the household appliances during that particular time.

7.5 Outlier Detection

The objective of the outlier detection process was to recognize sensor stream values that appeared very dissimilar from their spatio-temporal values in their past (i.e., the values in the recent history of the sensor stream were different from the past history). This issue is vital in WSN settings for the wellbeing determination of the elderly person in a smart home environment because it can be used to identify the ADL behaviour as regular or irregular. Even if the measurements collected from the heterogeneous sensing systems are accurate, the recognition of outliers (Elderly behaviour recognition as regular or irregular) determine an effective method to focus on the interesting events in the sensor stream system.

The outlier detection strategy was based on a two level reasoning technique. The first level of the reasoning took place during the daily activity recognition process. The elderly independent operational performance was assessed in terms of domestic appliances usages following data driven approach. Based on the forecasting process the behavioural patterns of an elderly person are determined as regular or irregular. If the actual duration was out of the range as given in Eq.6-4, an irregularity flag was set.

The second level of the outlier detection reasoning task was to match the activity patterns of the sensors obtained as a time series sensor stream for effective recognition of the movements. The sequence pattern of the sensors with temporal constraint was analyzed using SAP technique. The sequence of sensor streams on the basis of the day of the week and time were considered in analyzing the pattern. In the SAP technique the sequences of sensor stream are analyzed to check any irregular behaviour.

The outlier detection strategy based on the two level reasoning techniques has a notable feature: The recent past sensor data readings are characterized in spatio-temporal reasoning, thus reducing the number of false warning messages about the elderly behaviour recognition process.

7.6 Chapter Summary

In this chapter, effective sensor sequence pattern matching technique associated with the motion sensors for tracking the in-house movements of an elderly person in a smart home was presented. The movements performed by an elderly person were captured by the passive infra-red sensors and are transmitted wirelessly to a central coordinator. The sensor data fusion of heterogeneous sensing devices along with a motion sensor activity pattern enabled the system to have a proper reasoning process for the wellbeing assessment. This sensor activity pattern can assist the healthcare provider with an alert if the daily activity pattern is regular or irregular. The system is robust and flexible for real-time monitoring of the inhabitant movements in the assessment of daily activities performance.

The novelty of the presented task is the design and development of a procedure for proper reasoning related to a set of motion detection sequences with a support threshold, to detect a set of frequent sequences of movement's activity that happens at a particular hour of the day. The non-redundant generation of frequent patterns related to movements of an elderly person, enables us to have an appropriate ADL recognition of an elderly person happening at an instance of time. Additionally, this will support proper wellness assessment even if the person is not using any domestic objects in the daily activities performance.

Thus, the dynamic movements' monitoring environment is guided by the sequences' behaviors of an elderly person in a smart home. The developed system will be able to adapt to the changes in the discovered patterns in real time and inform the probable patterns of PIR sensor activations at a particular instance of time. This feature will support the proper assessment of the wellbeing of the person living alone in their own home.

The SAP technique can efficiently discover the sequence sensor pattern that satisfies the support strategy. The pruning time and computational space are decreased thereby enabling a better reasoning process of the sensor activity pattern in the wellness determination process. The SAP technique has been implemented on two different reasoning tasks: i) movements of an elderly person inside the house at an instance of time and as well in ii) determining the behavior of the elderly person in terms of the ADL assessment. Thus, the SAP technique is a valuable asset in the wellness determination process for reducing false abnormal messages.

Chapter 8. Conclusion and Future Works

The presented work in this thesis is the on-going research and development towards the transformation of old residential homes to smart homes. The need for transformation is to monitor the well-being conditions of an elderly person living alone in their home. Significant outcomes have been achieved in developing an integrated health informatics framework for long term monitoring of an elderly person living independently. The wireless sensing systems were indigenously designed and developed at the Massey University-Smart Sensing and Intelligent System research group. Novel artificial intelligent methods have been devised to determine the wellness of an elderly person living alone. The deployed sensor systems at the home of an elderly person do not require any direct contact with the inhabitant. The ubiquitous computing environment allows the elderly person to stay as they normally do while providing the monitoring system to be able to recognize their daily activities, and assess and determine the behaviour of the elderly person as regular or not.

In this research, wellness is about monitoring the well-being condition of an elderly person in performing their daily activities effectively at their home. A wellness determination process helps the healthcare providers to see the performance of daily activities of an elderly person. Data relating to the wellness model indices and daily activity recognition process can guide the healthcare professionals to know the starting variations on the performance of daily activities. The developed home monitoring system is robust and stable in executing multiple tasks concurrently. The sensor data collection and the framework of the developed HMS are capable of analyzing the sensor stream data in near real time. The wellness determination process as presented in the present research study is a novel framework verifying the behaviour of an elderly person at three different stages of daily living monitoring (i.e., usage of household appliances, recognition of daily activities and forecasting about the household appliances usages). A combination of the techniques will help in the reduction of generating frequent false alarms from the monitoring system.

The developed system can be easily augmented with other co-systems such as: i) physiological parameter monitoring and household energy consumption monitoring systems. This physiological parameter monitoring system will provide supplementary information of health parameters like body temperature and heart rate, so that elderly health perception and daily activity behaviour recognition together can be assessed to determine the wellness of a person. ii) A smart power monitoring and control system has been designed and developed towards the automation of household appliances and efficient usage of household electrical appliances. The real-time monitoring of the electrical appliances can be viewed through an internet enabled website. The developed system is robust and flexible in operation. Local and remote user interfaces are easy to handle by a novice consumer and are efficient in handling the household appliances operations. The developed home monitoring software system efficiently collects the heterogeneous sensor data in real-time. The presented results of the artificial intelligent methods are executed in offline. However, the home monitoring system framework is capable of executing the designed wellness determination methods in near real-time.

8.1.1 FURTHER WORKS

The human emotion feature extractions using a physiological parameters monitoring system have not been fully realized into real time analysis. At present the emotions have been determined based on the offline clustering process. As far as the sensing units are concerned the developed system has shown accurate and reliable readings. The system is capable of wirelessly communicating with the computer and storing data into the computer for processing.

At present, the wireless sensing nodes do not have processing capability. It would be better to have a sensor data event handling mechanism at the sensing systems rather than at the data sink so that the overhead at the wireless data sink can be reduced and efficient real-time processing of sensor data can be achieved.

The home monitoring software system was developed using the open source software technologies for web based and computer based applications. The computer based applications were executed through the windows based operating system. It would be better to run the computer based applications using a real-time operating system efficiently to analyze the sensor stream data in near real-time.

The analog data received from the sensing systems attached to the various household appliances is continuous and huge. Efficient data storage mechanisms are required to handle the “Big Data” of the continuous monitoring of usages of household appliances. The methods presented in this thesis rely on the events data generated from the household appliances rather than continuous data. Since, the energy consumption monitoring system requires a continuous data reception appropriate data handling algorithms need to be devised. Since, the same wireless sensing systems are used for various tasks of the home monitoring system efficient handling of continuous sensor data and security procedures need to be implemented. The system can be deployed and tested at old age residential care homes for assessing multiple elderly people behaviours who are residing at different flats

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