Occupancy Monitoring and Prediction in Ambient Intelligent Environment

MOHAMMAD JAVAD
AKHLAGHINIA

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Abstract

Occupancy monitoring and prediction as an influential factor in the extraction of occupants' behavioural patterns for the realisation of ambient intelligent environments is addressed in this research. The proposed occupancy monitoring technique uses occupancy detection sensors with unobtrusive features to monitor occupancy in the environment. Initially the occupancy detection is conducted for a purely single-occupant environment. Then, it is extended to the multiple-occupant environment and associated problems are investigated. Along with the occupancy monitoring, it is aimed to supply prediction techniques with a suitable occupancy signal as the input which can enhance efforts in developing ambient intelligent environments. By predicting the occupancy pattern of monitored occupants, safety, security, the convenience of occupants, and energy saving can be improved. Elderly care and supporting people with health problems like dementia and Alzheimer disease are amongst the applications of such an environment.

In the research, environments are considered in different scenarios based on the complexity of the problem including single-occupant and multiple-occupant scenarios. Using simple sensory devices instead of visual equipment without any impact on privacy and her/his normal daily activity, an occupant is monitored in a living or working environment in the single-occupant scenario. ZigBee wireless communication technology is used to collect signals from sensory devices such as motion detection sensors and door contact sensors. All these technologies together including sensors, wireless communication, and tagging are integrated as a wireless sensory agent. The occupancy data is then collected from different areas in the monitored environment by installing a wireless sensory agent in each area. In a multiple-occupant scenario, monitored occupants are tagged to support sensory signals in distinguishing them from non-monitored occupants or visitors. Upon enabling the wireless sensory agents to measure the radio signal strength of received data from tags associated with occupants, wireless localising sensory agents are formed and used for occupancy data collection in the multiple-occupant scenario. After the data collection, suitable occupancy time-series are generated from the collected raw data by applying analysis and suitable occupancy signal representation methods, which make it possible to apply time-series predictors for the prediction of reshaped occupancy signal. In addition, an occupancy signal generator is proposed and implemented to generate sufficient occupancy signal data for choosing the best amongst the prediction techniques.

After converting the occupancy of different areas in an environment to an occupancy time-series, the occupancy prediction problem is solved by time-series analysis and prediction techniques for the single-occupant scenario. The proposed technique has made it possible to

predict the occupancy signal for 530 seconds in a real environment and up to 900 seconds for a virtual environment. The occupancy signal generator created based on the proposed statistical model is proved to be able to generate different occupancy signals for different occupant profiles incorporating different environmental layouts. This can give a good understanding of the occupancy pattern in indoor spaces and the effect of the uncertainty factors in the occupancy time-series. In the multiple-occupant scenario, the tagging technology integrated with data acquisition system has made it possible to distinguish monitored occupants and separate their occupancy signals. Separated signals can then be treated as individual time-series for prediction. All the proposed techniques and models are tested and validated by real occupancy data collected from different environments.

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Abbreviations and Symbols

Abbreviations:

AC	Alternating Current
ACHE	Adaptive Control of Home Environment
ADL	Activities of Daily Living
AES	Advanced Encryption Standard
AI	Artificial Intelligence
AmI	Ambient Intelligent
ANFIS	Adaptive Nero Fuzzy Inference System
ANN	Artificial Neural Network
APS	Application Sub-layer
ARMA	Auto Regressive Moving Average
AOFIS	Adaptive Online Fuzzy Inference System
BP	Back-Propagation
Cat-5	Category-5
CASAS	Centre for Advanced Studies on Adaptive Systems
CBR	Cased-Based Reasoning
C-Bus	Clipsal-Bus
CO2	Carbon Dioxide
CSMA-CA	Carrier Sense Multiple Access-Collision Avoidance
dBM	Desibels of the measured power referenced to one milliWatt
ESN	Echo State Network
FCM	Fuzzy C-Means
FFD	Full Function Device
F.O.S	Final Occupancy Signal

FLC	Fuzzy Logic Controller
GA	Genetic Algorithm
GHz	Giga-Hertz
GPS	Global Positioning System
GTS	Guaranteed Time Slot
GTSH	Gator Tech Smart House
HMM	Hidden Markov Model
Id	Identification
iDorm	Intelligent Dormitory
IE	Intelligent Environment
IEEE	Institute of Electrical and Electronics Engineers
IHome	Intelligent Home
IP	Internet Protocol
iSpace	Intelligent Space
Kbps	Kilo Bit Per Second
KHz	Kilo Hertz
LM	Levenberg-Marquardt
MAC	Media Access Control
MARS	Multivariate Adaptive Regression Splines
MavHome	Managing an Adaptive Versatile Home
MF	Membership Function
NN	Neural Network
O.S	Occupancy Signal
PaIE	Predictive ambient Intelligent Environment
PAN	Personal Area Network
PC	Personal Computer

PCA	Principal Component Analysis
PIR	Passive Infra-Red
PLC	Programmable Logic Control
RF	Radio Frequency
RFD	Radio Function Device
RFID	Radio Frequency Identification
RNN	Recurrent Neural Network
RSOM	Recursive Self Organising Map
RSSI	Radio Signal Strength Indicator
SA	Simulated Annealing
S.O.S	Simulated Occupancy Signal
SUI	Simulator's User Interface
SVM	Support Vector Machine
TDNN	Time Delay Neural Network
UART	Universal Asynchronous Receiver/Transmitter
UTP	Unshielded Twisted Pair
UWB	Ultra Wide Band
WSN	Wireless Sensor Network
WSA	Wireless Sensory Agent
WLSA	Wireless Localising Sensory Agent
WLAN	Wireless Local Area Network
XML	Extensible Mark up Language
ZDO	ZigBee Device Object

Symbols:

$\Theta_n(s)$	Reverse Bessel Polynomials
w_0	Cut-off Frequency for Bessel Filter

$x(t)$	Combined Occupancy Signal as a Time-Series
$\hat{x}(t)$	Predicted Occupancy Signal
t	Time
Θ_{ij}	Fuzzy Rule Base System
$E(\Theta)$	Prediction Error
e_k	Difference Between Actual Value and Predicted Value
∇e_{ij}	Gradient of Parameters
η	Rate of Descent
J	Jacobian Matrix
σ^2	Variance
μ	Mean
σ	Variance
R	Random Number
p_i	Probability
u	Movements Uncertainty
σ	Durations Uncertainty
T_i	Transitions
D_i	Durations
A	Occupancy Signal Level
$\bar{D}(i)$	Expected Durations
$\bar{A}(i)$	Expected Levels
v	Return Force Probability
π	Unexpected Duration Mean Time
C	A Coefficient Representing Number of Days
R_{ij}	RSSI Readings Matrix
C_{ij}	Cluster Centres Matrix

p	Mapping Points of a Time-Series
Δ	Prediction Step in Time-Series
δ	Prediction Time in Time-Series
R_i	Fuzzy Rule
B_i	Real Number or a Combination of Inputs in a Fuzzy Rule
w_i	Rule Firing Strength
$\mu_{\tilde{A}_i^j}$	Membership Function
$\tilde{A}_i^j$	Fuzzy Label
ρ_i^j	Mean in Gaussian Membership Function
σ_i^j	Spread in Gaussian Membership Function
p	Auto-regression Parameter in ARMA
q	Moving Average Parameter in ARMA
$z(t)$	White Noise in ARMA
ϕ	Coefficient of Auto-regression in ARMA
θ	Coefficient of Moving Average in ARMA

Publications Arising from this Work

Journal Articles:

M.J. Akhlaghinia, A. Lotfi, C. Langensiepen and N. Sherkat, "Occupant Behaviour Prediction in Ambient Intelligence Computing Environment," *International Journal of Uncertain Systems,* Vol. 2, No. 2, May 2008.

M.J. Akhlaghinia, A. Lotfi, C. Langensiepen and N. Sherkat, "Single Occupancy Simulator for Ambient Intelligence Environment," *Journal of Internet Technology, special issue on "Agents and Data Mining"*,Vol. 9, No. 4, pp. 333-338, October 2008.

Conference Papers:

M.J. Akhlaghinia, A. Lotfi and C. Langensiepen, "Localising Agents in Multiple-Occupant Intelligent Environments," in *proceeding of the IEEE World Congress on Computational Intelligence* (WCCI-2010), Barcelona-Spain, 2010.

M.J. Akhlaghinia, A. Lotfi, C. Langensiepen and N. Sherkat, "Occupancy monitoring in intelligent environment through integrated wireless localizing agents," in *proceeding of the 2009 IEEE Symposium on Intelligent Agents*, Nashville-USA, 30 March-2 April 2009, pp. 7.

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M.J. Akhlaghinia, A. Lotfi, C. Langensiepen and N. Sherkat, "A fuzzy predictor model for the occupancy prediction of an intelligent inhabited environment," in *proceeding of the IEEE World Congress on Computational Intelligence*, Hong Kong, 1-6 June, 2008.

M.J. Akhlaghinia, A. Lotfi and C. Langensiepen, "Soft computing prediction techniques in ambient intelligence environments," in *proceeding of the IEEE International Conference on Fuzzy Systems*, London-UK, 23-26 July, 2007, pp. 1-6.

Chapter 1

INTRODUCTION

1.1 Predictive Ambient Intelligent Environment

The creation of an intelligent environment is defined as the intention of turning ordinary living or working spaces into an environment which can enhance the convenience of its occupants. In such an environment, safety, security, and energy saving are also considered as the main objectives [1], [2]. For instance, a contemporary intelligent home is expected to automate some of the actions in the environment to provide its occupants with their preferences e.g. adjusting the air-conditioner to maintain a desired temperature. It is also expected to consider the safety of its occupants e.g. monitoring actions and health factors to assess their health status. In addition, it should make the intelligent environment a secure place in which occupants and their properties are protected against threat and theft. Moreover, the utilisation of electrical appliances should be under control to reduce energy consumption in an intelligent environment.

Intelligent environments are categorised into three generations. In the first generation, despite the lack of sensory devices some of the above objectives such as security are satisfied. A bank equipped with a conventional security system in which employees can press a button to call the police in a bank robbery, is an example of the first generation intelligent environments. In the second generation, intelligent environments are equipped with individual or a network of sensors. This generation of intelligent environments is called automatic environment. A smart building with automatic lights and heater control is an example of the second generation. An intelligent environment equipped with sensors is also called Ambient Intelligent (AmI) environment, which is aimed to support people in carrying out their Activities of Daily Living (ADL) in easier ways [3].

With growing interests in the use of intelligent environments, a new generation of such environments has drawn the attention of many researchers. The Predictive ambient Intelligent Environment (PaIE) as the third generation in intelligent environments provides more intelligence capabilities in comparison with former generations [4]. An Ambient Intelligent environment [5], [6] can be defined as a digital environment that proactively, but sensibly, supports people in their daily lives [7]-[10]. Predictive AmI incorporates the predictive features in an AmI environment. It contains both manual and automatic control features from the former generations of intelligent environment; moreover, it can learn from the past situations and predict the future situation. PaIE can learn from environmental changes, and interactions among occupants and devices, as well as behavioural patterns of the occupants [11], [12].

In such an environment, a data acquisition mechanism is used in which sensory devices observe situations and alterations. The data acquisition mechanism is also a mean of communication by which the observed data is transmitted to a base station for further analysis. Hence, a sensor network as the data acquisition system and a base station for data logging, analysis and prediction would be a reasonable solution in the third generation of intelligent environments [13]. Some PaIEs employ intelligent agents for creating such an environment in which the agents are responsible for observation, communication, and even data analysis and prediction [14]-[17], [130].

The data collected by the data acquisition system include a variety of attributes such as environmental changes and occupants' interactions with the environment. These data are used in a learning approach to make a predictive environment that can predict the occupancy of different areas, utilisation of objects and resources, as well as the requirements and preferences of occupants at different times. In PaIE, the focus of prediction techniques is mostly on the pattern recognition by which the sequence of actions in the intelligent environment can be recognised, learnt and predicted. The behavioural pattern of any residents in the environment contains a series of actions and reactions. For example, the action of going to the kitchen, turning the light on, and turning a kettle on as a pattern can be summarised as making coffee or tea. In a PaIE, such a pattern should be recognised, learnt and predicted [18].

The predictive feature in PaIE can increase the number of objectives in intelligent environments [2]. Safety of occupants and their health have always been a concern in living and working environments. In an intelligent environment, the health parameters of occupants, specially elderly people and those who are living alone with care needs, can be monitored and learnt to help them live safely and in control [2], [19]-[21], [135], [136]. Safety and convenience are the factors of a good life style which can also be a duty for predictive control mechanisms in an intelligent environment. Moreover, to increase the efficiency of energy consumption in living and working spaces has been considered and is becoming more important nowadays. Therefore, the responsibility can be given again to intelligent control mechanisms rather than having occupants managing directly. These issues all can be improved if in an intelligent environment, intelligent mechanisms first of all can learn the behavioural pattern and then act accordingly.

Before it can be claimed whether an environment is a PaIE, it is important to establish answers to the following questions:

1. *What location is occupied by the monitored occupant at different times?*
2. *What actions are made by the monitored occupant in the occupied area when he/she is present there?*

Either of the above questions sometimes can be answered by the other one e.g. turning a kettle on can identify the action of visiting kitchen by the monitored occupant. However, to know what an occupant is doing should primarily be identified by where he/she is located e.g. it is not possible to guarantee that the occupant is in the kitchen even if the kettle is still on. In addition, sometimes, it is not possible to track an occupant if he/she is not using any appliances which can assist to find his/her location. Therefore, having the first question answered is vital and fundamental in the discovery of residents' actions and behaviours in their living/working environments.

In this thesis, terminologies, namely Predictive Ambient Intelligent Environment (PaIE), Intelligent Environment (IE), ambient intelligent environment, and smart environment are used interchangeably and should be interpreted as an ambient intelligent environment with predictive features.

In addition, terminologies such as person, resident, living object, and occupant are used interchangeably too and should be interpreted as a monitored person living in a predictive ambient intelligent environment.

Furthermore, terminologies, namely occupancy detection, tracking, and movement detection are used interchangeably and should be interpreted as the detection of occupancy in different areas of a predictive ambient intelligent environment.

1.2 PaIEs Elements and Current Issues towards Realising them

In a PaIE, a number of elements for sensation and communication, intelligence, and control are involved. Figure 1.1 illustrates these as data collection which include sensation and communication, predictive control or intelligence, and actuation.

As the PaIE is designed for the real world i.e. physical environments, the physical attributes of the environment should be initially sensed [7]. For example, to provide occupants with desired temperature, a PaIE should have a perception of current temperature. For the sensation or in other words, perception, sensory devices such as Passive Infra-Red (PIR) sensors, door contact sensors, light intensity sensors, temperature sensors, and other type of sensors can be employed [22], [23]. These sensors are typically small and thus can be integrated into almost any AmI applications [7]. For more information about sensors technology, readers are referred to the Chapter 3. The data collection mechanism should also make the communication between devices

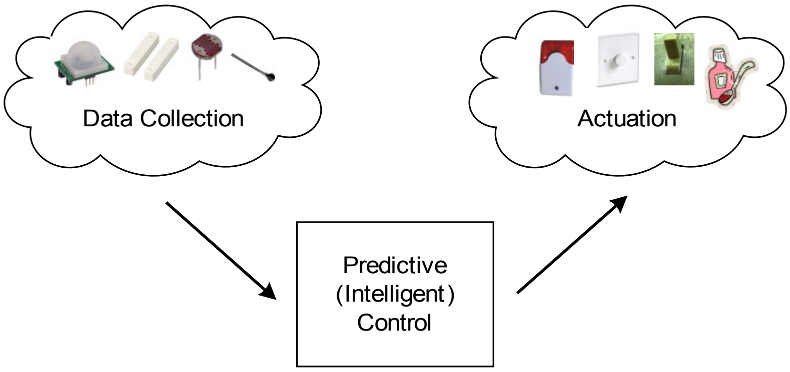


Figure 1.1 - PaIE elements.

and a base-station possible.

The predictive control consists of a control mechanism which uses intelligent techniques including Artificial Neural Network (ANN) control, Bayesian control, Fuzzy (logic) control, Neuro-Fuzzy control [134], Expert systems, Genetic algorithms, and Intelligent Agents [24]. Generally, predictive controllers act in two phases including training and predictive control as explained below:

1. **Training Phase:** In this phase, the intelligent technique is trained to create a model of a real system by using a training data samples of a real system. For example, in ANN control, a neural network model of a real system is created in training phase. In the training phase, derivative optimisers such as Back-propagation are used in order to adjust the ANN parameters for minimising the difference between model and the real system [25],
2. **Predictive Control Phase:** The predictive control usually includes the predictive model created in training phase and an optimiser. The optimiser generates values and apply them to the model, the model output is then used by the optimiser to find the minimum error between the output of the model and a reference output. The determined value by the optimiser is then applied to the real system to result in an output similar to the desired reference output.

For more information in the field of predictive control, readers are referred to the literatures in Chapter 3 and Section 4.5 in Chapter 4.

After that the sensory devices provided the intelligent control with the inputs and the decision made by intelligent control, this should come to action in the real environment. Actuators are the responsible for applying inputs to the system for creating a desired output. For instance, a resistive actuator like dimmer can adjust a desired light intensity, a simple switch can turn the air-condition on or off, an indicator can alert for an altered health status, or an alarm can notify for fire.

Although the elements in PaIE explained in this section are currently available and employed based on the objectives in intelligent environments, the requirements can alter for different environments with different objectives. For example, in a PaIE only energy saving could be considered whereas in another PaIE both energy saving in the environment and safety or health status of occupants could be considered. However, in a predictive ambient intelligent environment, its essential elements explained above including data collection, predictive control, and actuation are the challenging issues towards realising it.

The realisation of a comprehensive data collection mechanism is one of the outstanding issues in creating such an environment which should be addressed appropriately. Some intelligent environments employ a simple sensor and communication mechanism to address the data collection issue whereas in some intelligent environments advanced sensor network technologies and computer devices or intelligent agents are employed [26].

The second most important issue in creating a predictive ambient intelligent environment is the prediction system. PaIE should be able to predict the next state of consecutive interactions with the use of the knowledge it has learnt from previously observed interactions. For instance, it can predict normal ADLs for an occupant with mental impairments such as dementia or Alzheimer disease and report abnormalities in the occupant's behaviour. The challenge of prediction consists of first pattern extraction to identify sequences of actions, and then sequence matching to predict the next action in one of these sequences [27].

The final issue in realising a PaIE is the actuation in which the decision made by the predictive control should turn into action by actuations or interactions amongst residents, environments and devices. The first and third challenges explained above are mostly technological problems whereas the second issue i.e. predictive control is a problem which should be dealt with mainly using computational intelligence techniques.

1.3 Problem Justification – Addressed Issues in this Research

The behavioural pattern of an occupant living in an ambient intelligent environment includes a pattern of his/her interactions and a pattern of his/her movements through different locations or areas. The pattern of interactions represents how regular a set of interactions with surrounding equipments is taking place while the occupant's pattern of movements is to track the location of the monitored resident in his/her living/working environment in daily, weekly, monthly, or annual basis.

The extraction of any of these patterns can be a significant achievement in the realisation of a predictive ambient intelligent environment because the extracted pattern enables the intelligent system to predict an occupant's behaviour in future or discover any abnormality in his/her behaviour. For example, in an elderly-living ambient intelligent environment if the monitored elderly person is not behaving according to his/her extracted (expected) daily behavioural pattern, then a health warning can be raised to inform a carer or the health services of the elderly person's new situations.

As a contribution in realisation of predictive ambient intelligent environments, the focus of this research is mainly on the movements pattern of residents (occupants) in the environment by proposing ideas and solutions for data collection, data representation and analysis in simple scenarios and expanding the scenarios to the solutions in more complicated situations.

Object tracking in various environments has been considered using different technologies and techniques [28], [29]. Most of the approaches employ visual equipments such as cameras [30], thermal cameras, or a fusion of sensory devices [31] and cameras [32] to carry out people tracking in the environment. Along with the technology there has always been the issue of extracting identifying information from the imagery data collected by cameras; hence, intelligent techniques, face recognition techniques, image and signal processing techniques have been applied to reduce the problem [33].

Despite the interests for occupants' tracking in an environment using visual equipments, using cameras for tracking occupants has always had its corresponding issues. These issues include the costs i.e. the value of equipments, imagery data transfer efficiency and the vulnerability of the monitored occupants' privacy [34], [35].

The cost of camera equipments varies based on their type, resolution, and features like zoom, motorised tilt and rotation. However, the flexibility and expandability of data acquisition system using visual equipments can be affected by the high cost of these equipments. For example, covering all areas of an environment by cameras can be extremely costly.

Some currently available techniques have reduced the cost of communication for imagery data. Some of these techniques suggest data compression for compressing the video or image stream before they transferred for further analysis through the communication mechanisms. Some other techniques suggest image processing built in cameras which can make camera equipments more expensive. These techniques aim to reduce the data transmission overhead of imagery data.

Furthermore, and most importantly, using visual equipment is not convenient for people because it degrades their privacy. Although the application of visual equipments in surveillance has made the use of these devices reasonable in several situations such as some medical or sensitive industry, it does not seem to be a reasonable method in many other applications. For example, tracking people with normal activities who are living in their premises by using cameras can be a real threat to their privacy; hence, their convenience. Therefore, an inexpensive unobtrusive movements monitoring and movements pattern extraction using simple sensory devices does worth investigations which is addressed in this research.

1.4 Research Objectives

To realise a predictive ambient intelligent environment, some of the technical and theoretical issues are investigated in this thesis. A number of new and innovative ideas are proposed and experimented to assist with the collection, representation, and prediction of the occupants' movements.

In this research, the following objectives are addressed:

1. A data acquisition system is proposed and implemented which collects occupants' movements data in an inexpensive and unobtrusive manner. The data acquisition mechanism should be easy to install and have expandability and flexibility to work in both single-occupant and multiple-occupant situation. This data acquisition is created by integrating different elements for shaping up an efficient sensor network for data collection purposes,
2. A new form of movements signal is proposed which should be a good representation of the raw occupancy data collected by the data acquisition mechanism. This representation of the occupancy data should provide prediction techniques with a suitable signal for prediction and pattern extraction,
3. Along with data acquisition and signal representation, a model of occupancy is created to simulate the movement pattern of different occupants in different environments. The model should create a simulator that is able to generate movements signal to test prediction techniques for different form of activities,
4. Finally, real occupancy signals are applied to prediction techniques along with simulated occupancy signal to choose the best amongst the prediction techniques.

In spite of challenges ahead of accurate object tracking in indoor environments, this research is an attempt to reduce the problem and contribute to approaches for achieving better solutions in the field.

Further to the above research objectives, the application objectives of this research is to assist the health and well-being control of elderly people and people with mental impairments such as dementia and Alzheimer disease; it is aimed to improve their independence, safety, and convenience in their life-style. This is carried out through processes in which it is attempted to:

1. Collect the ADLs data from an elderly-living apartment using a proposed data acquisition mechanism, representing occupant's data with the proposed

occupancy data representation and using a number of techniques to predict her/his occupancy signal,

2. Modelling occupant's movements as an occupancy signal for the flexibility of generating the signal in different environments with different occupant behavioural profiles,
3. Approaching to separate her/his occupancy pattern in the presence of uncertainty and noise signals e.g. when the occupant is visited by a carer, member of families, and friends.

1.5 Methodology (Overall Picture)

One of the major challenges in this project is to identify the position of occupants (or inhabitants) at any point of time. Global Positioning System (GPS) is a reasonably reliable system for outdoor tracking but not applicable for indoor spaces as not only the GPS signal is not precise enough for smaller scales but also a line of sight is required between GPS satellites and the tracker. Therefore, alternative mechanisms are needed for indoor tracking. However, the final goal in the investigation of indoor tracking is to invent solutions as efficient as the Global Positioning System.

For indoor tracking to simplify the problem, in this research, occupancy of areas is proposed instead of accurate tracking and localising the occupants. So, the occupancy of different areas by the occupants are detected and identified instead of finding precise coordinates of an object in the environment. The research has started with simple scenario of the occupancy where only a single occupant lives or works in the environment which is called a single-occupant PaIE in this research. Simple sensory devices including motion detection or Passive Infra-Red (PIR) sensors , temperature sensors, door contact sensors, and light intensity sensors are employed in the absolute single-occupant environment along with a wireless network (ZigBee) to collect the occupancy data and environmental attributes in the scenario. An occupancy signal which incorporates both the occupied location (area) and the time of occupancy (with spatio-temporal characteristics) is then shaped and passed to the prediction techniques to predict the further occupancy of different areas in the environment. To extend the

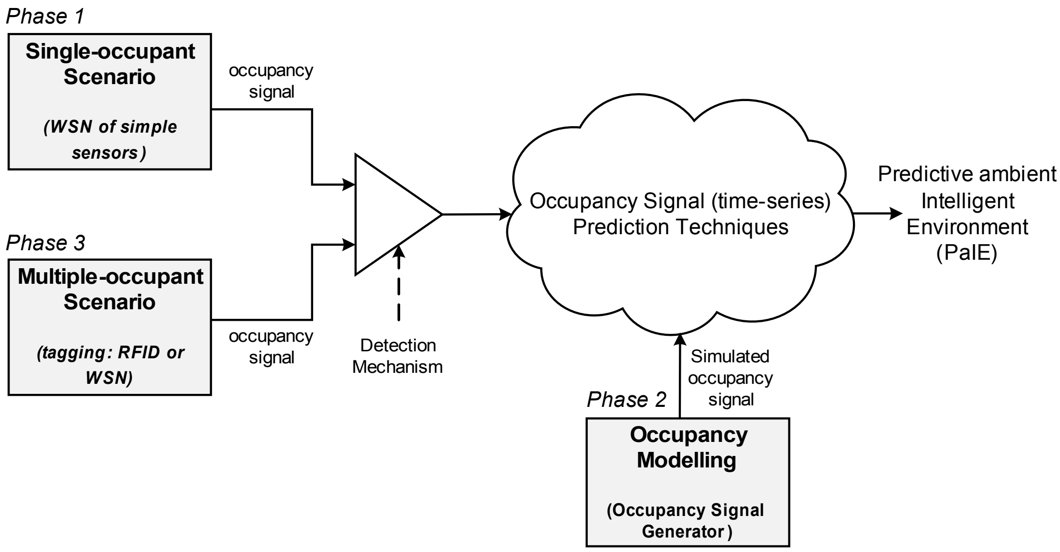


Figure 1.2 - Phases of the research (overall picture).

single-occupant scenario to a multiple-occupant scenario, tagging mechanisms are experimented and occupancy signal of each occupant is separated by tagging him/her in the environment. In this research, Received Signal Strength Indicator (RSSI) is used to locate and identify occupants in different areas in the multiple-occupant scenario. Furthermore, a statistical model of occupancy in the ambient intelligent environment is proposed and implemented to generate occupancy signal for different occupant's profile as well as different environmental layouts which can help to train and find best prediction techniques for occupancy detection.

In this research, a number of real data sets collected by data acquisition systems are used to prove the performance of the proposed data acquisition system. These sets of data are also used to validate the proposed signal representation, incorporated tagging technologies, and occupancy signal modelling in the research.

Figure 1.2 shows a diagram representing different phases of the research as explained above including phase1: Single-Occupant Scenario, phase2: Occupancy Modelling, and phase3: Multiple-Occupant Scenario.

1.6 Thesis Contributions

The overall contribution of this thesis to knowledge is to propose, formulate, and evaluate a new approach to represent occupancy data so that:

- The problem of occupancy prediction in PaIEs is addressed by applying time-series prediction techniques.
- Different occupancy situations in terms of complexity of the problem in an unobtrusive, simple, and inexpensive manner is considered.
- Modelling the occupancy in order to approximate the uncertainties involved in occupants' movements is addressed.

This hypothesis is supported and evaluated by number of techniques presented in Chapters 4, 5, and 6.

1.7 Thesis Organisation

Context of the thesis is organised in six chapters as follow:

Chapter 2 is a review of similar works in the field of intelligent environment where a number of approaches for creating a smart environment are explained and compared. These techniques are taken from a variety of literature with the same objectives in the field of soft computing, data mining, and statistical data analysis and modelling. Most of the techniques reviewed in the chapter are using sensor network or a network of intelligent agents to collect and process data in the smart environments. Moreover, a number of realised intelligent environments are mentioned mostly used for academic researches in worldwide research institutions in which the reviewed intelligent techniques are applied. Due to the main focus of this research which is occupancy detection and data representation for occupancy prediction in intelligent environments, some approaches for occupancy detection and tracking occupants in intelligent environments are also explained in the chapter.

In the third chapter, technologies available for sensation, communication, and tagging are briefly introduced. In this chapter, other mechanisms applicable in ambient intelligent environments such as agents and middleware are also introduced. Moreover, current available technologies for occupancy monitoring and tracking occupants in the environment are introduced.

In Chapter 4, occupancy detection and prediction in a single-occupant scenario is addressed. A data acquisition system is proposed consisting of a number of wireless sensory agents and a monitoring portal. The wireless sensory agents are developed by integrating sensory devices and ZigBee wireless technology in a single circuit board. These wireless sensory agents collect sensory data and transmit them to a base station in the PaIE. In addition, a mechanism for the occupancy data representation (data reshaping) in the single-occupant scenario is proposed to create an occupancy signal as a time-series. A number of time-series prediction techniques are explained and examined. Finally, the proposed data acquisition system and the data representation are tested and verified by collecting real occupancy data from a single-occupant environment and applying some prediction techniques to a virtual data set and the collected real occupancy data.

A model of occupant's movements in an indoor environment is created in Chapter 5. The implemented simulator accepts a variety of occupant's profiles in different layouts of the simulated environment. Using a statistical modelling approach, the occupancy of different areas in the environment is simulated. In the simulator, the profiles of the occupants are presented with a number of parameters such as movement and duration uncertainties. The simulator is validated using a real dataset by applying optimisation techniques for minimising the difference between the model generated by the simulator and the real occupant's movement in the environment. The simulator can provide sufficient occupancy data based on different environmental and behavioural settings. This has proven to be very useful to test prediction techniques.

In Chapter 6, single-occupancy solution is expanded for multiple-occupancy problem. Exploring and employing tagging technologies have enabled the data acquisition system to distinguish amongst different occupants. The wireless sensory agents are programmed to measure the distance of every tagged occupants from the agent creating localising wireless sensory agents. In this chapter, some intelligent techniques such as clustering techniques are used to determine the area which is occupied by the tagged occupant. In addition, a set of experiments are carried out to evaluate the approaches proposed in this chapter.

Concluding remarks and future works are drawn in the final chapter (Chapter 7) where the idea of the thesis is summarised and discussed in details and remaining issues for future works are explained.

Appendix A in this thesis represents the implementation of the data acquisition system used in Chapters 4 and 6. Appendix B is the graphical user interface in the occupancy signal generator which is created based on a model described in Chapter 5 and Appendix C describes the ZigBee technology, its architecture, and protocols.

Chapter 2

INTELLIGENT ENVIRONMENTS in LITERATURE

2.1 Chapter Overview

In the research literature, variety of issues are addressed in ambient intelligent environment. Applied technologies for monitoring, learning, intelligence, prediction, and adaptation are amongst challenges addressed by researchers. However, the subject of intelligent environment has been attractive for researchers and sufficiently potential for further investigations and researches.

This chapter represents a review of issues addressed in the literature in three sections. The first section is a review of learning, and prediction (intelligence) techniques in predictive ambient intelligent environments where they use data acquisition mechanisms such as network of sensory devices and intelligent agents. In the second section, some of the realised intelligent environments are reviewed. They are mostly available for research purposes in the subject of intelligent environment or multi-disciplinary purposes. In the final section, due to the focus of this research on the occupancy detection, simulation, and prediction in PaIEs, some of the techniques which address or employ such features in the literature are reviewed.

2.2 Prediction Techniques in PaIE

In PaIEs, various prediction or pattern extraction techniques coming from the area of statistical modelling, soft computing, or data mining are employed to make the environment intelligent. In this section some of these techniques are reviewed and compared in various aspects and the intelligent environments employed them are compared based on the data collection mechanisms in following criteria of:

- Distributed versus centralised techniques i.e. the data analysis is performed on the sensory agents or in a base station,
- Utilisation of the computational power of sensory devices or agents,
- Data storage used for keeping the data collected for training.

2.2.1 CASE Based Reasoning

CASE Base Reasoning (CBR) is a classification method in intelligent environments that uses previous experiences to find a solution for current problem. CBR has two basic operations including case-generation and case-selection [27].

As a method of prediction, context-aware based CASE based reasoning proposed in [36] is used as a method of pattern extraction of occupant's behaviour in a predictive environment. In this method, the context in a smart home is classified into three dimensions, namely time, environment and person [37] and each case is represented as follows:

Case=(case_ID, person_ID, habit_ID, environment_ID, active_ID, time)

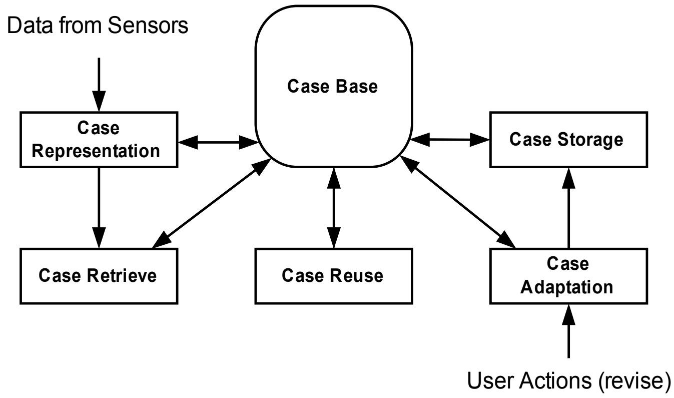


Figure 2.1 - Case base reasoning framework.[37]

System framework proposed for implementing this method is shown in Figure 2.1.

As an example to show how this method works, assume a person with a specific person_ID goes to the lounge in a predictive building at *8:00 pm* and sets his/her favourite light intensity and temperature. In this case, system generates a new case in its cases database for the situation. If in the other day the same person goes back to the same place at the same time, then the system sets his/her favourite light intensity and temperature automatically as an existent case in the database matches this situation. Similarity calculation is used to overcome the case-selection problem in CBR.

Context-aware based CBR is a centralised prediction technique. It stores all cases in a central database, but the case adaptation phase in its system framework reduces the number of cases should be kept in the data base.

2.2.2 Lazy Learners

Lazy learners or instance-based learners in ambient intelligent environments are learning techniques in which an instance is classified based on minimum distance classification. Lazy learners store all the training data samples. This may present difficulties when the learning is from very large data sets. Modular approach is an example of lazy learners in a sensor network. Modular organisation of the sensor network proposed in [38] addresses two main issues in mining sensor network data:

1. Minimisation of communication effort with compression of aggregated data of

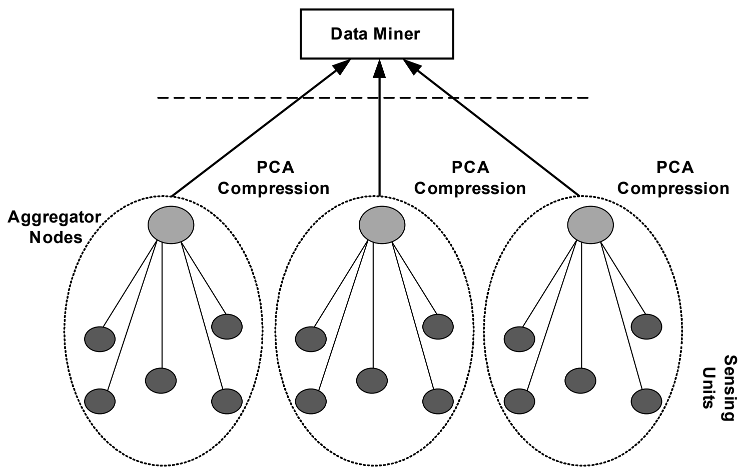


Figure 2.2 - Modular Approach.[38]

each cluster,

2. Extraction of high-level information from a massive data set.

In modular approach shown in Figure 2.2, sensory devices are clustered in sensing units. Then a data compression technique such as Principal Component Analysis (PCA) [38] is applied to the data received by aggregating nodes. Finally, the collected data set is used by a lazy learning algorithm to produce a model of the mapping and then the data set is discarded and only the model is kept. Despite the utilisation of computational power in aggregating nodes, modular approach is categorized as a less distributed technique.

Modular approach minimises the data should be kept in the data miner by applying compression and modelling techniques. On the other hand, it could be problematic in terms of robustness as the system may lose some data by applying these techniques.

2.2.3 Distributed Voting Approach

Due to the distributed nature of sensor networks in ambient intelligence environments, implementing distributed algorithms for learning approaches becomes possible. Most of these algorithms use small computational power of individual sensors to construct a powerful learning approach in the whole network. Distributed voting algorithm

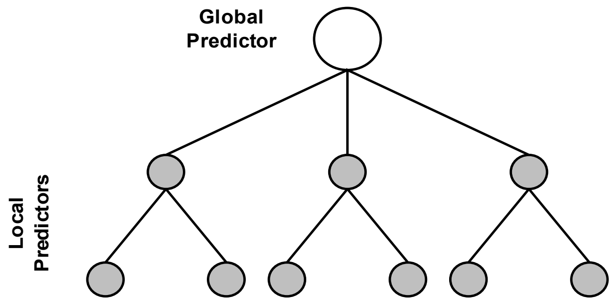


Figure 2.3 - A tree structure in a distributed voting approach.[39]

proposed in [39] is one of these algorithms. In this algorithm a tree structure of sensors as small computing devices and a powerful computing device in the root of this tree is constructed to solve a classification problem. This tree structure is shown in Figure 2.3. Each sensor as a leaf of the tree uses neural network or decision tree approaches for local prediction. Due to the shortage of memory in sensory devices, all training data for different classes are stored in the root.

During the learning process, each sensor receives a training data from the root. After training phase, each node can measure and classify one or more attributes in a local policy. Eventually, in a global prediction, the root receives local classification decisions from sensors and performs a global classification by applying a voting strategy.

Distributed voting approach is categorized as a distributed approach. In spite of the distributed nature of this technique, a huge training data is stored in the root. Utilisation of sensor's computational power is the most significant advantage of distributed voting approach in realising an ambient intelligent environment.

2.2.4 Reinforcement Learning

Reinforcement learning is a method of learning that learns the relation between input and output with trial and error. In this method, a function called reinforcement signal must be maximised [27]. Any significant difference between input signal and target signal is considered as a punishment; therefore, the value of reinforcement signal decreases. On the other hand, a slight difference between input signal and target signal is considered as a reward; hence, the value of reinforcement signal increases.

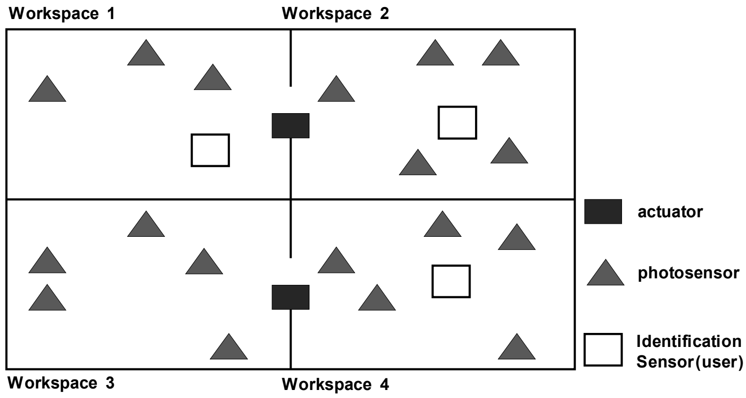


Figure 2.4 - Intelligent lighting control using Reinforcement Learning.[40]

As an example of reinforcement learning technique, [40] proposes an intelligent lighting control in which a multi-agent system controls lights. This technique concerns varying lighting preferences of different users for different tasks. Figure 2.4 shows a physical space equipped with identification sensors, photo sensors and actuators. In [40], reinforcement learning technique is used to train the agents. An agent uses user's location and light readings as the state space for the reinforcement learner and attempts to take actions that lead to appropriate light settings. For example, the absolute difference between the light intensity sensed by an agent before and after the user action is used as a negative reinforcement or punishment. Also, if an agent turns a light on and the user turns it off then the agent receives a negative reinforcement. In contrast, if a person does not change anything the agent receives a positive reinforcement as a reward. Due to the multi-agent nature of this technique, it is categorized as a distributed approach, but it does not utilise the computational power of sensory devices.

2.2.5 Fuzzy Rule-Based Learning

Multi-agent framework proposed in [41] can be deployed in an intelligent building equipped with sensors and effectors. In this approach, each agent controls and learns about a small sub-region of the entire environment. In this technique, knowledge is represented by fuzzy rules and learning process is an unsupervised algorithm. In the learning process, inputs from sensors are sampled and transformed to fuzzy sets in a fuzzification phase. Then, the learning process compares the fuzzy inputs with stored

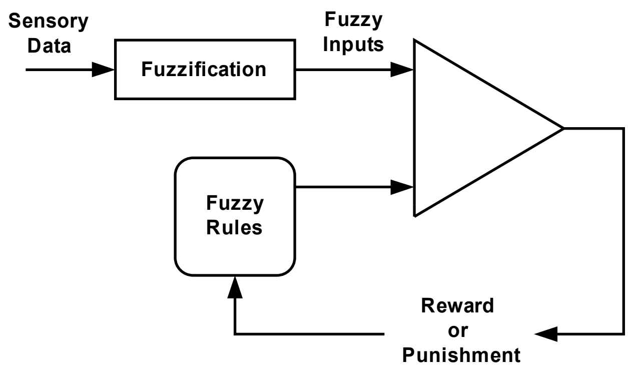


Figure 2.5 - Fuzzy rule-based learning.

fuzzy rules. Any significant difference between fuzzy inputs and stored fuzzy rules is considered as a punishment. On the other hand, slight difference between fuzzy inputs and fuzzy rule is a reward to the fuzzy rule. This technique is illustrated in Figure 2.5.

2.2.6 Adaptive Online Fuzzy Inference System

In [14], Adaptive Online Fuzzy Inference System (AOFIS) as a learning and control system is proposed. The authors have performed their experiments in the Essex intelligent dormitory as a test-bed. AOFIS prediction approach contains three phases for learning and two phases for control and adaptation:

1. Monitoring the user's interactions and capturing input/output data associated with their actions,
2. Extraction of the fuzzy membership functions from the collected data,
3. Extraction of the fuzzy rules from the recorded data,
4. The agent controller,
5. Life-long learning and adaptation mechanism.

In the first phase, sensors take a snapshot from user's action, as well as sensors readings before the user's action. For instance, assume that the temperature of a space is 30 and user sets the air conditioner to 25. The system takes a snapshot from the both current temperature and user's temperature preference.

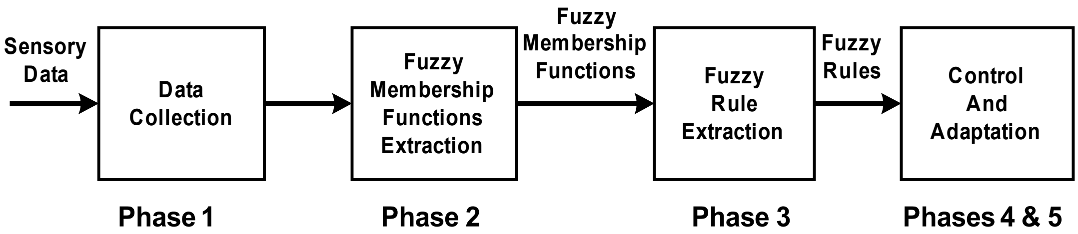


Figure 2.6 - Five phases of AOFIS.[14]

In the second phase, different techniques of clustering such as Fuzzy C-Means, Double Clustering, Agglomerative Hierarchical Clustering Approach and Quantification of Fuzzy Membership Functions are used to extract fuzzy Memberships Function (MF). With these techniques the accumulated user input/output data is categorized into a set of fuzzy MFs which quantify the raw crisp values of the sensors and actuators into linguistic labels, such as normal, cold, or hot. In the third phase, the defined set of membership functions are combined with the existing user input/output data to extract the rules defining the user’s behaviours. The fuzzy rule extraction approach used by AOFIS is based on an enhanced version of Mendel Wang method that is a one-pass technique for extracting fuzzy rules from the sampled data. With extraction of membership functions and set of rules, the agent’s Fuzzy Logic Controller (FLC) becomes capable to capture human behaviours. Therefore, in the fourth phase, the agent monitors the state of the environment and affects actuators based on its learnt FLC that approximates the preferences of the user. Finally, in the fifth phase, the agent adapts its existing rules or adds new rules based on the new preferences of the user. For example, if the user changes the settings of the environment, then the agent would adapt itself with new preferences. Five phases of AOFIS are illustrated in Figure 2.6.

Due to the use of fuzzy MFs, the amount of data should be kept in AOFIS technique is reduced. This technique can be categorised either as a centralized or as a multi-agent approach due to the flexibility of the technique.

2.2.7 Mixture-Model

In [42] data collected from motion detectors are used to determine four attributes including the location of occupant, the start time of being in the location, the length of

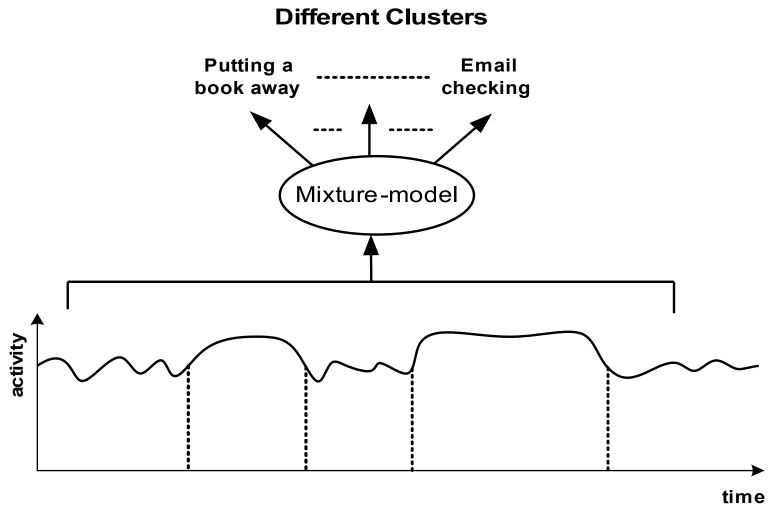


Figure 2.7 - Clustering in a Mixture-model.[42]

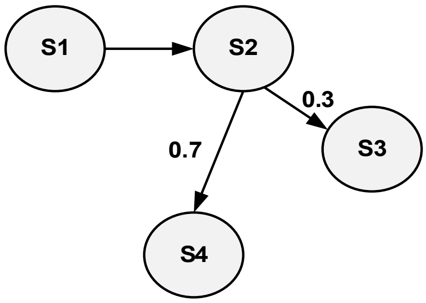
the time spent in it, and the activity level of the occupant in the location. In the training phase, a mixture-model makes a cluster of each activity.

In this method an activity is recognised based on the time spent in a specific location and activated sensors during this activity. For instance, the activity of putting a book in the library needs less time rather than checking email in the same room. In addition, a different set of sensors will be activated during the activity of putting a book in the library rather than checking email in the same room. The mixture-model is a combination of different methods including event estimation, self organizing maps, and fuzzy K-Means clustering. The power of the mixture-model is due to its capability to distinguish different mixed activities. For instance, the activities of putting a book and checking email can occur simultaneously. Simultaneous activities make it more difficult to identify them.

For example, it would be difficult to recognise which activity has fired a sensor. The mixture-model concerns the time spent in a location and fired sensors in it to calculate the probability of each trained activity. Finally, the more probable activities are expected ones. Figure 2.7 is an illustration of clustering with mixture-model.

2.2.8 Statistical Modelling Prediction Techniques

Statistical approaches such as Markov Model and Hidden Markov Model (HMM) are



	S1	S2	S3	S4
S1	0	1	0	0
S2	0	0	0 .3	0.7
S3	0	0	0	0
S4	0	0	0	0

Transition Probability Matrix

Figure 2.8 - Markov chain and transition probability matrix.[43]

also considered in ambient intelligent environment. A brief description of these models are presented below:

2.2.8.1 Markov Model

Markov model is a statistical method of modelling that uses Markov chain to define a process. In a Markov chain next state of the system only depends on the present state. Transition probability between two states in a Markov chain is represented by a transition matrix. Figure 2.8 is a simple example of a Markov chain, as well as its transition probability matrix. Markov chain is used in [43] to model daily activity of elderly people living alone in a predictive home. In this approach, first of all, a profile transition probability matrix from observed sensory data for each elderly person is generated and stored in a database. Then, during a daily activity, a test transition probability matrix is generated.

Minor differences between profile and test matrices with an acceptable tolerance shows that the health status of the elderly person is not changed. In contrast, any significant statistical difference between these two matrices can be considered as an abnormal health status of the elderly person.

2.2.8.2 Hidden Markov Model

Hidden Markov Model (HMM) is also a statistical model in which the data is generated by a stochastic process but the process is not observable (hidden). These processes are assumed to be Markovian and can be known through another set of stochastic processes that produce the sequence of observed features. HMMs perform well in behavioural pattern recognition. For example, in [44], HMM is used for the pattern recognition in a smart environment which aims to discover activities in CASAS project which is explained in Section 2.3.

The significance of a statistical model such as Markov chain in modelling ambient intelligent environments is due to its simplicity and capability of representing systems with multiple transitions. For example, occupancy detection as an important application in an ambient intelligent environment is multiple transition and can be modelled as a Markov chain.

2.2.8.3 Bayesian Classifiers

Bayesian classifier is a method of classification based on probability distribution. In this approach, the classifier calculates the probability of being a member of different classes for each sample and predicts the class of the sample. A belief network is a collection of conditional probability distributions associated with a directed graph [45].

In the probability model, each variable X is associated with a node of same name in the graph. The parents of the variable X are the variables which appear on the right-hand side of the vertical bar in a conditional probability. For example, if the conditional probability is $P(X|Y,Z)$, then Y and Z are the parents of X . The graph has an arrow leading from each parent into X , which is called the child. The power of such a probabilistic approach is that several important and interesting operations can be defined as the calculation of probability distribution [46]. Thus, one can define a single

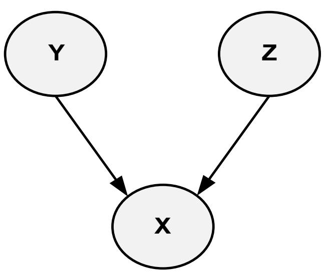


Figure 2.9 - Bayesian belief - Parents and Child.[46]

probabilistic model and examine it in different ways to perform prediction, revision of hypotheses, carry out “what if?” reasoning, and “ruling out” hypotheses as such the prediction of effects can be formulated as $P(effects|causes)$. For example, “What are typical sensor readings when the lounge is occupied but the bedroom is not?” or, “How many people are expected in the building today?” can be formulated and analysed through a set of calculations in belief network. The occupancy prediction proposed in [45] employs the Bayesian classifier which will be explained in Section 2.4 with more details.

2.3 Realised Ambient Intelligent Environments

The ideas of intelligent environment have been implemented by various research institutions as laboratory or test-bed mostly for their research purposes. These realised ambient intelligent environments include:

1. Neural Network house [47],
2. Intelligent Home (IHome) [48],
3. House_n [49],
4. Aware home [50],
5. Artificial Intelligence Lab (AI Lab) [51],
6. MavHome [53], and
7. Intelligent Dormitory (iDorm or iSpace) [54].

In the Neural Network house [47] at the university of Colorado, researchers have implemented a system named Adaptive Control of Home Environment (ACHE) as one of the first attempts to tackle the programming challenges associated with intelligent environments. ACHE monitors the environment, observes the actions taken by occupants, and attempts to infer patterns in the environment that predict these actions [47]. The predictors in ACHE are implemented as feed-forward neural networks trained with back-propagation, or as a combination of neural network and a look up table. After the prediction e.g. expected hot water usage, the decision making process for the control takes place in two stages of set-point generation and the device regulation. The 2-stage decision making allows the adaptability of the system which needs the set-points to be learnt in the case if the preferences of the occupants changed.

The intelligent home test-bed is investigated at the computer science department of the university of Massachusetts at Amherst. In IHome, researchers have designed and implemented a set of distributed autonomous home control agents and deployed them in a simulated home environment [48]. The main goal of the IHome is to test the idea of multi-agent systems in intelligent environments. The idea of adaptability and responsiveness of agents to control the IHome has been investigated in this project. In IHome, each agent is associated with an appliance e.g. water heater, dishwasher, etc. These agents try to complete allocated tasks based on the task priority by sharing required resources.

House_n project in Massachusetts Institute of Technology [49] is a broad research approach which incorporates the technology and services for challenges of the future. PlaceLab as a part of House_n project is a real environment which is used to study technology and design strategies in the context. PlaceLab has facilitated the study of human interaction with new technologies and home environments. In PlaceLab, hundreds of sensing components are installed in nearly every part of the home. These sensors are used to develop innovative user interface applications which help people control the environment, save resources, and remain mentally and physically active, and stay healthy. The sensors are also used to monitor interactions in the environment so that researchers can study people reactions to new technology, devices, systems, and design strategies in the complex context of home. One of the advantages of PlaceLab is the multi-disciplinarian focus of the lab which can be used by researchers of computer science, architecture, social sciences, etc.

Aware home [50] of Georgia Institute of Technology is another example of realised intelligent environments. In the aware home project, a sensor network of simple sensors and high precision detectors such as thermal cameras and microphones collect the information which makes the home aware of the occupants situation and their interactions with devices and their living environment. Monitoring the elderly people in their living premises is amongst one of the objectives of the aware home.

Artificial Intelligence Lab at the Washington State University has also been one of the test-beds for the ideas of intelligent environments. AI Lab has been used to realise different approaches such as Centre for Advanced Studies on Adaptive Systems (CASAS) smart home project [51] as the test-bed for learning and adaptation techniques such as pattern recognition techniques described in [52].

MavHome smart home project [53] is a multi-disciplinary research project at Washington State University and the University of Texas at Arlington. This project is an approach to smart home which perceives the environment through the use of sensory devices and can act accordingly through the use of actuators. This smart home goals are to minimise the cost of maintaining the home and maximising the comfort of the residents by reasoning and adapting to the perceptions through the data acquisition system.

Intelligent Dormitory (iSpace) in University of Essex [16], [54] has been a test-bed for a number of prediction and adaptation techniques such as Adaptive Online Fuzzy Inference System [14] and type-2 fuzzy embedded agent [55] explained in previous section. The iSpace is a single bedroom student accommodation equipped with sensors, agents, and gadgets which learn from occupant's behaviour and adapt to their needs to improve the quality of live for them. The university of Essex has also developed a 2-bedroom apartment (iSpace2) as a test-bed for the research in intelligent environment. The iSpace2 is equipped with ubiquitous networked sensors and actuators and offers the deployment of agents and user interfaces in the context of intelligent environment.

2.4 Occupancy Detection, Prediction, and Modelling in Ambient Intelligent Environments

Due to the main focus of this research i.e. occupancy detection, prediction, and simulation, some of the localising techniques or location-aware systems applied in ambient intelligent environment are reviewed in this section. The mechanisms must have the unobtrusive feature; hence, the mechanisms with visual equipments are excluded in this review. The occupancy detection techniques are compared based on the following criteria:

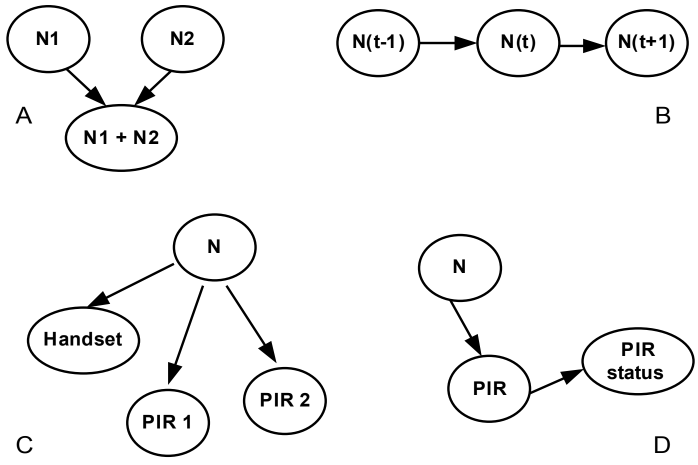


Figure 2.10 - Separate relations for constructing a belief network.[45]

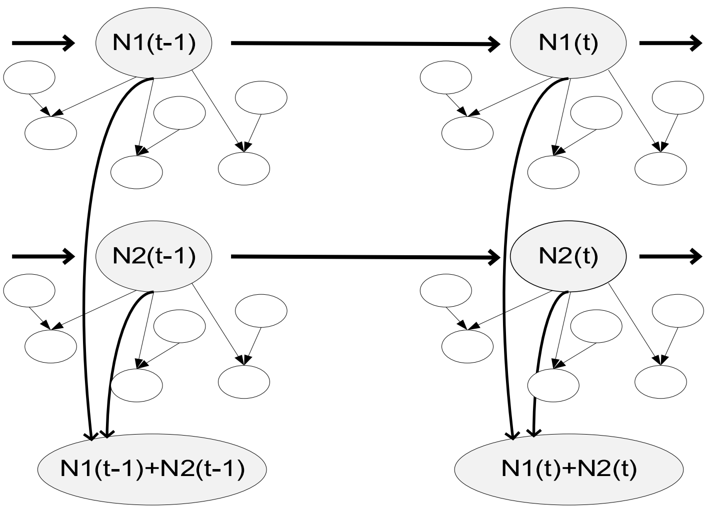


Figure 2.11 - Two slices of a belief network to model occupancy in a building.[45]

- The type of the environment including single-occupant and multiple-occupant,
- The intelligent techniques incorporated in the occupancy detection or prediction,
- The technologies used for the occupancy detection or tagging occupants.

The belief network proposed in [45] is an attempt towards the occupancy detection and prediction which is constructed using three Passive Infra Red (PIR) occupancy detectors and a telephone off-hook sensor for data acquisition in each office based on following rules:

1. The total number of occupants in all rooms is the sum of the numbers in each room (Figure 2.10-A),

2. The number of occupants persists over time (Figure 2.10-B),
3. Sensor measurement depends on the number of occupants (Figure 2.10-C),
4. Each sensor may respond to occupancy in different ways depending on its status (Figure 2.10-D).

The combination of all dependencies is illustrated in Figure 2.11. The number of occupants and their location in a building is determined by analysing the acquired occupancy data in a belief network analysis framework. As the occupancy control plays an important role in behavioural patterns extraction, the belief network was considered

as a technique in this area. Belief network is based on a probability distribution. It is categorized as a centralized approach and it does not utilise the computational power of sensory devices in the employed sensor network. This technique is able to diagnose the sensor network because the status of each sensor is concerned in the belief network.

The occupancy detection mechanism in [56], proposes algorithms for finding the number of occupants by analysing the data captured from networks of six different types of sensors. The sensor network consists of sensors capable of measuring CO2, temperature, lighting, relative humidity, motion, and acoustics. The data collected from the fusion of sensors are applied to prediction techniques for learning the relation between the number of occupants and the sensory data in the environment. Three prediction techniques including Support Vector Machine (SVM), Neural Network (NN), and Hidden Markov Model (HMM) are used for the occupancy prediction in [56].

Developed by Michigan State University and Hong Kong University of Science and Technology, LANDMARC uses Radio Frequency Identification (RFID) technology for indoor localisation [57], [58]. In this approach some of the tags are fixed and used as reference points (see Figure 2.12). LANDMARC finds the tracking tag by measuring the signal strength of the tracking tag and comparing it with the signal strength of reference tags at the readers installed in specific locations of the environment. Therefore, the location of the moving tag can be estimated to be close to the reference tags which have minimum difference between their signal strength with the tag's signal strength at readers.

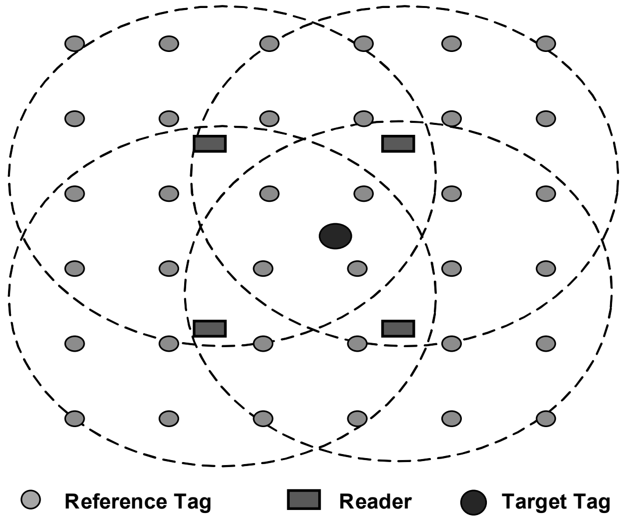


Figure 2.12 - LANDMARC Localisation.[58]

Using RSSI of wireless mobile devices, [59] has proposed a method of indoor localisation named fingerprinting localisation. This approach operates in two phases of offline and online monitoring. The signal strength of the beacon received from a mobile tag by every readers installed in the environment is labelled in the offline mode. This labelled data is then used for finding the estimated location of the mobile node in online monitoring. For example, in Figure 2.13 all three readers read the signal strength of the mobile node in position *(x0,y0)* and keep it as a labelled location *(x0,y0,S1,S2,S3)*. If the signal strengths labelled in the readers match a new reading, then the mobile node is localised to be in position *(x0,y0)*. Variety of learning and classification techniques can be used for training based on the labelled data in fingerprinting localisation including

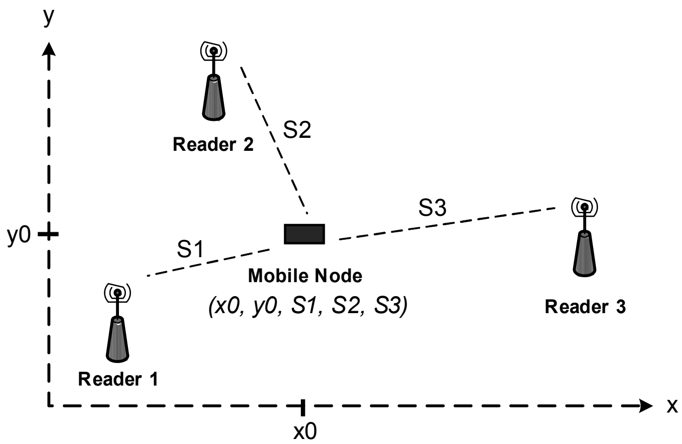


Figure 2.13 - Fingerprinting localisation.

Fuzzy C-Means (FCM) [60] and Support Vector Machines (SVM). Despite the advantages of fingerprinting localisation, the training phase is still a challenge because of the huge data should be saved for an efficient training of this technique. Some of the techniques have addressed to find alternative training scheme.

The research reported in [61] is an attempt to model occupancy in single person offices. In this work, motion detection sensors are used to recognise the occupancy of an office aiming to model the vacant and occupied daily times for energy saving in working spaces. In the approach, an exponential trend is fitted to vacant and occupied situations. As the result of the work, a simulator is created which can simulate working days in a single person office. The motion detection sensors employed in this research are shown not capable of recognising complicated situation e.g. when someone else is present in the office. In such a case if the monitored person leaves the office i.e. vacant office, then the motion detection sensor sense it as occupied. This has made modelling the occupied situation more challenging.

In [67], authors suggest a Hidden Markov Model for identifying occupants by using the data collected from passive sensors such as motion and door contact sensors in an unobtrusive manner. In this approach, the data was collected from Washington State University's CASAS test-beds which provides the system with spatial and temporal information. The algorithms are then able to detect the unique behaviours of the various residents. To do this, their test-bed is equipped with a vast number of motion detection sensors which are able to monitor every 1.5 by 1.5 squared meter in the environment. In the HMM used in this work (Figure 2.14):

- The hidden states represent the possible residents in the data set collected from the monitored environment,
- The observations from sensors are combined with the sensor value i.e. on and off for motion detectors,
- The transition probabilities are the likelihood that the event is from the same or different person in the environment,
- The emission probabilities are the likelihood that the person cause a sensor to detect a change.

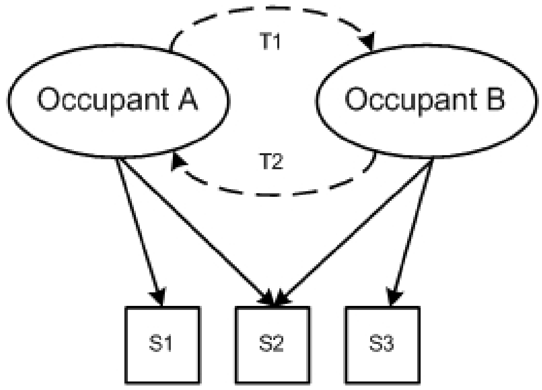


Figure 2.14 - HMM for Occupancy Identification.[67]

The HMM was shown to be able to distinguish between two residents with about 90% success.

In [139], authors suggest a distributed mechanism for observing walking patterns in an intelligent environment. In this approach a floor based ZigBee sensor network (Smart Floor [140]) is deployed in a Gator Tech Smart House (GTSH) as a pervasive computing environment located at Oak Hammock retirement community in Florida. The sensory devices are actual floor tiles with force sensors attached beneath them. By using this technology, the detection of the foot steps without a need for wearing sensory devices or using cameras on any location of the house is possible. The approach suggests the hypothesis of the phenomenon cloud in sensor networks where a number of sensors within a region are activated to represent an action. The phenomenon cloud in [139] is the representation of foot pressure on the tracking tile as well as the neighbouring tiles which is contiguously changing when the occupant is moving.

2.5 Summary and Discussions

Prediction techniques as the key feature of an ambient intelligent environment were reviewed in this chapter. It was shown that the prediction problem in an ambient intelligent environment is mostly the pattern extraction problem in a distributed sensor network or via intelligent agents. Reviewed prediction techniques were from three research areas namely, statistical modelling, data mining, and soft computing. Also, a number of realised ambient intelligent environments as test-beds were reviewed in the chapter. This chapter was also a review of available occupancy detection, localisation , and occupancy prediction techniques in the literature.

It was mentioned that due to the distributed nature of sensor networks, it becomes possible to apply distributed prediction approaches to sensor networks. Distributed voting approach shown as a prediction technique in data mining area is one of them. In contrast, small computational power of individual sensors makes it difficult to execute complicated prediction techniques with their huge training datasets. Therefore, the push is to less distributed techniques or multi-agent techniques. However, the enhances in the technology is addressing the problem with more powerful intelligent agents. Lazy learning, reinforcement learning and fuzzy rule-based learning reviewed in this chapter are multi-agent techniques. Case-based reasoning, Bayesian classifier, and mixture-model are centralized techniques in which patterns and training datasets are stored in a database. AOFIS can be used either as a centralized approach or as a multi-agent approach. Collected data from sensory devices in a sensor network can become extremely huge and problematic. It was shown in this chapter that some prediction techniques apply compression, regression or fuzzy methods to overcome this challenge. On the other hand, it could be problematic in terms of robustness as the system may loose some data by applying these techniques. It was also shown that lazy learning approach applies PCA compression in aggregating nodes as well as a modelling technique in data miner to reduce the amount of data should be kept in its database. Moreover, prediction techniques based on fuzzy approaches such as fuzzy rule-based learning and AOFIS keep smaller amount of data as they store fuzzy membership functions based on linguistic labels instead of raw data in their databases. It is unlikely that a prediction technique contains all features discussed above. However, the most effective prediction technique for an environment is strongly depended on the characteristics of the environment it should be applied to. For example, occupancy control as an application in a predictive environment does not need fuzzy approaches as the collected data from sensory devices in this case are not continuous. Therefore, applications like occupancy control can be done by simpler approaches such as Bayesian classifiers. On the other hand, in temperature or light intensity detection and control, fuzzy approaches could become useful as they reduce the amount of data should be kept by applying fuzzification.

The complexity of the application should be concerned for choosing an appropriate method of prediction. In this case, applying a fusion of different techniques is useful. For example, a predictive environment with occupancy, temperature, and light intensity control might need a fusion of techniques for prediction purposes.

- In the occupancy detection and prediction approaches reviewed in this chapter, regardless of the technology applied for monitoring occupants, yet they suffer from intrinsic uncertainty for distinguishing among occupants or finding the accurate location of tagged occupants. For instance, techniques in which motion detection sensors are employed ([45], [56], and [61]) are not able to distinguish occupants in multiple-occupant PaIEs. Bayesian Belief network reviewed in this chapter is not able to distinguish amongst different occupants. It also contains a degree of uncertainty for determining the occupancy of the environment. Despite the performance of the work suggested in [67] in distinguishing between two occupants, due to the complexity of HMM for multiple occupants this performance cannot be guaranteed for more than two residents. Moreover, the number of sensors used in the CASAS test-bed are not yet available for many environments. The smart floor used in [139] and [140] can track a single occupant in the environment. However, it needs to be supported by additional techniques to distinguish between occupants. Sensing tiles used in the smart floor is not applicable for many situations. The single occupancy modelling approach in [61] also suffers from uncertainties involved in the recognition of occupied situation in presence of other occupants. On the other hand, occupancy detection mechanisms that use tagging technologies for localising the occupants bring radio signal uncertainties such as signal fading to locate living objects precisely. Hence, a more comprehensive occupancy detection and prediction technique that covers both single-occupant and multiple-occupant situations in this research is investigated. In this research, maintaining an acceptable level of uncertainties will address the problem of uncertainty level in the reviewed literature.
- The focus of some reviewed techniques such as [56] and [61] is in working spaces like office occupancy. None of these techniques has considered to support

elderly people lives as an application which is getting increasingly important these days [141]. Therefore, the conducted research here is to address the issues related to occupancy detection and prediction in elderly persons lives more specifically.

- The occupancy detection and prediction techniques reported in this chapter use statistical or intelligent approaches for the occupancy prediction. However, the power of time-series prediction techniques cannot be underestimated or neglected in the prediction and forecasting. Hence, to find the solutions for incorporating time-series prediction techniques does worth investigations.
- Modelling the occupancy in PaIE can play an important role in understanding and analysis of the occupancy situation in the environment. Unfortunately, this issue has not been considered widely in the literature. The occupancy modelling reported in [61] also lacks the requirements for occupancy modelling in different environments with a number of areas for different occupants. Therefore, a proper model of occupancy in which the flexibility of the model can incorporate different environments as well as different people with various behavioural parameters is a good contribution to the field.
- The techniques involving visual equipments which are excluded in the literature review still remain as the threat to privacy of the occupants. This fact leads to the techniques which are able to detect occupancy by excluding cameras.

In summary, it is aimed to perform occupancy detection and prediction with solutions for the raised issues above. This can be done by creating the situations in which these solutions are taken into account as a real PaIE. Therefore, in the next chapter, the required technology infrastructure for creating an appropriate data acquisition system in the PaIE is reviewed in which the occupancy detection in both single and multiple-occupant scenarios should be considered.

Chapter 3

TECHNOLOGY INFRASTRUCTURE

3.1 Chapter Overview

In a predictive ambient intelligent environment, a data acquisition system should be used to collect required information from the environment and the interactions between the residents and objects. The technology infrastructure required for creating a data acquisition system is a mean for sensation or data collection, communication, and actuation. The sensory data can be collected using different types of sensors. The data acquisition system should also provide a mechanism for data transmission by which the data collected by sensory devices can be transmitted to a base station for analysis and making subsequent decisions. This can also make the communication amongst sensory agents possible if the PaIE is equipped with agents. The other requirements in terms of technology is dependent on particular applications in ambient intelligent environment. For example, if the identification of occupants is an important factor in an environment, then devices for identifying occupants and distinguishing amongst them such as tagging technologies should also be employed.

To create an appropriate data acquisition system for occupancy detection in PaIE as one of the main focuses of this research, the elements for sensation an communication in single-occupant environments are introduced in this chapter. Furthermore, the elements for tagging monitored occupants in multiple-occupant environments are also explained. In Section 3.2, data acquisition technologies in ambient intelligent environment is introduced. In this section technologies for sensation and communication in data acquisition systems are reviewed. In Section 3.3, agents technology as a method in data acquisition systems is described. Section 3.4 considers middleware technology in data acquisition systems. In addition, due to the focus of the thesis on tagging technologies, a number of these technologies for identifications in the environment are also introduced in Section 3.5. Finally, the content of this chapter is summarised in Section 3.6.

3.2 Data Acquisition Technologies in Predictive Ambient Intelligent Environment

Data acquisition is the first phase in the realisation of a PaIE. The data acquired can include the occupancy of different areas, environmental attributes, the state of the intelligent devices, and interactions between occupants and devices. This data is then used by intelligent approaches for training, predictive control, and adaptation in a PaIE. A basic data acquisition system should perform two major tasks - sensation and transmission which are explained below:

- Sensation: Employing appropriate sensor technologies to the applications in ambient intelligent environments, the behaviour of the occupants and the status of the environment can be monitored for further intelligent control, adaptation, and actions. Available sensors and their applications are explained in Section 3.2.1.
- Transmission: Sensory information produced by sensory elements should be transmitted to the base station which can be either a database or a processing

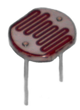
unit for further analysis or subsequent actions. The responsibility of data transmission goes to a wired or wireless interconnection amongst sensors called sensor network. The specifications of wired sensor networks and wireless sensor networks are explained in Section 3.2.2.

3.2.1 Sensors Technology

Sensory devices are responsible for sensation in a data acquisition system. Nowadays, variety of sensors can be used to perform this task. Typical sensors are as follow:

- ***Passive Infra-red Sensor (PIR)*****:** PIR or motion detector is sensitive to the movements of living objects. This sort of sensors is normally used to control the occupancy of different areas for different applications e.g. buildings' energy saving and security. In energy saving application, PIRs function as a timer sending a signal to the lights control to turn of the lights after a specific period. In addition, in security application, an armed system initiates an alarm as soon as a signal is received from PIRs,
- ***Door Contact Sensor*****:** Door contact sensor is a type of magnetic switch which can detect the open and closed states of a door. These sensors have a widespread application e.g. buildings' security,
- ***Temperature Sensor*****:** A temperature sensor is basically a type of resistive sensor which is sensitive to the environmental temperature. These sensors also have a variety of applications including buildings' automation and industrial control and automation,
- ***Light Intensity Sensor*****:** Light intensity sensor is also a type of resistive sensor which is sensitive to the light intensity of the environment. Energy saving and automation is amongst the applications of such sensors,
- ***Electrical Current Sensor*****:** A type of sensor that can monitor the activity of electrical devices by measuring their electrical current consumption. In an electrical current sensor a magnetic ring around the electrical appliance wire that

Table 3.1 - Sensor Types Commonly used in Smart Environments.

	PIR	***Door Contact***	***Temperature***	***Light Intensity***	***Electrical Current***	***Pressure***
Type	infra-red	magnetic switch	resistive	resistive	resistive or magnetic	resistive
Data Type	digital	digital	analogue	analogue	analogue	analogue
Application	motion detection	door open, close	temperature changes	light changes	electrical current change	pressure changes
Image						

converts the AC current to a measurable voltage. Maintenance in power electronics and industrial automation are amongst the applications of these sensors, and

- ***Pressure Sensor*****:** A type of resistive sensor which is sensitive to the weight of the objects such as mat sensor. Mat pressure sensors can convert the load of the objects to a measurable voltage.

There are other type of sensors available in the market including humidity, vibration, gravity, and ultrasound sensors with their particular applications. However, choosing a proper sensor is not only dependent on the application but also the size and the perception resolution of that sensor. The size of the sensor is important because large sensors can reduce the pervasiveness in on hand and small sensors can reduce the resolution or the accuracy of the readings on the other hand. A summary of the sensory devices commonly used in intelligent environments are shown in Table 3.1.

3.2.2 Sensor Network Technology

A wired or wireless interconnection among sensory devices or sensory agents in a PaIE is called a sensor network. Sensor networks have been employed in various applications. The applications of sensor networks vary from home applications including home automation, home security systems [62], and smart homes to industrial automation and control [63], [64].

Table 3.2 - Samples of X10 commands.

Code	*Function*	*Description*
0 0 0 0	All Units Off	Switch off all devices with the house code indicated in the message
0 0 0 1	All Lights On	Switches on all lighting devices (with the ability to control brightness)
0 0 1 0	On	Switches on a device
0 0 1 1	Off	Switches off a device
0 1 0 0	Dim	Reduces the light intensity
0 1 0 1	Bright	Increases the light intensity

In the following two sections, a number of sensor networks with different infrastructures namely, wired and wireless are explained and the advantages and disadvantages of these two types of sensor network are compared in details.

3.2.2.1 Wired Sensor Networks

In a wired sensor network, wired connections makes communication between sensory devices and the base station possible. Two common wired sensor networks used in smart environments namely, X10 and C-Bus are explained below:

- **X10:** X10 is an example of wired sensor network standard for communication amongst electronic devices in an intelligent environment. X10 uses power line wiring for signalling and control. As X10 does not need any infrastructure by sharing power line wiring which is already available in any working or living environment, it has been very popular and successful since it was introduced in 1975. In X10, the digital data transmitted through the power line is a 120 KHz carrier which is transmitted as bursts. Carried digital data contains an address and a command sent from X10 controller to the controlled device. More advanced controllers can query advanced controlled devices for their current status i.e. on/off or current dimming level. Devices can be easily plugged in normal power outlets. In X10 protocol, each device can react either to a command specifically addressed to it or any broadcasting commands. A four bit command code produces sixteen commands used by X10 controller to control X10 devices in an intelligent environment (see Table 3.2),

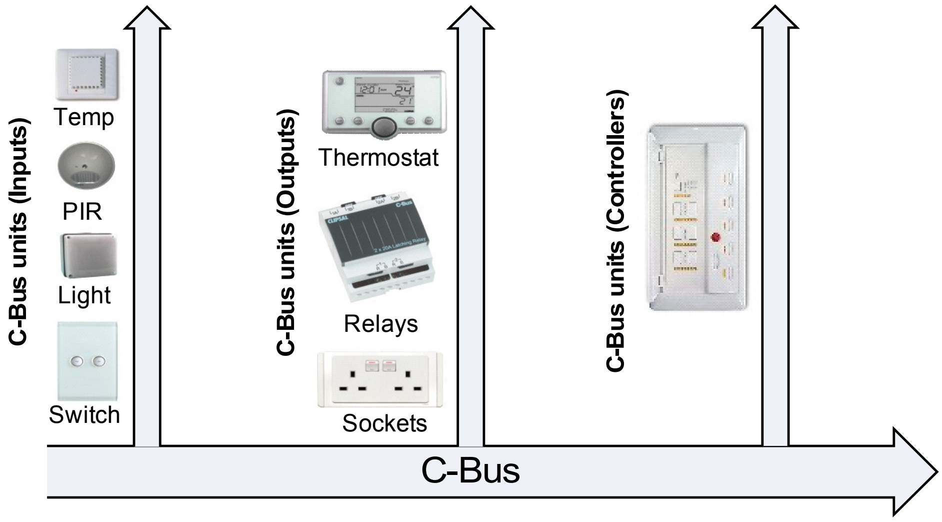


Figure 3.1 - C-Bus Schematic.

- **C-Bus:** Clipsal-Bus (C-Bus) is another example of wired sensor network standard which is used in home automation. C-Bus uses its dedicated low-voltage cabling instead of AC power line to carry command and control signals. A C-Bus system can be used in control of electrical devices and lighting; moreover, it can be interfaced to a building security system. A Cat-5 UTP wiring (i.e. Ethernet) connects all C-Bus units including inputs (e.g. switches, PIR, light intensity and temperature sensors, etc.), outputs (e.g. relays, dimmers, sockets, thermostats, etc.), controller, and power units (Figure 3.1). So, the communication between C-Bus units and the controller allows a full control on the devices connected to this bus. The wireless version of C-Bus units are also available, in which C-Bus wireless units are connected via a WLAN.

- **LonWorks:** LonWorks is designed to address control applications which is built on a protocol for networking devices over media including twisted pair, power lines, fibre optics, and Radio Frequency (RF). Devices in a LonWorks network communicate through a control network specific protocol originally created by Echelon [138]. The protocol can optionally provide end-to-end acknowledgement of messages, authentication of messages, and priority delivery to provide bounded transaction times. Support for network management services allows remote network management tools interact with devices over the network, so they can configure network addresses and parameters and download application programs. It can also diagnose network problems or start/stop/reset device application programs.

Other wired sensor network are also available. For example, Fieldbuses are networks that are specifically designed for operation under hard real-time constraints and usually with inbuilt fault tolerance ([65] and [66]). They are mainly used in industrial automation for a networking amongst sensors, actuators, and Programmable Logic Controllers (PLC).

3.2.2.2 Wireless Sensor Networks

In a Wireless Sensor Network (WSN), wired infrastructures are replaced with radio signal transmission. Therefore, sensory devices accompanied with their wireless modules can be deployed anywhere in an ambient intelligent environment. Wireless sensor networks, in comparison with wired sensor networks such as X10, are more flexible in terms of the deployment and the required infrastructure of the network in the environment. Power consumption is the most important concern in wireless sensor networks because sensory devices and their wireless modules are usually powered by batteries [63], [68].

IEEE standard (IEEE 802.15.4) in wireless technology for low speed communications has opened a new direction in WSN [69], [65]. This standard can support up to 250Kbps data rate which is a very good speed for communication in the scale of a sensor network. This standard was then applied by the ZigBee Alliance to develop the ZigBee protocol as a wireless network suitable for low speed communications in the scale of a network of sensory devices. The ZigBee protocol supports three topologies: star or single hop, cluster tree and mesh to provide a larger range of activity [65], [69]. Star topology is the simplest form of a ZigBee WSN in which all installed wireless devices only communicate with one wireless device that is interfaced with a PC or a base-station (see Figure 3.2). This topology is suitable in a short range WSN. On the other hand, for long range communication in bigger environments or in the case of existence of obstacles in the environment which can decrease the wireless communication range, tree or mesh topologies can be used. For example, in a tree topology some devices can act as

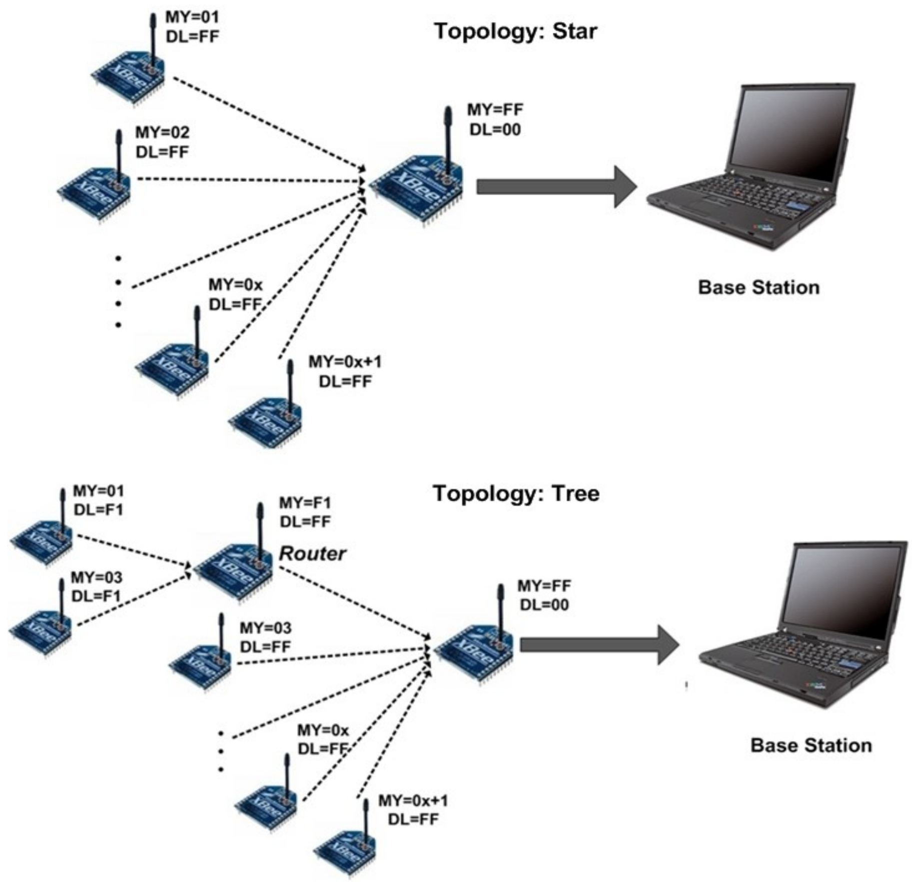


Figure 3.2 - Wireless sensor network of XBee modules (Topologies: Star and Tree).

routers in the wireless sensor network to resolve the problem of either long range communication or obstacles in the environment. This is illustrated in Figure 3.2. For more information about ZigBee wireless technology, readers are referred to the Appendix.

For creating a data acquisition system in this research, a prototype of wireless modules with ZigBee communication protocol is chosen which is produced by Digi International/Maxstream. This product which is named XBee is available with variety of features. Taking the advantage of ZigBee protocol, XBee wireless modules can provide the following features [70]:

1. An XBee module is able to communicate with digital devices using UART serial communication. Therefore, a wide range of micro-controllers can be interfaced with XBee modules. The serial communication can also ease the programming of the module by connecting it to a PC serial port,

2. Any XBee module have a flow control of the data received from other modules. So, it is not needed to handle the flow control as it is already provided by the module,
3. An XBee module can operate in four different modes including idle, transmit/receive, sleep, and command modes. In the idle mode, the module does not anything. In the transmit mode, the module sends data packets to other modules and in the receive mode, module waits to receive data packets from other modules. In the sleep mode, XBee transmitter is powered down waiting for incoming packets and as soon as a data packet is addressed to the module it switches to transmit/receive mode. In the command mode, the configuration of the module can be changed using a number of AT commands,
4. Any XBee module have the feature of addressing for unicast and broadcast communications. In unicast communication, XBee module will send data packets to another unique XBee module whereas in broadcasting, the module can send data packet to all nearby modules,
5. The sleep mode, can dramatically reduce the power consumption on any XBee modules.

XBee modules are available in two revisions XBee and XBee Pro. For long distance communication XBee Pro modules are recommended. However, the range and the data rate of the normal XBee modules are adequate for data collection in the scale of sensory data for indoor spaces.

Some of the PaIEs, instead of a sensor network, employ agents with a range of capabilities to create a data acquisition system. Agents are the hardware units for this kind of data acquisition system which is explained in Section 3.3. In this case a mechanism can also be employed to do the software part named middleware which is explained in Section 3.4.

3.3 Agents in Predictive Ambient Intelligent Environment

In PaIEs, an agent is a computer system which is capable of autonomous action in the

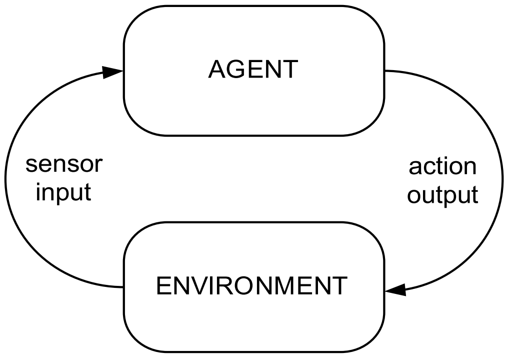


Figure 3.3 - An abstract view of Agent.[71]

environment to meet the objectives it is designed for [71]. Figure 3.3 illustrates an abstract view of an agent. As illustrated in this figure, an agent in abstract view should take a perception of its environment and then apply decisions as actions to that environment. In this view an agent is very similar to a computer program which acts based on assumptions and conditions. Agents are not always complex and intelligent; however, intelligent agents are mostly employed in intelligent environments and PaIEs. Russell and Norvig [25] group agents into five classes based on their intelligence and complexity. The classes of agents are described as:

1. **Simple Reflex Agents:** Simple reflex agents act only based on current perceptions. This class of agents stick to condition-action rule where the actions are made when a set of condition is satisfied. This is shown in Expression 3.1:

$$f : P^* \to A \qquad \textbf{\textit{(3.1)}}$$

   where f is a function or a program which relates perceptions (P^*) to actions (A) ,

2. **Model-based Reflex Agents:** Model-based agents can act in environments which are partially observable. These agents have some kind of structure which describes the part of the environment which cannot be observed. Apart from their modelling feature, model-based agents act as simple agents,

3. **Goal-based Agents:** In goal-based agents, a set of desirable situations are stored. It allows this class of agents to choose amongst multiple possibilities; selecting one which is better to achieve the goal,

4. **Utility-based Agents:** In goal-based agents, only two types of states are considered: goal states and non-goal states. But utility-based agents use a measure of how desirable a particular state is. They can obtain this measure by using a utility function which maps a state to a measure of the utility of the state,
5. **Learning Agents:** Learning allows agents to start operating in an unknown environment. These agents then start learning about the environment; so their information about the surrounding environment increases helping them to act more appropriately.

In the realisation of PaIEs, an intelligent agent may integrate sensation, actuation, intelligence and even communication technologies which results in an autonomous entity for data acquisition and prediction. In some cases, intelligent agents are able to interact with other agents and possibly occupants in order to satisfy their objective goals [71].

To consider an agent to be intelligent, that agent is expected to have features of reactivity, proactiveness, and social ability as explained below [71]:

- **Reactivity:** Intelligent agents should be able to perceive their environment, and respond to changes in an appropriate time to satisfy their design goals,
- **Proactiveness:** Intelligent agents should be able to show a goal-directed behaviour taking the initiative in order to satisfy their objectives,
- **Social ability:** Intelligent agents should be able to interact with other agents in order to satisfy their design objectives.

It is not difficult to create a system with goal-directed behaviour (Proactiveness). Every function in computer programs are goal-directed systems. The intention of a procedure or function is to achieve a goal if its assumptions are satisfied. Otherwise, the produced results of that function will be incorrect. In non-functional systems, the simple model of goal-directed programming is not valid as the assumptions do not remain fixed. Such functions assume that the environment does not change while the function is executing. If the environment does change, in other words if the assumptions turn false while the function is running, then the function may crash and the results will be invalid [71].

In many environments, neither of these assumptions are valid. In such environments, blindly executing a function will be a poor strategy. In such dynamic environments, the agent must be reactive, that is it must be responsive to events that occur in its environment whether these events affect either agent's goals or the assumptions. Social ability in intelligent agents means that they should communicate with other agents and cooperate with other agents to carry out a common objective.

In this research two types of agents are proposed and implemented. The first type is Wireless Sensory Agent (WSA) which is the integration of sensory devices for sensation, a micro-controller for computation and processing, and an XBee (with ZigBee standard) chip for communications between devices and also a base station. WSAs will be explained in Chapter 4 with more details. Wireless Localising Sensory Agent (WLSA) is the second type with enhanced capability of localising mobile tags which is described in Chapter 6.

3.4 Middleware in Ambient Intelligent Environment

Middleware is a mechanism which relates together the elements of an intelligent environment. Sometimes, middleware is recognised as the software interface which interconnects communication devices, intelligent system, database, agents, and devices in an intelligent environment. In other words, middleware is a mean to manage the complexity of elements in intelligent environment [72].

For specific applications in an ambient intelligent environment, other technologies should also be involved. For example, in the case of this research tagging technology should be integrated in data acquisition to identify occupants. Hence, tagging technologies are explained in the next section.

3.5 Tagging Technologies

In order to identify objects, a tagging mechanism should be integrated to the data acquisition system. The tagging of mobile nodes has been considered in the literature [73], [74], [75]. The tagged node can be a person, asset, or other objects [76]. Currently, with the spread of wireless technology due to its ease of installation, fewer needed resources and bringing more mobility for users, the focus of tagging is on the infrastructure of wireless networks including WSNs inside ambient intelligent environments. Localisation of the objects is one of the applications in tagging technologies [77], [78] which is based on a wireless approach named Received Signal Strength Indicator (RSSI) explained below:

3.5.1 Received Signal Strength Indicator

In wireless technology, RSSI is defined as the strength or the quality of radio signal detected at the receiver side. By measuring this quality factor, the distance between transmitter and receiver can be approximated.

The distance between transmitter and receiver is in inverse relationship with the transmitted signal's RSSI as given by:

$$RSSI \propto \frac{1}{d^2} \tag{3.2}$$

This relation is illustrated in Figure 3.4 . Therefore, the relation has been used in many localisation techniques. Basically, RSSI-based localisation has the advantage of using the data communication infrastructure for the localisation of mobile nodes. Despite its advantages, RSSI has its limitations due to the physical characteristics of radio signal propagation including multi-path propagation and signal fading [75].

Some localisation techniques employ hybrid technologies such as ultrasound to reduce

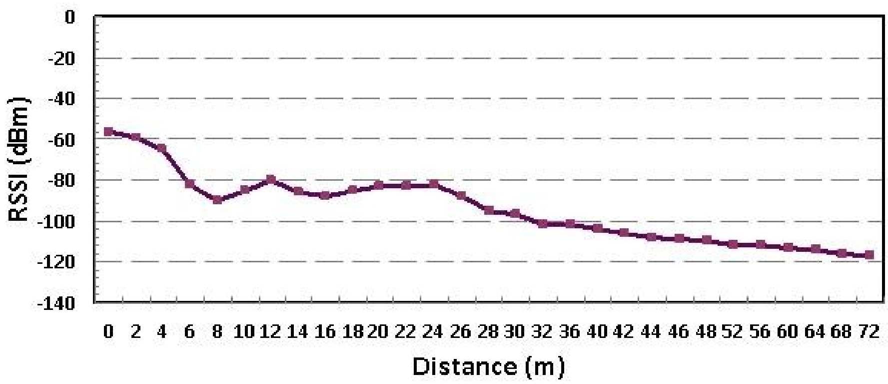


Figure 3.4 - Radio Signal Strength over distance.

these limitations and improve the effectiveness of the RSSI-based localisation [73].

RSSI is dependent on the following factors:

- ***Transmission Power:*** Transmission power means how far a radio signal can travel. The RSSI-distance measuring resolution decreases for higher powered transmitted signals,
- ***Hindrance:*** The signal strength received by the receiver is affected by environmental hindrances. Metal objects or thick walls can decrease the signal quality remarkably,
- ***Receiver Sensitivity:*** Receiver sensitivity means how faint a Radio Frequency (RF) signal can be detected by the receiver. The lower the power level that the receiver can successfully process, the better the receive sensitivity. Higher sensitivity receivers can provide higher resolution of RSSI distance measurements,
- ***Data rate:*** The accuracy of the RSSI distance measurement is dependent on the baud rate of the wireless communication. Lower baud rates can result in higher resolution RSSI-distance measurements,
- ***Interference:*** Interference of the tag radio signal with other radio signals can decrease the quality of RSSI-distance measurements.

There are two major technologies for tagging a person inside an environment which use radio signal strength; namely, Radio Frequency Identification (RFID) [79] and Localising Wireless Sensor Network (WSN) or Wireless Local Area Network (WLAN) [80], [81]. These two technologies which are based on the RSSI are explained below:

3.5.2 RFID Tagging

Radio Frequency Identification (RFID) is a method of tagging which is commonly used in different applications nowadays. Any RFID tag consists of a small microchip and an antenna around it. The microchip generates a unique identification number for the tag

Figure 3.5 - RFID tags and Readers.

which can be read by RFID readers. There are two major RFID technologies; namely, Passive RFID, and Active RFID.

In passive RFID technology, tags have no source of energy (e.g. batteries) and their range of detection is not more than normally 20-30 centimetres and in some products up to one meter. Passive RFID applications has spread very quickly in recent years. Key-less access, shopping bonus cards, identification cards, and bus and train card tickets are amongst these applications. On the other hand, in active RFID technology, active RFID tags have a source of energy and the range of detection is up to several meters [57]. The technology of active RFID has been employed in a number of applications including asset tracking, stock inventory, and shops security.

Any active RFID tag broadcasts a unique beacon periodically. This beacon can be received by nearby active RFID readers. By using the RSSI technique with active RFID technology, the distance of the RFID tag from readers can be approximated.

In this research, active RFID from different companies are investigated and employed for tagging in Chapter 6. Syris and WaveTrend active RFID tags including personal tags, asset tags, key-fobs, and wristband tags are investigated.

Various RFID readers made by these companies with different features such as small sized, gain adjustable, and Ethernet interfacing will be used for RSSI detection and identification. For more information about these products, readers are referred to [70], [128] and [129].

3.5.3 Wireless Sensor Network Tagging

For localising a mobile node in wireless sensor networks [82], two different approaches are available including range-free localisation [83] and range-based localisation [84]. In the range-free localization which is used in large scale WSNs (normally in environments including indoor and outdoor spaces) the location of the mobile node is determined by tracing the nodes hopped by the data packet or beacon transmitted from a mobile node. Therefore, the localisation resolution is low for range-free localisation in WSNs. Range-based localisation works using the RSSI technique to find the distance of a mobile node from a fixed node. This approach is more applicable for small WSNs with a small number of nodes.

3.6 Available Occupancy Monitoring and Tracking Technologies

Tagging, occupancy tracking and monitoring has been more considered in the technology market in recent years. The applications of these technologies vary from security, energy saving to elderly care. Nowadays, the applications in the field of security have been of more interest in the market. These technologies are employed by some of the companies such as JustChecking [85], Alertme [62], and Ubisense [86].

JustChecking system is an effort to allow people with dementia or memory loss, to live independently but still under control. JustChecking system uses a wireless network of motion detection sensors to monitor single-occupant environments and provides a chart of activity via the internet for elderly person's children or carers [62]. The simplicity of JustChecking system and its unobtrusive manner are the advantages of this system. However, the JustChecking does not address further data analysis and prediction of elderly person's behaviour.

Alertme products target the market of home security and energy saving [62]. Similarly, Alertme uses network of sensory devices to monitor the activity in home environments. Their security package offers a range of sensory devices such as PIRs and door contact sensors to inform residents of the strange activities in their premises when they are not present. The energy saving package of Alertme uses electricity current sensors to inform the residents of their energy consumption.

UbiSense uses Ultra Wide Band (UWB) Active RFID to localise tagged people in their working environments. The interrogators read the tags from as far as 150 feet away, then forward the data to Ubisense Smart Space software platform, integrated into an organisation's existing information system. Unlike conventional RFID systems, which operate on single bands of the radio spectrum, UWB sends a signal over multiple frequency bands simultaneously, from 3.1 GHz to 10.6 GHz. UWB signals are also transmitted for a much shorter duration than those used in conventional RFID [86]. Despite the claimed accuracy of UbiSense system the cost of their tags and installation process is still not the interest of smart environment. However, this system has started to spread in some demanding markets such as nuclear sites and large plants.

3.7 Summary and Discussion

In this chapter, some of the technologies employed in intelligent environments were briefly reviewed. These technologies can be used to create data acquisition mechanisms in the environment. It was mentioned that simple agents, intelligent agent, and middleware are used in some of the realised approaches. However, the main focus of this chapter was on the technologies required for occupancy monitoring, communication, and tagging.

In order to choose appropriate technologies, it is important to consider not only the application requirements but also the expandability of the data acquisition mechanism and the flexibility for further enhancements. For instance, if in a PaIE the tracking of living objects is required, then the employed technology for data acquisition in that environment should be able to address the requirement in less expensive and more efficient manner.

In Chapters 4 and 6 of this thesis, some of the reviewed technologies will be experimented, compared, justified to use, and finally employed for creating a data acquisition mechanism for occupancy detection in PaIEs.

In summary, the advancements in sensation, actuation, communication, and integration technologies have been assisting the realisation of ambient intelligent environments. Future advancements in these technologies will provide the area with new and more reliable means and infrastructures.

Chapter 4

OCCUPANCY MONITORING and PREDICTION in SINGLE-OCCUPANT PaIE

4.1 Chapter Overview

The increasing interests and demands for predictive ambient intelligent environments is a motive to investigate their realisation possibility in various perspectives. In connection with the behavioural pattern extraction in a PaIE, to make the occupancy detection and prediction possible in living/working environments, first, a data acquisition system should be employed to collect occupancy information from the environments. The data acquired by the data acquisition system should then be presented in an appropriate format for further analysis and prediction purposes. Furthermore, for creating a PaIE, intelligent techniques should be integrated into the control mechanism of the environment.

The technologies required to realise a PaIE with occupancy monitoring and prediction features can vary based on the situations in that environment. For example, creating a data acquisition system of simple sensory devices with unobtrusive features seems appropriate in one hand. However, using simple sensory devices can reduce the practicality of the data acquisition system in the environments with more complicated situation on the other hand.

This chapter is to investigate the realisation of an ambient intelligent environment with occupancy prediction features by proposing and employing required elements for occupancy monitoring, data representation and prediction in a PaIE. This will enable a PaIE to monitor the occupancy of different areas and predict the future occupancy situation in those areas. To achieve an occupancy detection and prediction mechanism in real environments, a simpler scenario i.e. single-occupant is considered in this chapter. The single-occupant scenario addressed in this chapter denotes environments in which absolutely one person is living as a resident. This simplification along with the idea of area occupancy detection instead of finding the precise coordinates of the occupant, as will be shown in this chapter and next chapters, can lead to the solutions for occupancy detection and prediction in more complicated i.e. multiple-occupant situations.

Single-occupant environments can be found everywhere nowadays. For example, an environment where an elderly person lives alone can be considered as a single-occupant environment. On the other hand, maintaining pure single-occupancy situation is rather unlikely to happen in reality i.e. single person living absolutely alone without any visitors. The prime application of the solutions proposed in this chapter is to deliver a well-being monitoring and assistive environment to support elderly people or people with mental impairments such as dementia or Alzheimer disease to live independently, in control and able to care for themselves within the limits of their abilities.

For the realisation of a single-occupant PaIE, this chapter considers the problem in three phases:

1. Proposing and implementing a data acquisition system for occupancy monitoring in a single-occupant PaIE which incorporates the novelties of

simplicity, expandability, unobtrusiveness in inexpensive entities,

2. Representing the occupancy data collected by the data acquisition system in a suitable format which represents the raw sensory data in an understandable unique graph called occupancy signal. This representation can also provide the time-series prediction techniques with a well-represented occupancy time-series,
3. Predicting the occupancy of the single-occupant PaIE by employing time-series prediction techniques and comparing their performances in virtual and real situations.

As stated above, this chapter considers the scenario when only one occupant is present in the environment at any time. The problems associated with multiple-occupant scenario are addressed in Chapter 6. In this chapter, simple sensory devices such as motion detection sensors along with a ZigBee wireless sensor network are integrated as Wireless Sensory Agents (WSA) in Section 4.2. WSAs are used to implement a data acquisition system for an ambient intelligent environment. WSAs are designed and implemented in a way to bring simplicity, expandability, and unobtrusiveness to the proposed data acquisition system in an inexpensive manner. Collected data by the data acquisition system is recorded in a base station using a monitoring portal software which enables monitoring and logging all sensed events in the environment. Then the raw occupancy data collected is reshaped and presented as a time-series in Section 4.4 in a way which includes the spatio-temporal characteristics. Representing the occupancy data in the proposed single time-series will make the use of powerful prediction techniques possible. Time-series prediction techniques are explained in Section 4.5 and then applied to the occupancy time-series in Sections 4.6 and 4.7. In this chapter, the experiments are conducted on both virtual and real environments. The data collected from an elderly-living environment for a period of couple of weeks is used for the comparison, experiments and evaluation.

4.2 Data Acquisition System

The data acquisition system for the application of occupancy detection should comprise appropriate sensory devices for occupancy detection and also a communication network to transmit the collected data to a base station. Hence, to test the hypothesis of a PaIE system, a wireless sensor network of motion detection sensors and door contact sensors as the data acquisition system is proposed and implemented. Employing both technologies namely, sensors and wireless network was resulted in the development of a Wireless Sensory Agent (WSA). Furthermore, a monitoring portal for visualising the sensors' activities and readings, and logging the data received for further processes and analysis was implemented. The whole system was installed in an elderly person living flat for collecting ADL i.e. daily activities and occupancy data. The implementation of WSAs and monitoring portal are explained in Appendix A in more details.

For creating a predictive control mechanism in a PaIE, an intelligent control mechanism should be able to perform prediction. Prediction techniques are able to extract meaningful statistics and other characteristics of the data. They can also forecast future events based on known past events: to predict data points before they are measured. These events are the same sensory data collected by the data acquisition system. The way the prediction techniques work is very dependent to the characteristics of the sensory data which is described in the next section.

4.3 Sensory Data Characteristics for Prediction

As it was described in Chapter 3, based on the type of the sensors, their output can be either analogue or digital. Considering the characteristic of the sensor behaviour and consequently sensor output is essential for the data representation and analysis. Figure 4.1 illustrates the output of four different type of sensors including temperature, light intensity, motion detection, and door contact sensors connected to wireless sensory agents. The output of the first two sensors i.e. temperature and light intensity has analogue characteristics whereas the output from other two i.e. motion detection and door contact sensors has digital characteristics.

A class of prediction techniques used for continuous signal prediction can be applied to the first type of signal generated by analogue output sensors such as light intensity signals with analogue characteristics, but the digital characteristics of signals from

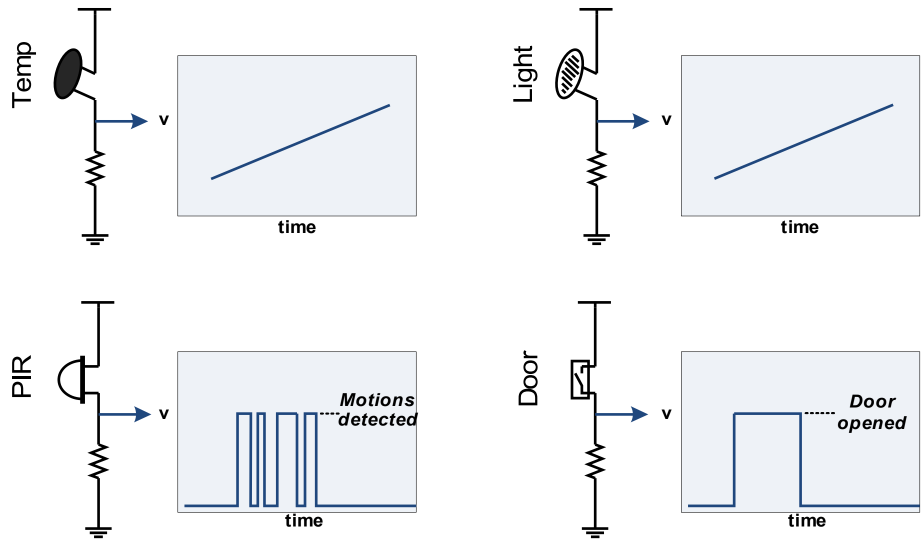


Figure 4.1 - Sensory Data characteristics.

motion detection sensors and door contact sensors makes them a challenge for analogue prediction techniques in one hand. On the other hand, due to the characteristics of digital signals, such signals has always been a challenge for prediction.

The characteristics of the sensory data explained above shows that these data can be interpreted as time-series signals. For example the light intensity varies over the time as an analogue time-series signal or the motion activities vary over the time as a digital time-series signal. These type of sensory data as time-series are the motives to use time-series prediction techniques for creating a PaIE.

To deal with the challenge of digital signal prediction, a new technique is proposed in the next section to interpret the data generated by motion detection sensors to a new form of signal. This signal will be called occupancy signal which is a continuous time-series and reshaped from the signals from motion detection and door contact sensors. The method for reshaping these signals is an approach to make them predictable by analogue time-series predictors which are considered in Section 4.5.

4.4 Data Representation - Signal Reshaping

In an example scenario of a PaIE, a virtual single-occupant home environment including

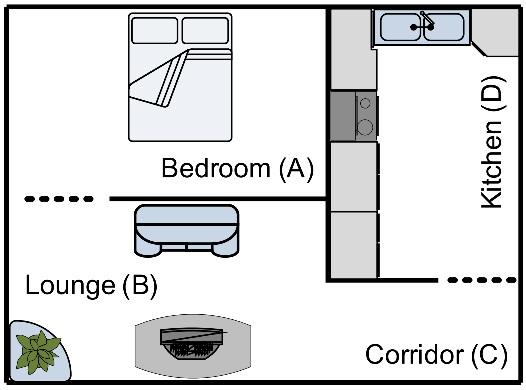


Figure 4.2 - A Virtual Single-Occupant PaIE.

four different areas is proposed. As it is shown in Figure 4.2, this environment consists of a bedroom, a lounge, a corridor, and a kitchen. In the virtual single-occupant PaIE, the occupancy of different areas for a single occupant is considered.

To identify the occupancy of different areas in real environments, a data acquisition system can collect sensory data from the whole environment. In order to detect if an area is occupied, a PIR motion detection sensor installed in that area can detect the movement of living objects. In this scenario, four PIRs can cover the entire proposed environment. To support PIR devices in occupancy detection, different types of sensors can be used. For example, a light intensity sensor in the bedroom, a light intensity sensor and an electrical current sensor (for a TV) in the lounge, and a light intensity sensor, a temperature sensor and a gas flow sensor in the kitchen can be used to support PIR activations in such areas. Although supporting sensors and detectors can help to determine the occupancy of an area, the occupancy detection is mostly the responsibility of PIR motion detection sensors in that area.

As it was mentioned in Section 4.3 the signal generated by a PIR is intrinsically a digital signal. PIR sensors are sensitive to the movement of living objects. Any movement within the detection range of a PIR will cause a logical 1 signal until the object stops its movement. As soon as the moving object stopped its movement, the signal level returns to logical 0 again. The behaviour of a PIR sensor is illustrated in Figure 4.3. A sample of ADL detected by PIR sensors over 24 hours in the virtual environment is depicted in Figure 4.4. In this figure, the first, second, third, and forth levels show PIR activities in different areas: Bedroom, Lounge, Corridor, and Kitchen respectively.

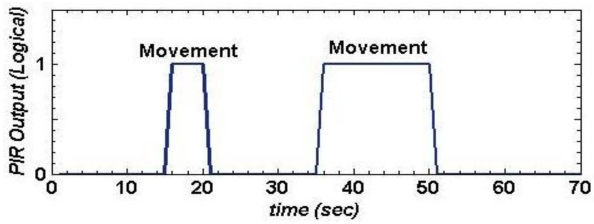


Figure 4.3 - PIR Signal Activity.

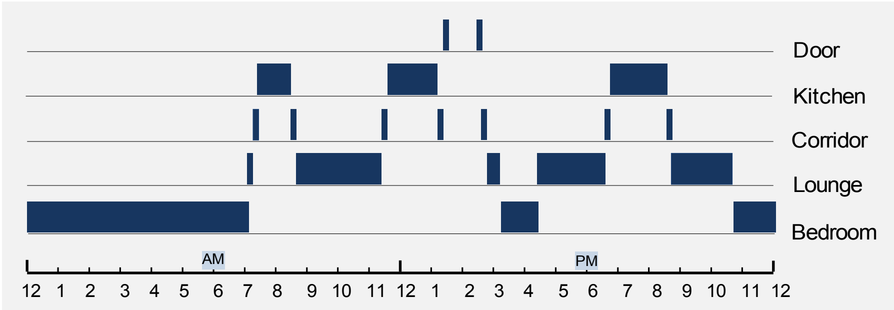


Figure 4.4 - Passive Infra-red signals for daily activity in the proposed virtual environment.

The top row in the signal is the activities of main door contact sensor. This signal representation gives a good understanding of the activities in a single-occupant PaIE. However, it lacks the benefits of representing ADLs in a single signal because it only shows PIR signals in different levels.

Time-series prediction techniques e.g. Adaptive Neural Fuzzy Inference System (ANFIS) are interested in continuous single signals rather than discrete separate signals. The signals from PIRs and door contact sensors are in discrete digital format which should be reshaped to continuous form for being analysed by time-series predictors described in Section 4.5.

In order to generate a suitable continuous form of signal for prediction, a transformation of a crisp signal to a continuous signal is proposed. The proposed occupancy signal should contain both spatial and temporal characteristics [88]. Spatial characteristic refers to the label of area which separates the occupancy of different areas and temporal characteristic refers to the time that the event or occupancy is detected. This transformation is performed in two phases: ***Signal Integration*** and ***Signal Conditioning***.

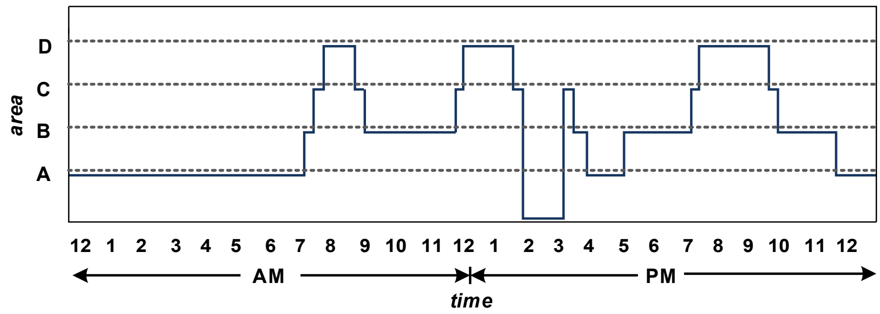


Figure 4.5 - The first phase of continuous representation of passive infra-red signals in a single graph.

4.4.1 Signal Integration

In signal integration, for each PIR a new level is assumed representing the area in which the PIR is installed and they are represented in a time based combined signal. The combined signal representation for passive infra-red signals in Figure 4.4 is shown in Figure 4.5. In this figure, each level represents the occupancy of an area. For instance, level B in this graph shows the occupancy of the area B (lounge as shown in Figure 4.2) or the firing of the PIR sensor in that area. In this representation, if a PIR in an area shows activities then the associated area is considered as the occupied area until the PIR activities in other areas of the single-occupant scenario are observed.

In the case of parallel PIR activities e.g. PIR activities in Bedroom and Kitchen at the same time, there will be an ambiguity of the activities. This ambiguity can be due to the presence of others in the monitored environment which makes the combination into a single occupancy signal almost impossible. However, as the proposed environment is a single-occupant environment, there will be no parallel activation of PIR sensors; hence no activity level conflicts for shaping a combined occupancy signal. Otherwise, the PIR activities cannot be identified to incorporate for creating the combined occupancy signal. This situation will be addressed in Chapter 6 of this thesis.

4.4.2 Signal Conditioning

The combined occupancy signal integrated in Section 4.4.1 is intrinsically a digital

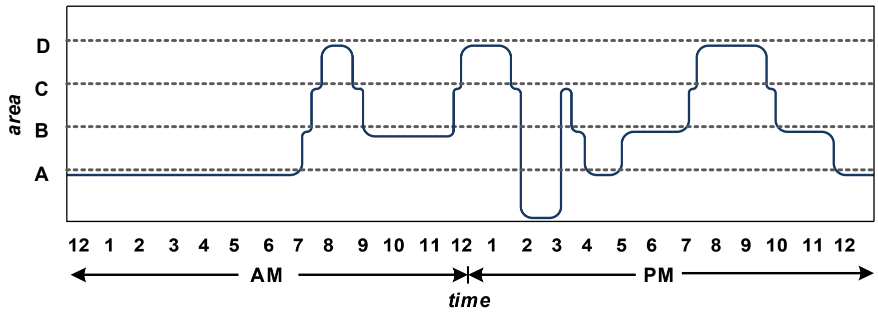


Figure 4.6 - Softened edge combined occupancy signal.

time-series because the combined occupancy signal is a time based signal and the levels in the signal belong to a discrete domain (1, 2, 3, 4, …). The learning and prediction of digital signals has been a challenge and addressed in a number of researches. However, it is aimed in this thesis to predict the combined occupancy signal using well-known time-series prediction techniques such as ANFIS and ARMA which are explained in Section 4.5. The issue of using such time-series predictors is that they are designed to predict analogue time-series signal with continuous feature. Therefore, applying these techniques to a digital signal (e.g. combined occupancy signal) can cause a problem of determining a unique value at transition times i.e. edges between levels in the combined occupancy signal. For example, the occupancy level changes in the signal take place without any intermediate values (e.g. between 1 and 2). In order to overcome this challenge, the sharp edges in the combined occupancy time-series should be eliminated.

In the second phase of continuous signal representation, it is proposed that the combined occupancy signal shown in Figure 4.5 to be passed through a low pass filter to eliminate its sharp edges. In order to do this, a Bessel type low-pass filter as described in Equation 4.1 can be applied to the combined occupancy signal.

$$H(s)=\frac{\Theta_n(0)}{\Theta_n(s/w_0)} \tag{4.1}$$

In the Bessel filter equation, $\Theta_n(s)$ is a reverse Bessel polynomials from which the filter gets its name and w_0 is a frequency chosen to give the desired cut-off frequency.

Figure 4.6 is a softened edge representation of Figure 4.5 after passing it through a Bessel low-pass filter. This representation of the combined occupancy signal is more suitable for use by analogue time-series prediction techniques.

The combined occupancy signal $x(t)$ represents the behaviour of the occupant i.e. his/her movement in the proposed environment. As explained above, this signal is representing a continuous occupancy signal which is a continuous time-series. Therefore, the prediction of the behaviour of an occupant is formulated into prediction of the occupancy time-series $x(t)$. This series is mainly influenced by life style and the behaviour of individual occupant. However, daily temperature, time of the day, day of the week, week of the year and public holidays will have a big impact on the occupancy time-series. There are other factors that can affect the occupancy time-series which are extremely difficult to model. For example, the impact of either noise or uncertainty in the behaviour of occupant can make the prediction of the time-series more difficult. On the other hand, if there is a pattern of activity in the environment, then the existence of this pattern with a small uncertainty can make the activity more predictable. Such a pattern is more likely for people with daily routines and less uncertainty in their behaviour e.g. elderly people.

4.5 Time-Series Prediction Techniques

A time-series is defined as a set of quantitative observations arranged in chronological order [89]. Hence, a form of data collected time-to-time can represent a time-series. The monthly consumption of energy e.g. electricity or gas, or the exchange rate of currencies changing over time are some of the time-series examples. Time-series analysis and prediction was considered more seriously when the importance of its benefits in terms of saving resources, safety, and security became more known [133]. There are two main goals of time-series analysis. Firstly, identifying the nature of the phenomenon represented by the sequence of observations, and secondly, forecasting or predicting future values of the time-series. Both of these goals require that the pattern of observed time series data be identified and approximately formally described [90].

In the literature, several techniques have addressed time-series prediction [91]. Stochastic models and dynamic-based techniques are the main classical techniques reported in the literature [92]. However, these techniques are found to under perform in predicting the behaviour in complex systems. Hence, alternative approaches have been investigated by many researchers. These approaches use computational intelligence techniques such as Neural Networks, Neuro-Fuzzy and Evolutionary Fuzzy Systems [93]-[102]. In recent years, more attention has been paid to learning and adaptive systems integrated with computational intelligence techniques. Evolving predictive systems capable of updating the parameters and structure simultaneously are proposed in [103]-[105].

The goal of the prediction task is to use past values of time-series to the time t to predict the values at some point in the future $t+\delta$. Consequently, a mapping from p points of the time-series spaced Δ apart should be created to predict future value $\hat{x}(t+\delta)$ i.e.

$$[x(t-(p-1)\Delta) \ \dots \ x(t-(p-j)\Delta) \ \dots \ x(t-\Delta) \ \ x(t)] \ \rightarrow \ \hat{x}(t+\delta) \qquad \textbf{\textit{(4.2)}}$$

The predicted values of the combined occupancy time-series $\hat{x}(t+\delta)$ is then translated into the occupancy of the environment as described in the preceding section.

Time-series prediction techniques explained in this chapter are categorised as statistical modelling techniques and intelligent techniques. The statistical modelling techniques are described in Section 4.5.1 and the intelligent techniques are considered in Section 4.5.2.

4.5.1 Statistical Modelling Techniques

In time-series analysis, it is assumed that the data consist of a systematic pattern i.e. a set of identifiable components, and a random noise (error) which makes the pattern difficult to identify [90].

Most time-series patterns can be described by two components including trend and seasonality. Trend is a general linear or non-linear component which changes over time but does not repeat or at least does not repeat within the range of time-series data. For example, the time-series shown in Figure 4.7 represents the increasing gross profit of a company over 10 years which can be analysed as the trend. On the other hand, seasonality repeats itself in systematic intervals in the time-series.

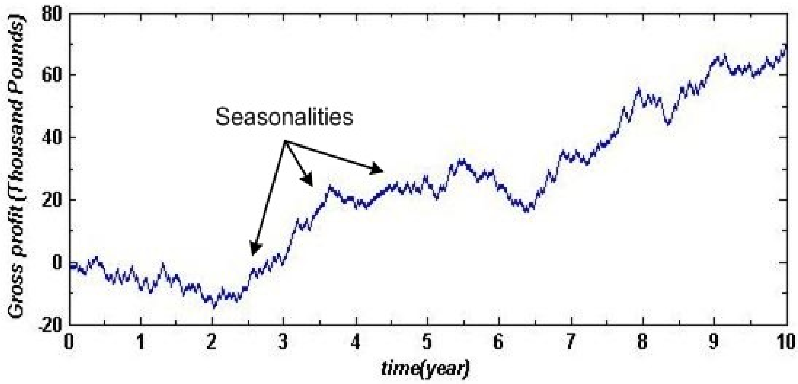


Figure 4.7 - A time-series example: Gross profit of a company in 10 years.

For example, gross profits in different seasons of a year can be considered as the seasonality in the company's gross profit time-series. If the error in the time-series is not considerable then it is possible to fit a linear, logarithmic, or polynomial function as the trend for the time-series.

For finding the seasonality, the similarity in different intervals is of interest. By finding the autocorrelations in the time-series and removing serial dependencies, the hidden nature of seasonal dependencies in the series can be identified.

The statistical modelling prediction invokes knowledge about mathematical model of the process by which the time-series is produced. However, in the research and practice in reality, patterns of the time-series are unclear, the time-series can involve considerable error, and it still needs not only its hidden pattern uncovered but also generate forecasts or prediction. The Auto Regressive Moving Average (ARMA) model described in the following section allows to do just that. ARMA has gained enormous popularity in many areas and research practice confirming its power and flexibility.

Most time-series prediction techniques including ARMA are based on the assumption that the time-series can meet a minimum of the characteristics related to stationary features. In a stationary time-series, the statistical properties including mean, variance, and covariance remain unchanged over the time. A time-series may be stationary in respect to one characteristic, e.g. the mean, but not stationary in respect to another, e.g. the variance.

4.5.1.1 Auto Regressive Moving Average

ARMA model sometimes called Box-Jenkins model proposed by G. Box and G. M. Jenkins [106], [107] employs two types of process with autoregressive and moving average properties as explained below:

4.5.1.1.1 Autoregressive Process

Most time-series consist of elements that are serially dependent in a sense that you can estimate a coefficient or a set of coefficients that describe consecutive elements of the series from previous elements [90]. This can be summarized as:

$$x(t)=\zeta+\phi_1 x(t-1)+\phi_2 x(t-2)+\phi_3 x(t-3)+\ \ldots+z \tag{4.3}$$

where ζ is a constant, ϕ_i are the autoregressive model parameters and z is the error (white noise) component. Note that an autoregressive process will only be stable if the parameters are within a certain range; for example, if there is only one autoregressive parameter then it must fall within the interval of $-1<\phi<1$. Otherwise, past effects would accumulate and the values of successive $x(t)$'s would move towards infinity, that is, the series would not be stationary.

4.5.1.1.2 Moving Average Process

Independent from the autoregressive process, each element in the series can also be affected by the past error that cannot be accounted for by the autoregressive component [90], that is:

$$x(t)=\mu+z(t)-\theta_1 z(t-1)-\theta_2 z(t-2)\ \ldots \tag{4.4}$$

where μ is a constant, and θ_i are the moving average model parameters.

An ARMA model employs both autoregressive and moving average features. This model is used as a basis for the analysis and it is a well established technique in prediction of financial time-series. Any ARMA model has two parameters where the first parameter, p, is the auto regression parameter and the second parameter, q, is the moving average parameter. Hence an ARMA process $x(t)$ can be presented as [108]:

$$x(t)-\phi_1 x(t-1)- \ \dots\ -\phi_p x(t-p)=z(t)+\theta_1 z(t-1)+ \ \dots\ +\theta_q z(t-q) \quad \textbf{(4.5)}$$

where $z(t)$ is the white noise with mean 0 and variance σ^2, ϕ is the coefficient of the auto regression part, and θ is the coefficient of the moving average part. Equation 4.5 can be formulated as:

$$x(t)=z(t)+\sum_{i=1}^{p} \phi_i x(t-i)+\sum_{i=1}^{q} \theta_i z(t-i) \quad \textbf{(4.6)}$$

with the polynomials ϕ and θ which will be referred to as the autoregressive and moving average polynomials respectively. Applying the Innovations Algorithm Proposition as described in [108] to the transformed process $x(t)$, it is obtained:

$$\textbf{(4.7)}$$

$$\begin{cases} \hat{x}(t+1)=\sum_{j=1}^{t} \theta_{tj}(x(t+1-j)-\hat{x}(t+1-j)) & 1 \le t < m \\ \hat{x}(t+1)=\phi_1 x(t)+ \ \dots\ +\phi_p x(t+1-p)+\sum_{j=1}^{q} \theta_{tj}(x(t+1-j)-\hat{x}(t+1-j)) & t \ge m \end{cases}$$

where $m=max(p,q)$. Equation 4.7 determines the one-step predictor, and also the recurrent prediction with more steps i.e. $\hat{x}(2), \hat{x}(3), \dots$ recursively.

Fitting an ARMA model to a given time-series can be done by minimising squared error between the desired output $x(t+\delta)$ and the predicted output $\hat{x}(t+\delta)$. So, the parameters are determined such that the squared difference between the model output and the observed value, summed over all time steps in the fitting region, is as smallest as possible [109]. To find the right order of ARMA model for a given time-series, it is advised to use some of the training data and use these to evaluate the performance of competing models [109].

4.5.1.2 Alternative statistical Modelling Techniques

ARMA model has shown a very good performance in modelling and prediction of time-series. However, this model can break down when there is not sufficient linearity and stationary in the time-series. For dealing with such time-series, intelligent techniques described in Section 4.5.2 and alternative statistical approaches such as Multivariate Adaptive Regression Splines (MARS) [109], Hidden Markov Models (HMM) [109], [110], and Bayesian methods [111] can be used. MARS uses recursive partitioning strategy for regression which uses spline fitting in lieu of other simple fitting functions and HMM has been extensively used for pattern recognition and classification problems because of its proven suitability for modelling dynamic systems.

In many of the prediction problems, there is insufficient historical information available at the time the initial prediction is required. Thus, the early prediction must be based on subjective consideration [111]. As soon as the time-series information becomes available, the subjective estimates must be modified based on the actual data. As an example of this process, a prediction of total sales for a product during a season can be made at the start of the season. As the season passes and actual orders are received, the original prediction should be modified in some manner. For such statistical inference problems Bayesian methods [111] are very useful techniques.

4.5.2 Intelligent Techniques

Intelligent techniques such as Artificial Neural Networks (ANN) have been typically used in pattern recognition and regression [109]. In both these cases, all the relevant information is presented simultaneously whereas time-series prediction involves processing of patterns that evolve over time i.e. the value of the time-series at a particular time point in future depends not only on the current but also the past value. However, the ability of intelligent techniques to cope with non-linearities, non stationary, lack of knowledge about the time-series or its data, and their accuracy has made them valuable tools of prediction.

Intelligent techniques do not require specific assumption about underlying model for time-series. For example, Artificial Neural Network allows the data itself be used to support the model estimation. This non-parametric feature of intelligent techniques has made them quite flexible in modelling real-world phenomena where observations are generally available but the theoretical relationship is not known or testable.

Two of intelligent techniques such as ANN and ANFIS are described in details in Sections 4.5.2.1 and 4.5.2.2.

4.5.2.1 Artificial Neural Networks

An artificial neural network is an abstract computer model of the human brain [101] which is composed of an input and an output layer along with a number of hidden layers between input and output. These layers are made of neurons and are connected to their subsequent layer by weighted edges (weighted links) [25]. Neurons are very simple computational units which can map their weighted sum of input vector to an output vector by applying an activation function to the weighted sum of input vector. For a simple neuron, it can be formulated as:

$$y = f(wx + b) \tag{4.8}$$

where, x is the input, b is the fixed bias, w is the weight on the input edge, f is the activation function, and y is the output of the neuron. The activation function can be a linear, hard limit, or sigmoid function.

Hence, a neural network is a model of an input vector $X = (x_1, x_2, \ldots, x_{n_i})$ to an output vector $Y = (y_1, y_2, \ldots, y_{n_o})$ where x_i is the input to neuron i in the input layer, y_i is the output of the neuron i in the output layer, n_i is the number of neurons in input layer, and n_o is the number of neurons in the output layer. In addition, $W_j = (w_{1j}, w_{2j}, \ldots, w_{n_i j})$ represents the weights from all the input layer neurons to the hidden layer neurons z_j and $W'_j = (w'_{1j}, w'_{2j}, \ldots, w'_{n_h j})$ represents the weights from all the hidden layer neurons to the output layer neurons y_j where n_h is the number of neurons in the hidden layer. Hence, the weights of the edges to all neurons in the input layer can be defined as a weight matrix:

$$W=\begin{bmatrix} w_{11} & w_{12} & \dots & w_{1,n_h} \\ w_{21} & w_{22} & \dots & w_{2,n_h} \\ \dots & \dots & \dots & \dots \\ w_{n_i,1} & w_{n_i,2} & \dots & w_{n_i,n_h} \end{bmatrix} \qquad \textbf{\textit{(4.9)}}$$

Similarly, a weight matrix for the weights on the edges from hidden layer(s) to output layer can be defined as W'. ANN can be trained with a set of facts that cover the solution space. During the training phase, the weights in the network are adjusted until the correct answer is given for all the facts in the training set.

After the training, the network can find outputs for inputs not in the training data as a model of the system by which the data was produced. In order to perform a time-series prediction using an ANN, the current and past values of the time-series should be used as inputs to the input layer of the neural network. The output of the neural network should then be considered as a one-step prediction. A schematic diagram of one-step time-series prediction using ANN is depicted in Figure 4.8. For the prediction, firstly, the network should be trained by the time-series data. A neural network learns a time-series pattern by adjusting its weights. A learning task is to adjust the weights so that it can output the target value $x(t+1)$ for each input pattern. In the training phase the predicted output $\hat{x}(t+1)$ is compared with the desired output $x(t+1)$ by creating an error function such as square error function E_1 as defined below:

$$E_1=\frac{1}{2}[\hat{x}(t+1)-x(t+1)]^2 \qquad \textbf{\textit{(4.10)}}$$

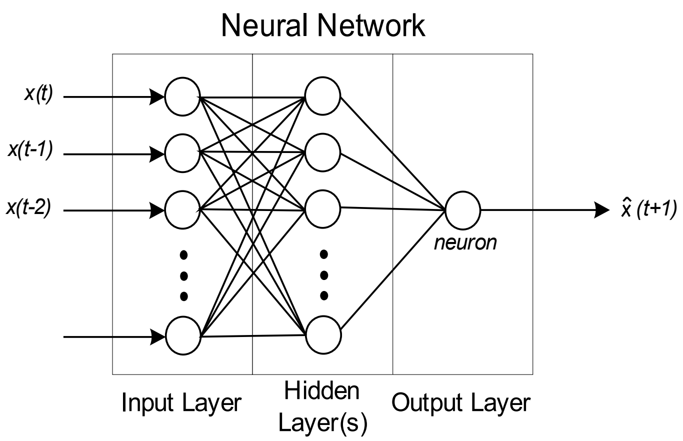


Figure 4.8 - One step time-series prediction using ANN.

To achieve a predicted value equal or close enough to the desired value, the error function described in Expression 4.10 should be minimised using optimisation techniques. Back-propagation technique [112] is a well-known optimisation technique used in the training of neural networks. Back-propagation improves W and W' to minimise the error function by applying steepest descent derivative based method. Its algorithm calculates the error in respect to the input weights of an ANN, and tries to alter the weights on the edges so that the error does not increase.

The steepest descent is formulated in Equation 4.11, where the new weight w_{new} is calculated from the subtraction of the old weight w_{old} from the derivative of error in respect to weight $\partial E / \partial w$ multiplied by a learning rate η .

$$w_{new} = w_{old} - \eta \frac{\partial E}{\partial w} \qquad \textbf{(4.11)}$$

In Equation 4.11, if the error gets more positive in respect to the weight then a new weight smaller than the old one is applied to keep the error minimised.

Similarly, if the error decreases in respect to the weight then a new weight larger than the old one is applied to keep the error minimised. As there are more than one layer in an ANN, the derivative of the error in respect to the input layer weights should be calculated by taking the partial derivatives of each layer, such that:

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial y} \times \frac{\partial y}{\partial z} \times \frac{\partial z}{\partial w} \qquad \textbf{(4.12)}$$

To perform a multi-step time-series prediction using neural networks, Recurrent Neural Networks (RNN) can be used [113]. In an RNN, the idea of one-step prediction by an ANN can be employed in a consecutive manner to provide the prediction for more than

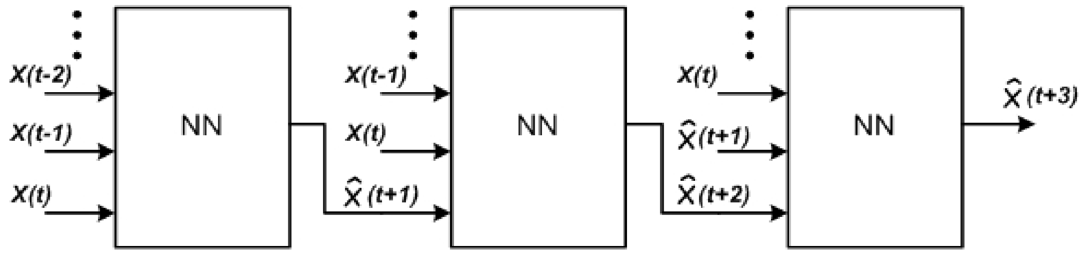


Figure 4.9 - A 3-Step Recurrent Neural Network.

one step. For example, the network illustrated in Figure 4.9 is a three-layer RNN for performing a 3-step time-series prediction. In an RNN, error function can be calculated by the summation of the errors in each layer: $E = E_1 + E_2 + E_3$ [113].

4.5.2.2 Adaptive Neuro Fuzzy Inference System

Adaptive Neuro Fuzzy Inference System (ANFIS) is a class of adaptive networks that is functionally equivalent to Fuzzy Inference Systems (FIS) [114]. As one of the powerful intelligent techniques, ANFIS can also be used for time-series prediction. For example, an ANFIS architecture equivalent to a Sugeno type FIS illustrated in Figure 4.10 is used for time-series prediction with the inputs of current value and two past values of the time-series. A normal ANFIS architecture consists of five layers. Layers 1 and 4 in ANFIS are adaptive layers consisting of adaptive nodes (neurons) with adjustable parameters. In the first layer, each node converts its crisp input (e.g. $x(t-\Delta)$ in Figure 4.10) to a fuzzy output using a fuzzy membership function through a fuzzification process.

The MF of the nodes in layer 1 can be any of the standard MFs including linear, sigmoid, and bell-shape. For example, a bell-shape fuzzy MF represented by Equation 4.13 includes three parameters $[a, b, c]$ which provides enough flexibility to adjust the function required for crisp input.

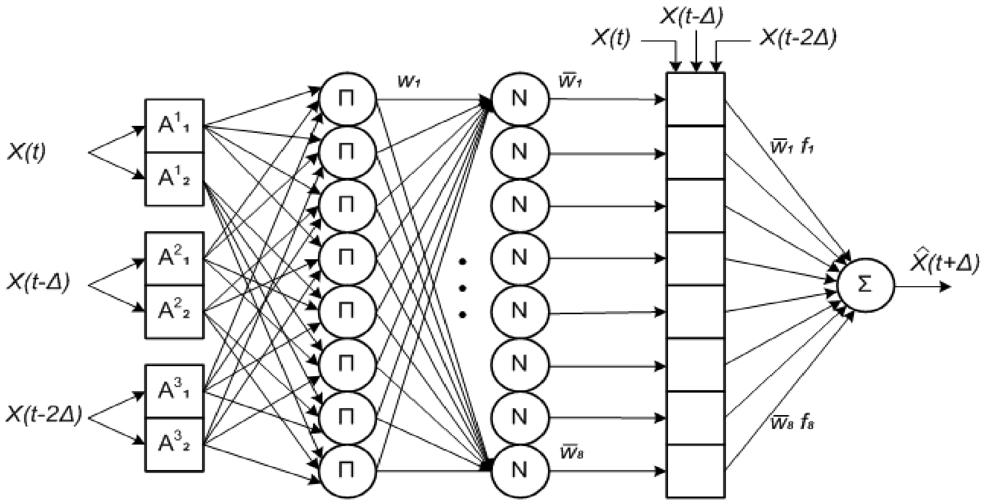


Figure 4.10 - ANFIS Sugeno-type Architecture for Time-Series Prediction.

$$\mu_A(x)=\frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \qquad \textbf{(4.13)}$$

Any ANFIS with bell-shape MF has $3*N_m*N_i$ input (layer 1) parameters called premise parameters, where N_i is the number of inputs and N_m is the number of membership functions for each input. In layer 4, adaptive nodes multiply a linear function f_i by a firing strength coming from the third layer $\bar{w}_i$, i.e.

$$f_k=q_{0k}+q_{1k}*x(t)+q_{2k}*x(t-\Delta)+q_{3k}*x(t-2\Delta)+... \qquad \textbf{(4.14)}$$

Any ANFIS network has $(N_i+1)*N_m^{N_i}$ output (layer 4) parameters called consequent parameters.

Other layers consist of fixed nodes with fixed operations such that:

- Layer 2 multiplies a composition of equivalent fuzzy value of crisp inputs by generating w_i where:

$$w_i=\prod_{j=1}^{p}\mu_{\tilde{A}_i^j}(x(t-(p-j))\Delta) \quad i=1,2,...,n \qquad \textbf{(4.15)}$$

- Layer 3 generates firing strengths correspondent to each input i.e. $\bar{w}_i$ where:

$$\bar{w}_i=\frac{w_i}{\sum_{i=1}^{n}w_i} \quad i=1,2,...,n \qquad \textbf{(4.16)}$$

- Layer 5 generates the output of the ANFIS by contributing all Sugeno linear functions f_i based on their firing strengths decided by the ANFIS network.

$$f=\sum_{i=1}^{n}\bar{w}_i*f_i=\bar{w}_1*f_1+\bar{w}_2*f_2+\bar{w}_3*f_3+... \qquad \textbf{(4.17)}$$

In general, to predict the combined occupancy time-series $x(t)$ using ANFIS, the current and past values of the signal are modelled as rules that represent the non-linear relationship between these values. A fuzzy rule of the following form is used as the model for prediction of the occupancy time-series:

$$R_i:\ if\ \ x(t)\ \ is\ \ \tilde{A}_i^p\ \ldots \wedge\ x(t-(p-j)\Delta)\ \ is\ \ \tilde{A}_i^1\quad then\ \ x(t+\delta)\ \ is\ \ f_i \tag{4.18}$$

where R_i is the label of i^{th} rule, $x(t-(p-j)\Delta):\ j=1,\ldots,p$ is the j^{th} input, $x(t+\delta)$ is the output, $\hat{A}_i^j$ $(i=1,2,\ldots,n\ \wedge\ j=1,2,\ldots,p)$ is a fuzzy label, and f_i is a linear combination of inputs $f_i=q_{0i}+q_{1i}*x(t)+\ldots+q_{pi}*x(t-(p-1)\Delta)$. Parameters n and p are the numbers of rules and individual inputs respectively. It is assumed that the universe of input variables is limited to a specific domain interval, i.e. $x(t)\in[x^{-}\ \ x^{+}]$.

The decision, $\hat{x}(t+\delta)$ for the i^{th} instance, as a function of inputs $x(t-(p-j)\Delta):\ j=1,2,\ldots,p$ is given in the following equation:

$$\hat{x}(t+\delta)=\frac{\sum_{i=1}^{n} w_i f_i}{\sum_{i=1}^{n} w_i} \tag{4.19}$$

where f_i is the consequent parameters and w_i is the rule firing strength given by:

$$w_i=\prod_{j=1}^{p} \mu_{\tilde{A}_i^j}(x(t-(p-j))\Delta)\quad i=1,2,\ldots,n \tag{4.20}$$

where $\mu_{\tilde{A}_i^j}$ is the membership function of the fuzzy value $\tilde{A}_i^j$. If bell-shape MF with three parameters $[a,b,c]$ is considered then the parameters of a fuzzy rule-based system are defined as $\Theta_{ij}=[a_i^j, b_i^j, c_i^j, f_i]$.

The prediction problem is now in the form of identifying the parameters of the ANFIS, Θ_{ij} . Starting from the initial values of the parameters, to update these parameters as more data is available, the adaptation technique as described below can be employed.

To minimise the difference between the predicted occupancy time series $\hat{x}(t+\delta)$ and actual occupancy time series $x(t+\delta)$, the error generated from all data must be minimised. The following mean square error function is considered for minimisation of the prediction error.

$$E(\Theta)=\frac{1}{2}\sum_{k=1}^{s} e_k^2(\Theta_{ij})=\frac{1}{2}\sum_{k=1}^{s}(x(t+\delta)-\hat{x}(t+\delta))^2 \tag{4.21}$$

where e_k is the difference between the actual value $x(t+\delta)$ and the predicted value $\hat{x}(t+\delta)$ for the k^{th} training data sample. It is assumed that there are a total of s samples in the training data set.

All parameters of the ANFIS, $\Theta_{ij}=[a_i^j, b_i^j, c_i^j, f_i]$, can be updated using a steepest gradient descent method to minimise the error function $E(\Theta)$ given in Expression 4.11. The parameters then will be updated by the following rule:

$$\Theta_{ij}|_{new} = \Theta_{ij}|_{old} - \eta \nabla e_{ij} \qquad \textbf{\textit{(4.22)}}$$

where ∇e_{ij} is the gradient of parameters and η is the rate of descent which may be chosen arbitrarily.

$$\nabla e_{ij}=[\frac{\partial E}{\partial a_i^j} \ \frac{\partial E}{\partial b_i^j} \ \frac{\partial E}{\partial c_i^j} \ \frac{\partial E}{\partial f_i}] \qquad \textbf{\textit{(4.23)}}$$

It is anticipated that when the parameters are adapted, the prediction error will be reduced. It should be noted that the gradient descent technique mentioned above suffers from various convergence problems. The convergence problem of the steepest descent technique in fuzzy inference systems modelling is discussed in [115].

It is reasonable to take large steps down the gradient at locations where the gradient is small and small steps where the gradient is large. If both gradient and curvature information namely the second derivatives are used then the error will be minimised in a shorter time with more accuracy.

4.5.2.3 Alternative Intelligent Techniques

There are other intelligent techniques arising from the concept of artificial neural networks which can be used for multi-step time-series prediction.

Time Delay Neural Networks (TDNN) which is a well suited technique in speech recognition is applied for time-series prediction [116] too. This technique relies on special kind of memory known as Tap-Delay-Line where the most recent inputs are buffered at different time steps between input layer and the hidden layers of an ANN [117]. Echo State Network (ESN) [118] is a special type of RNNs with its major feature in hidden layer (also called reservoir) allowing the echo of the past states which reduces the training time remarkably.

Recursive Self Organising Map (RSOM) [119] and Support Vector Machines (SVM) [120] have been also used for time-series prediction in some applications.

In the next section, some of these statistical and intelligent prediction techniques are applied for the occupancy time-series prediction in a number of experiments.

4.6 Experimental Results and Validations

In order to examine the performance of the proposed techniques including data acquisition technique explained in Section 4.2 and the occupancy data representation explained in Section 4.4, in this section, a number of experiments are conducted. Hence, two techniques for time-series prediction such as ARMA and ANFIS are employed to predict the single occupancy time-series.

The experiments conducted here will also test the performance of prediction techniques on the applied time-series. In the first experiment in this section, an occupancy signal generated for a virtual environment explained in preceding section will be used as the proof of proposed techniques whereas the second experiment will prove the applicability of these techniques in real situation by conducting experiments based on real data collected from a real single-occupant environment. The real environment is an elderly-living apartment in which WSAs are installed for data acquisition.

4.6.1 Experiment 1 – Virtual Environment

In this experiment, a prototype single-occupant environment with 4 areas equivalent to the proposed environment in Section 4.4 is considered. This environment consists of four different areas: A, B, C, and D as depicted in Figure 4.11. Concentrating on the occupancy prediction in the single-occupancy scenario, a time-series representing the occupancy of the virtual environment for 15 working days is generated.

In the generated signal illustrated in Figure 4.12, each level represents the occupancy of

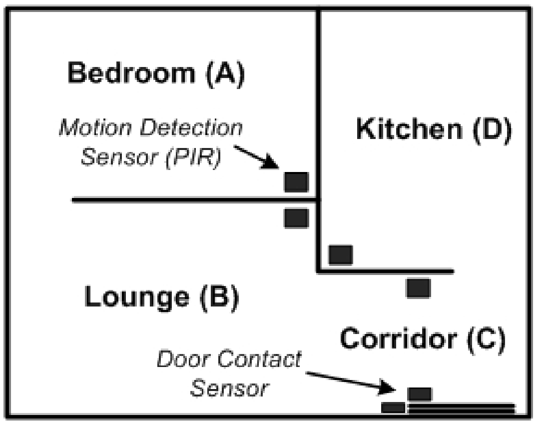


Figure 4.11 - A virtual single-occupant scenario.

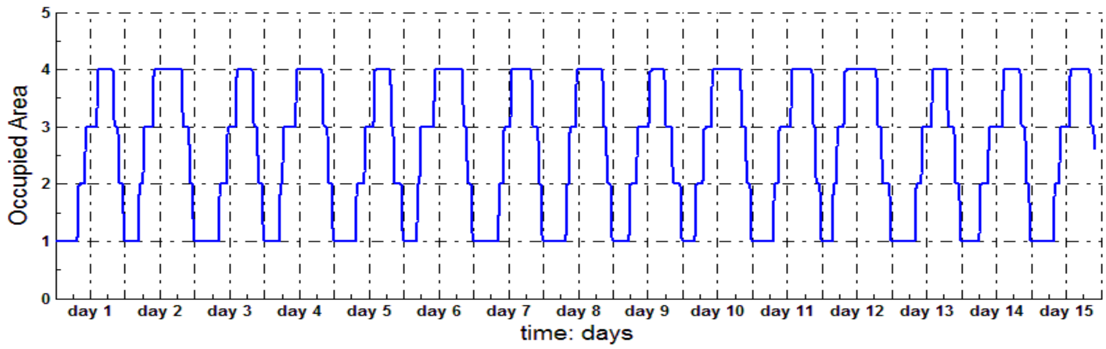


Figure 4.12 - A 15-day combined occupancy signal generated for the proposed environment.

an area, 1 for Bedroom (A), 2 for Lounge (B), 3 for Corridor (C), and 4 for Kitchen (D) respectively. This signal has the resolution of one minute with an expected occupancy pattern of ABCDCBAB for daily activity. The durations or the time spent by the occupant in each area is varied with the variance of 15% of the mean durations in the expected pattern. Assuming that only a pattern of usage for working days are included in our study, then it is expected that the generated time series would be a stationary time-series. Two time-series predictors are applied to the generated virtual time-series which are explained below:

ANFIS Model – Virtual Environment

An ANFIS model is set to predict the occupancy signal generated for the virtual environment based on 15 minutes (900 seconds) ahead prediction i.e. $\delta=15$. Only 5 samples of the time series $p=5$ and $\Delta=15$ are considered for this predictive model.

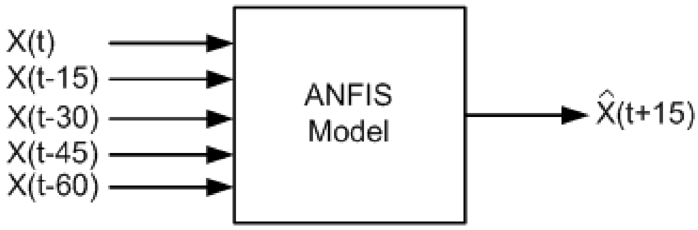


Figure 4.13 - An ANFIS model for 15-minute prediction.

Therefore, by monitoring the occupancy time series in every quarter of an hour of the last hour, the model should be able to predict the location of the occupant in the next 15 minutes or so which is formulated as:

$$\hat{x}(t+15)=f(x(t),x(t-15),x(t-30),x(t-45),x(t-60)) \tag{4.17}$$

An ANFIS model with five inputs and one output was generated. A schematic diagram of the ANFIS is shown in Figure 4.13. For all inputs two membership functions in the universe of [1 4] are defined.

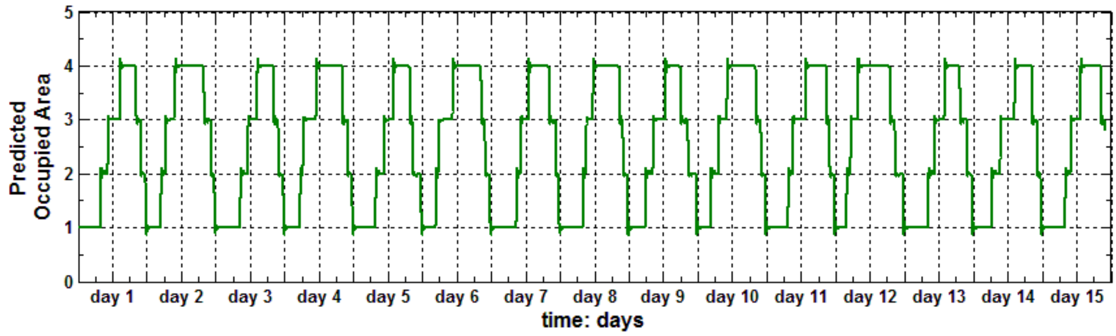


Figure 4.14 - Predicted occupancy signal by ANFIS model.

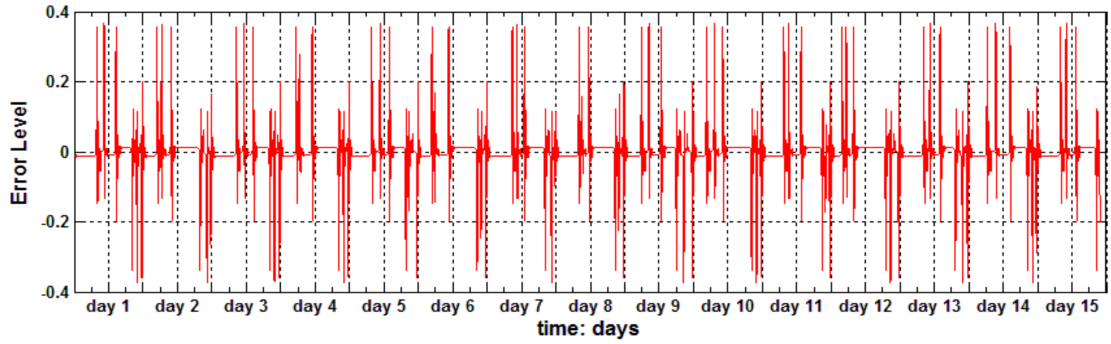


Figure 4.15 - ANFIS prediction error.

In this experiment, collected data for 12 days were used for training the ANFIS model. The rest of 3 days data were used for checking the results. The predicted signal by ANFIS is depicted in Figure 4.14. In the occupancy signal, the minimum difference between the occupancy of different areas in the combined occupancy signal is one level. Therefore, with differences less than half a level the actual value of predicted signal in different times can be recognised properly. Thus, the occupied area by the occupant can be recognised without ambiguities. Prediction error for the above experiment is shown in Figure 4.16.

The ANFIS model trained for 100 epochs and reached the minimum learning error of 0.0574 after 8 epochs. Moreover, the ANFIS prediction error of less than 0.36 shows that the technique has been successful in the prediction of generated occupancy time-series.

ARMA Model – Virtual Environment

The next applied prediction technique is an ARMA model to predict the occupancy combined signal. The applied model is an ARMA model of order four (ARMA [4, 4])

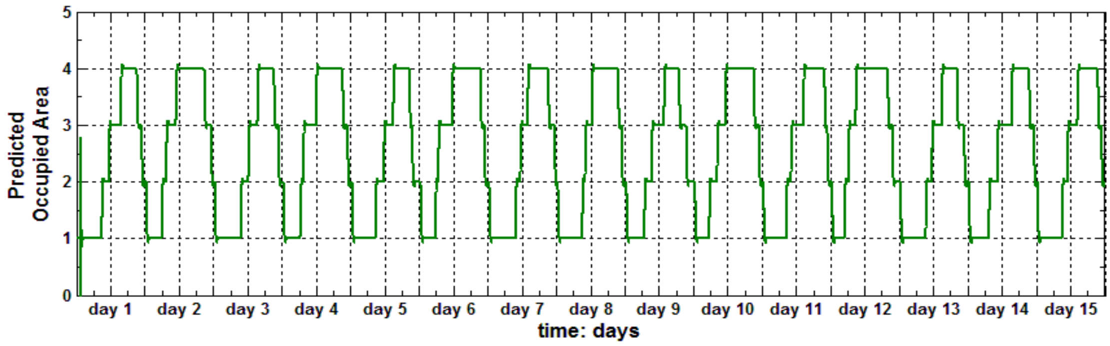


Figure 4.16 - Predicted occupancy signal by ARMA model.

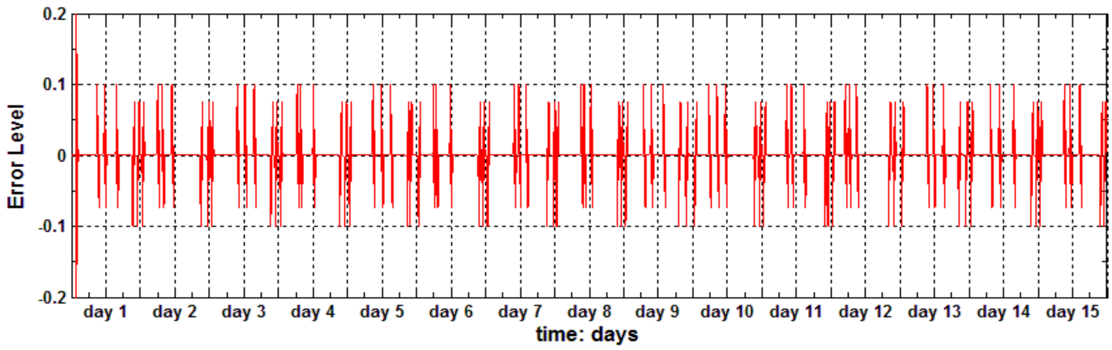


Figure 4.17 - ARMA prediction error.

with four autoregressive and 4 moving average parameters. The prediction step in this model is set to 15 which is equal to 15 minutes (900 seconds) in the generated virtual occupancy signal. Figure 4.10 illustrates the predicted signal after 20 iterations for the estimation of coefficients (parameters) in the proposed ARMA model. The absolute error for ARMA model predicted occupancy signal shown in Figure 4.17 is less than 0.2 which is smaller than our critical error (half a level). Therefore, the ARMA prediction works very well in the prediction of occupancy signal generated for the virtual environment.

4.6.2 Experiment 2 – Real Environment

The second experiment is performed using a real occupancy data collected from a single-occupant elderly-living apartment in Nottingham. The elderly lady is moving around by a walker support. There are daily routines that a carer cooks and cleans for the elderly lady and checks her health status. In addition, she has some visitors at different times on some of the days.

The schematic along with some pictures of the elderly lady's apartment layout is illustrated in Figure 4.18. In order to monitor the occupancy in her premise, a data acquisition system as explained in Section 4.2 was installed in the elderly lady's apartment. The installed data acquisition system includes four PIR wireless sensory agents for detecting movements in four different areas namely, bedroom, corridor, lounge, and kitchen. In addition, two door contact wireless sensory agents were used to monitor the main entrance door and bathroom door.

A base station consisting of a laptop computer with the monitoring portal installed on it and a wireless receiver agent plugged in it was left in a safe place in the apartment. Therefore, the data collected by wireless sensory agents were transmitted to the base station and logged in a database file through the monitoring portal on the base station.

The data acquisition system installed in the elderly-living apartment collected data for couple of weeks (Holidays and weekends are not included) of activity in the environment.

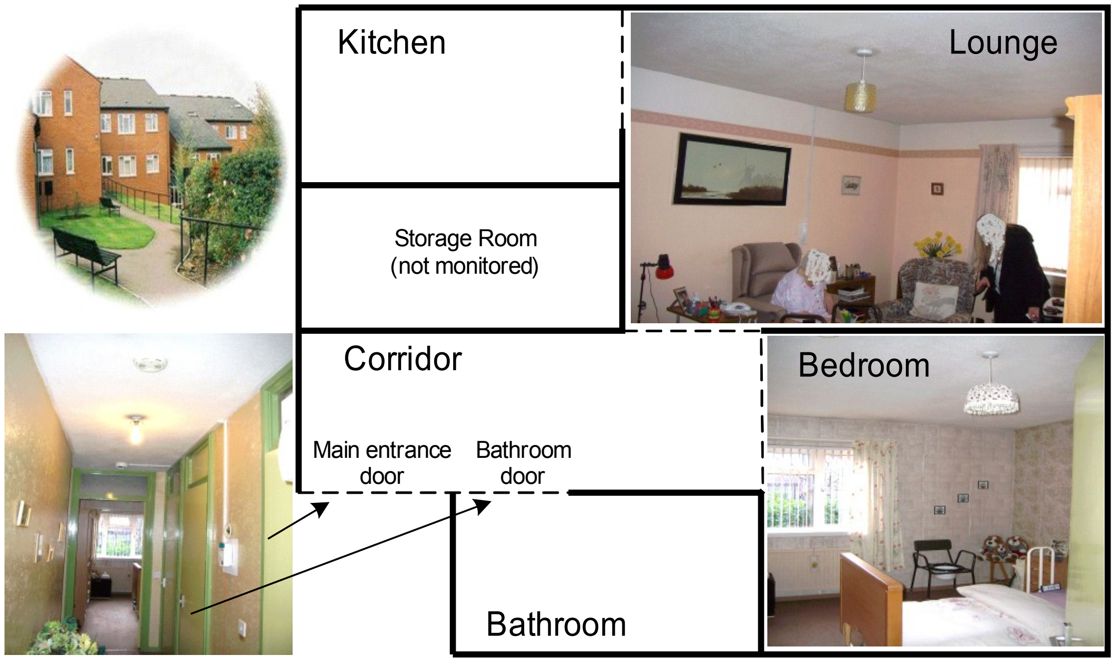


Figure 4.18 - An elderly-living single-occupant apartment.

The collected data as expected is not a crisp data for constructing the occupancy time-series signal due to the uncertainty and abnormalities included in detected motions data. As investigated, the uncertainty takes place when parallel activities in different areas are detected i.e. motion activities detected by PIRs and door contact sensors in different areas at the same time which invalidates the single-occupancy assumption. This uncertainty is due to the presence of more than one person in the monitored environment which happens when the carer or any other visitor is present in the elderly lady's apartment. This problem will be addressed in more details in Chapter 6. On the other hand, the abnormality is due to the uncertainty in the behaviour, in this case, movements of the occupant (e.g. going to kitchen for a coffee) which is inevitable in normal daily activities. The point here is that the focus of occupancy prediction is based on the normal daily routines which takes place in most of the days which is the occupancy pattern of the occupant. For elderly people this pattern can be more certain because of their daily routines. Hence, the uncertainty and abnormality in the data should be reduced or even eliminated for approaching the occupancy pattern of the monitored resident which is done in following steps:

1. *Eliminating uncertainty in raw data:* Any parallel activity at a certain time invalidates the PIR activities. The main door contact sensor can act as a trigger

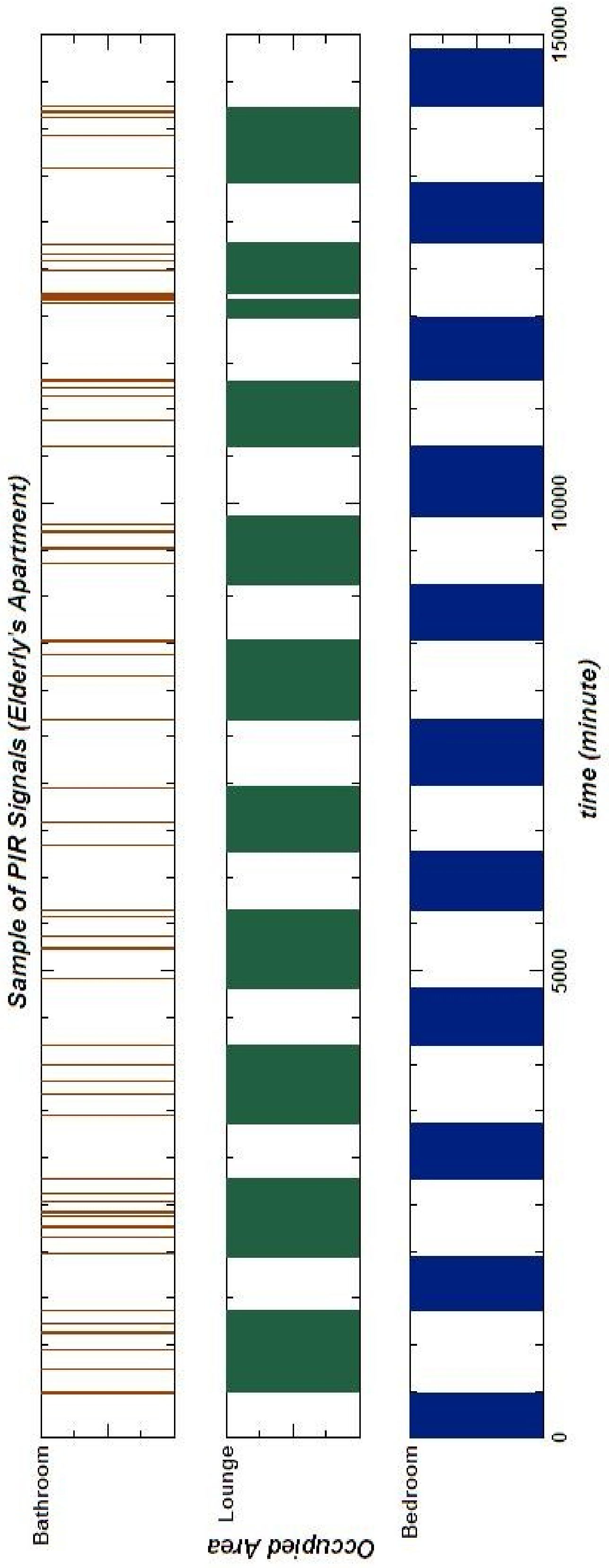


Figure 4.19 - A sample of ADL in elderly lady's apartment.

for the PIR parallel activity detection. The first firing of main door contact sensor in daily activity means that carer is in the elderly lady's apartment. In this case, the raw data is not used in occupancy prediction. This can sound problematic in the first look, but the cure to it is that the elderly lady is sitting in the lounge most of the time while the carer is in for cooking or cleaning unless the elderly lady wants to use the bathroom. It is the same situation while any other visitor is in the apartment which happens rarely in this case study. In this case, elderly lady is sitting in the lounge with her visitors. Therefore, unknown occupied area can be filled with the occupancy of lounge in the occupancy pattern of the elderly lady,

2. *Eliminating abnormality in raw data:* The abnormalities (uncertainty in elderly lady's sudden and rare movements) in the occupancy pattern should not be taken into account as they are not important in the routine daily occupancy pattern. To do this, simply, any jumping movements with short durations should be taken of the raw data,

3. *Excluding the corridor:* Occupancy of the corridor is not included in the occupancy pattern as the elderly lady only use the corridor for very short times to change her areas including, bedroom, bathroom, and lounge.

By applying the above mentioned steps, PIRs raw data is refined and an occupancy times-series is shaped. Combined occupancy time series is shown in Figure 4.19 where PIR sensors are monitored every minute (1440 samples per day). In Figure 4.19, levels 1, 2, and 3 represent areas Bedroom, Lounge, and Bathroom respectively. It is important to emphasis that the origin of collected data is from the normal ADL of the monitored elderly lady and she was not asked to act differently.

After creating an occupancy signal from the occupancy data shown in Figure 4.19 and passing the time-series through a low-pass filter, ANFIS and ARMA predictors are applied to the smoothed occupancy signal.

ANFIS – Real Environment

An ANFIS model with five inputs and one output was created. Every input has two

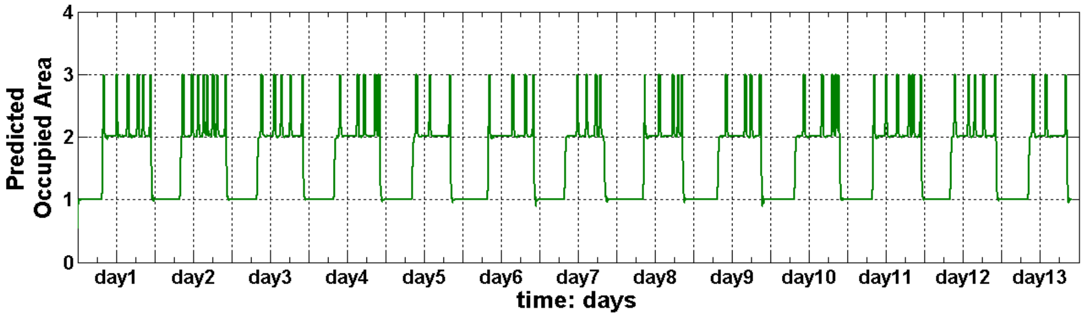


Figure 4.20 - ANFIS Predicted Occupancy Signal.

membership functions in the universe of [1 3]. The model was trained with 10 day of occupancy data and checked with a 3-day occupancy data.

The ANFIS model was able to predict the signal with the absolute error of less than 0.5 level for up to 510 seconds (see Figure 4.20). For longer prediction i.e. more than 510 seconds, the absolute error increases and passes the 0.5 level threshold causing ambiguity in recognition of the occupied area.

ARMA Model – Real Environment

The next applied prediction technique is an ARMA model for predicting the occupancy combined signal. The applied model is an ARMA model of order four (ARMA [4, 4]) with four autoregressive and four moving average parameters. The ARMA model was able to predict the signal with the absolute error of less than 0.5 level for up to 530 seconds (Figure 4.21). For the prediction time of more than 530 seconds, the absolute error increases and passes the 0.5 level threshold causing uncertainty in recognition of the occupied area.

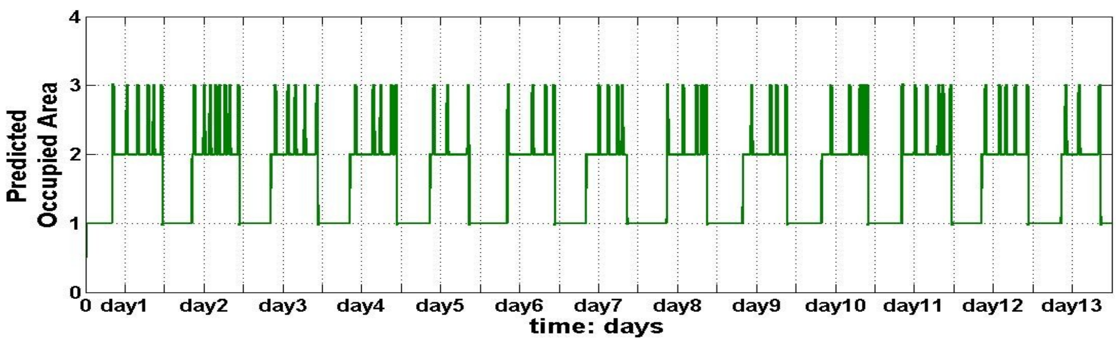


Figure 4.21 - ARMA Predicted Occupancy Signal.

Table 4.1 - Summary of prediction results.

Model	*order*	*training/estimation error*	*absolute error*	*Training time*	*Predicted time (sec)*
ANFIS (virtual)	MF=2 rules=32	0.0574 after 50 epochs	< 0.36	50 epochs	900 sec
ARMA (virtual)	p=4 q=4	0.03	< 0.2	20 iterations	900 sec
ANFIS (real)	MF=2 rules=32	0.0295 after 50 epochs	< 0.48	50 epochs	510 sec
ARMA (real)	p=4 q=4	0.03	< 0.46	20 iterations	530 sec

The cause of the more error and smaller prediction time for real data compared with virtual data is that the durations in level 3 i.e. bathroom occupancy is quite shorter than the occupancy of the bedroom and lounge in real the data. This fact restricts the smoothing process for preventing lost data; hence, sharper edges result in bigger prediction errors compared with virtual data. A summary of prediction results for both virtual and real scenarios are shown in Table 4.1.

The occupancy data provided by JustChecking company which was collected from a single-occupant house monitored by their kit was compared with the data collected from elderly lady's apartment. The nature of JustChecking is quite similar to the occupancy signal predicted in the second experiment. Hence, equivalent prediction performances are expected.

4.7 Summary and Discussions

In this chapter, the problem of occupancy detection and prediction in single-occupant environments was addressed. The proposed solutions were motivated to contribute the application of well-being monitoring in an assistive environment for elderly people who are living on their own with an unobtrusive feature. In this chapter, first of all, a mechanism for data acquisition was proposed and implemented in a real situation. Secondly, an occupancy data representation was proposed to create an occupancy time-series signal. Finally, two prediction techniques were used to evaluate the proposed ideas in both virtual and real situations.

It was proposed to create a network of wireless sensory agents as the data acquisition system. The data acquisition system proposed in this chapter is obviously not the only approach in the field. However, it brings a number of advantages and disadvantages. Using simple sensors such as PIRs and door contact sensors is an inexpensive way of occupancy detection. It is also unobtrusive compared with camera surveillance systems. Taking the advantage of wireless networking, the data acquisition does not need any infrastructure for installation like wiring and is very expandable compared with wired technologies. Moreover, most of the sensors employed for the data acquisition can be found in the buildings nowadays (e.g. motion detection sensors) and the use of them will be spread more in future. Therefore, the mechanism is beneficial in terms of value, convenience, expandability, and installation. On the other hand, it lacks the utilisation of the agents' processing capability due to the data analysis and prediction centralised in the base station. Furthermore, the occupancy cannot rely on the PIR data only when the situation is changed to other than the single-occupancy e.g. when a visitor is in the monitored environment.

To deal with the signal generated by motion detection and door contact sensors, an innovative way of data representation for these sensors was proposed which brings the following advantages:

- Representing the data of all motion detection sensors in a single occupancy signal (graph),
- Representing the occupancy signal with spatio-temporal characteristics as a time-series,
- Capability of applying powerful time-series prediction techniques for predicting the occupancy time-series.

Although the data representation technique for converting crisp motion detectors' digital signal is a potential to information loss after the applying a low-pass filter, the good interpretation of filtered signal would prevent any loss in the occupancy data. Figure 4.22 shows how a filtered signal can be reshaped. This figure illustrates how a smoothed signal (right red signal) can be interpreted as an occupancy signal with no ambiguity.

As it was shown, prediction techniques including ANFIS and ARMA were able to

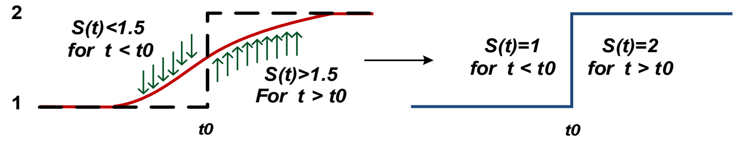


Figure 4.22 - Reshaping a Filtered Signal.

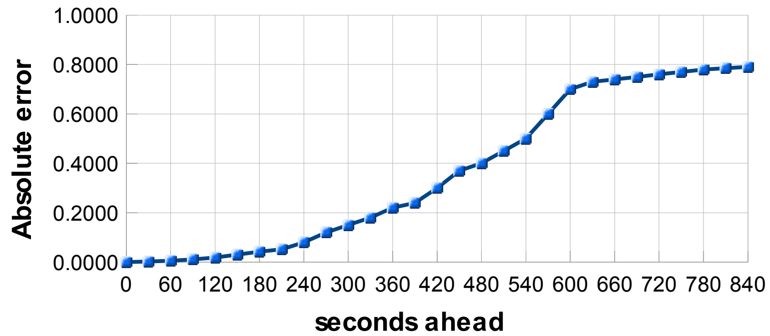


Figure 4.23 - Absolute error for ARMA prediction.

predict the virtual data up to 15 minutes (900 seconds) with the absolute error of less than 0.36 level and less than 0.2 level, but in the case of the real data, ANFIS did the prediction up to 510 seconds and ARMA did it up to 530 seconds. This has happened due to the nature of two signals. In virtual occupancy signal, durations are closer together rather than in real occupancy signal where the elderly lady occupies bathroom quite shorter than lounge or bedroom. To perform a good prediction with less uncertainty and a better fit, it is required to keep the absolute error less than a half level. The absolute error for ARMA model prediction based on real data is shown in Figure 4.23. It can be concluded from this graph that the prediction should be restricted to *time<530 sec*.

The uncertainties involved in the collected real data can be reduced by applying type-2 fuzzy techniques ([142] and [143]). Type-2 fuzzy brings the fuzziness to type-1 fuzzy systems; therefore, it can model and minimise the effect of uncertainties with more degree of freedom. Hence, it is suggested to incorporate type-2 fuzzy in the ANFIS model to create a more suitable model for single occupancy prediction.

Chapter 5

OCCUPANCY SIGNAL MODELLING

5.1 Chapter Overview

The proposed data acquisition system in Chapter 4 can collect the occupancy data from single-occupant environments. The elderly-living apartment in the real environment experiment of Chapter 4 is an example of single occupancy situation in which the proposed data acquisition system was installed.

Although the occupancy data collection for different durations in different environments is not impossible, it is subject to some restrictions. The restrictions in the number of required resources e.g. suitable residential apartments with internet connection and the restrictions in the number of hardware equipments such as WSAs can make the occupancy data collection fairly limited. The resources required for the maintenance of equipments should also be considered amongst these restrictions.

Taking into account the diversity of environmental designs as well as occupants' behaviour, to choose and adapt a suitable prediction technique, it is essential to do experiments considering different environmental profiles as well as different occupant profiles. Therefore, to reduce the number of experiments and substantially the number of resources required for these experiments, it is aimed to create a simulator that can generate the data required for more data analysis and subsequently evaluating different prediction techniques. In order to create this simulator, a model of the occupancy is required which incorporates the profile of both occupant and environment. Occupant profile describes the daily movements pattern and uncertainties involved with this pattern for each occupant and the environmental profile describes the design (layout) of the environment.

The nature of occupant profile in creating the occupancy signal which is related to human behaviour makes the modelling more challenging because modelling the human behaviour and representing it in a mathematical format is somewhat complicated [121]. However, the simplification of the human behaviour to a particular activity can reduce the modelling problem. For instance, it should be easier to model how an occupant occupies the areas in the environment where he/she is living rather than modelling all of her/his daily activities. On the other hand, including the environmental profile in the model seems to be simpler as the design of environment is assumed to be fixed and the layouts or the connections between areas are rather less complicated to be included in the model. It is aimed in this chapter to model the occupancy of a single-occupant PaIE for creating the above mentioned simulator.

The occupancy in a single-occupant environment can basically be modelled by using statistical techniques. This model simulates the occupant's pattern of occupancy and generates an occupancy signal which is ultimately formulated into a time-series. The model incorporates both different occupants' profiles and different environmental profiles. For creating this model, different parameters in occupant and environmental profiles are considered which are listed below:

In occupant profile:

- Expected daily occupancy pattern of the simulated occupant,

- Mean or average of the times spent by the simulated occupant at different areas in his/her ADL,
- Uncertainty in occupant movements between areas of the simulated environment,
- Uncertainty in the time spent by the occupant in each area.

In environment profile:

- Number of areas in the simulated environment,
- Layout and connectivity of different areas in the environment.

In this chapter, it is attempted to formulate the above parameters.

Initially, a modelling scenario is proposed in Section 5.2 where Sections 5.2.1 and 5.2.2 describe the modelling of different parts in an occupancy signal: *Durations* and *Transitions*. The model is then formulated in Section 5.2.3. In Section 5.3, the simulation algorithm is explained. The evaluation scheme for the model is proposed in Section 5.4. Generated signal specifications, the model validation results, and the model evaluation results are shown in Sections 5.5, 5.6, and 5.7 respectively. The chapter is summarised and the results are discussed in the final section.

5.2 Modelling Scenario

In a single-occupant environment consisting of several areas, the occupancy signal is basically a number of movements between different areas i.e. *transition* as well as the

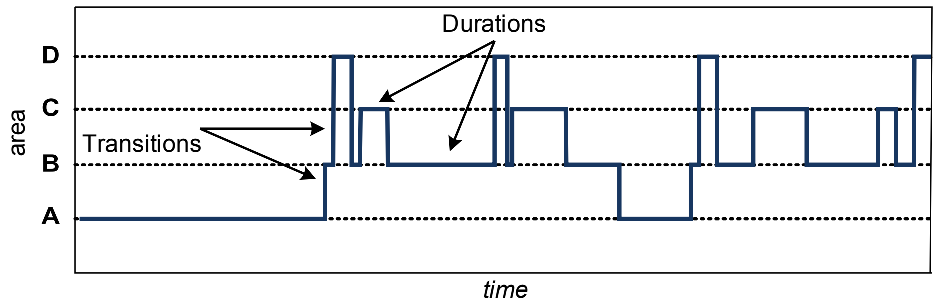


Figure 5.1 - An occupancy signal for a 4-area environment.

time spent by the occupant in each area i.e. *duration*. It was explained in Chapter 4 that such an occupancy signal can be created by assuming different levels for each area in the environment. For example, an occupancy signal for a 4-area environment is depicted in Figure 5.1.

To model such an occupancy signal, both parts of the signal, namely transition and duration should be modelled properly. Therefore, an occupancy signal generator can be created based on the model explained in the following sections:

5.2.1 Modelling the Durations

The duration in each state is defined as the time spent by the occupant in each area of the simulated environment. For instance, in the daily occupancy signal shown in Figure 5.1, the occupant spends *7* hours in area *A* e.g. bedroom at the beginning of a new daily activity and *10* minutes in area *B* e.g. lounge after he/she left area *A*. It is apparent that the occupant spends different times in each area (duration in that area). For example, the daily occupancy signal in Figure 5.1 illustrates that the occupant spends more time in area *A* e.g. bedroom than area *D* e.g. bathroom.

To fit a good model for the durations in occupancy signal, the behaviour of the occupant is very influential. For the occupants with a daily occupancy pattern, the average of the duration in each area (mean) can be calculated from the previous observations (data collection or observation). In addition, if the behaviour of the occupant does not involve vast variations or uncertainties, then the time spent by her/him in an area at a certain point of her/his expected occupancy pattern should be around the duration mean time in that area. The duration part is very similar to the behaviour of a system with normal distribution. This can be inferred from the occupancy pattern of the occupant where he/she is expected to have similar ADLs without large disorders. Therefore, to model the durations in the occupancy signal, it is proposed to apply a normal distribution for the time spent by the occupant in each area of the proposed environment. The normal distribution is often used to describe a variable or give a good approximation of that variable which tends to be around the mean [122].

A normal distribution of the duration in area *A* at the beginning of the daily activity with

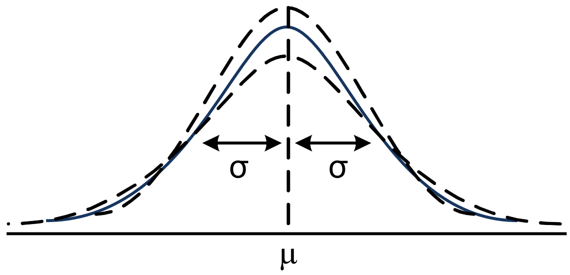


Figure 5.2 - A Normal Distribution for modelling a Duration.

the mean of μ is depicted in Figure 5.2 which has a variance of σ steps less or more than the mean of duration time.

For generating a model of durations, normal distributions are considered for each areas of the proposed environment. Furthermore, it is necessary to consider the pattern of occupancy for applying normal distribution to model duration for each area. For example, the normal distribution of the duration in which the occupant stays in area *B* (e.g. watching TV in the lounge) should be completely different to that where the occupant is only passing through area *B* (e.g. passing lounge to kitchen or bathroom).

By generating random numbers with normal distributions, it becomes possible to model the duration part of the single-occupant occupancy signal. Equation 5.1, which is a very good approximation of random numbers with normal distribution [123], [124], [131] is used to generate a random number with a normal distribution.

$$y_i = \mu + \sqrt{\sigma^2}\left(\sum_{i=1}^{p} R_i - p/2\right) \tag{5.1}$$

Equation 5.1 is generating normally distributed random numbers based on transformation of uniform distribution where y_i is a random number with normal distribution, $\mu * p/12$ is the mean of normal distribution, $\sigma * p/12$ is the variance of normal distribution and R_i is a random number with a uniform distribution. Therefore, in equation 5.1, by assigning $p=12$, y_i will be a normally distributed random number with mean μ and variance σ . So, the equation 5.1 will be changed to the following equation:

$$y_i = \mu + \sqrt{\sigma^2}\left(\sum_{i=1}^{12} R_i - 6\right) \tag{5.2}$$

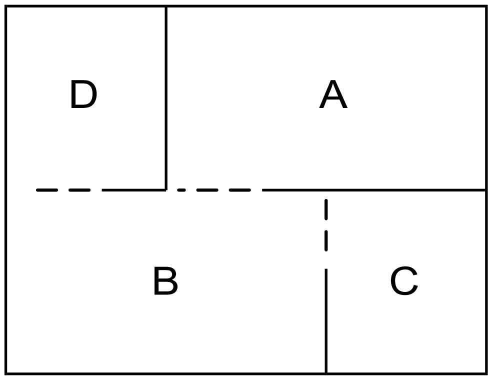


Figure 5.3 - A single-occupant environment with four areas.

5.2.2 Modelling the Transitions

The transition between different levels of a occupancy signal in a single-occupant environment, which is the representation of movement through the areas in that environment, is dependent on the profile of the environment including the number of areas and the design of the environment. For instance, in Figure 5.3 as a single-occupant environment, a transition between areas *A* and *B* is possible but there is not a possible transition between areas *A* and *C*, or *A* and *D*. In order to model these transition

	A	*B*	*C*	*D*
A	x	1	0	0
B	p1	x	p2	p3
C	0	1	x	0
D	0	1	0	x

Figure 5.4 - Transitions probability matrix.

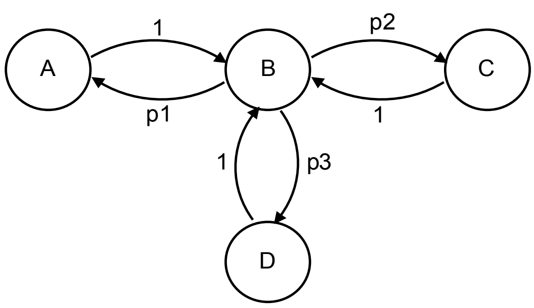


Figure 5.5 - Transitions state diagram.

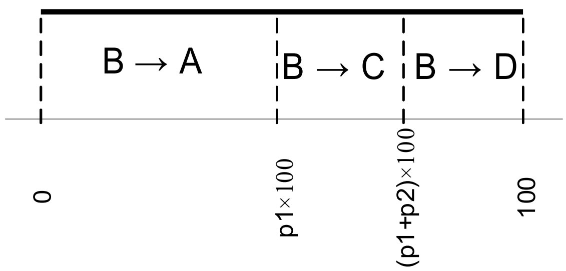


Figure 5.6 - Transitions modelling - Uniform Distribution.

possibilities, a state diagram is proposed. The states in the transitions state diagram represent each area and the transition possibilities are shown as the bidirectional links between the states.

For example, the transitions state diagram for the layout shown in Figure 5.3 is illustrated in Figure 5.5. In this diagram, the weights on the links are the probability of the transitions between states where for states with only one transition possibility the weight is *1* (e.g. states *A*, *C*, and *D*) and for states with more than one transition possibility the weights are the probability of that transition (e.g. state *B*). In the states with more than one transition possibilities, the sum of transition probabilities to other states should be *1* (e.g. for state *B*). This statement can be summarised as:

$$\sum p_i = 1 \tag{5.3}$$

To model the state diagram such as shown in Figure 5.5, it is proposed to apply a uniform distribution for any state of the diagram with more than one transition possibilities. For instance, state *B* of the diagram shown in Figure 5.5 in which the probabilities of transitions from this state to other states are shown in Figure 5.4 can be modelled by generating random numbers with uniform distribution which is depicted in Figure 5.6. For example, a uniformly distributed random number R_i with the condition $p_1 * 100 \leq R_i < (p_1 + p_2) * 100$ represents the transition from state *B* to *C*.

A snapshot of the occupancy signal in Figure 5.7 shows the overall model where a movement from area *B* to area *C* takes place. In the model, μ is the expected spent mean time in area *C*. Parameters u and σ are uncertainty parameters representing the behaviour of the occupant. In Figure 5.7, the current location of the occupant is assumed

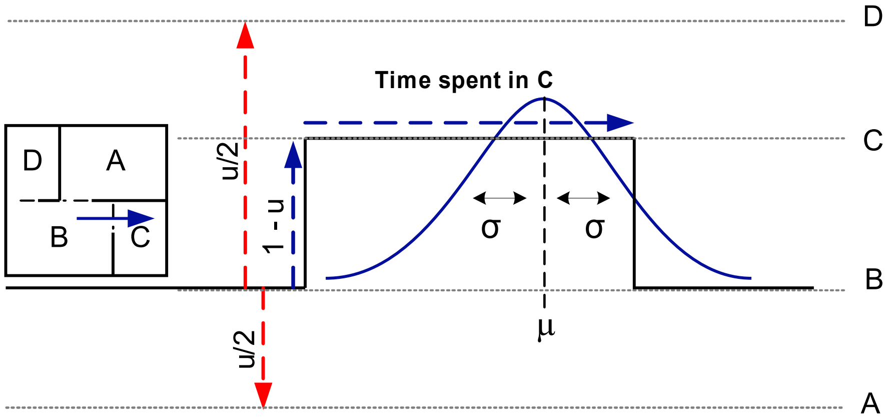


Figure 5.7 - Summary of the Occupancy Model - Transition from B to C.

to be area *B*. The layout of the environment allows the occupant to move from area *B* to areas *A*, *C*, and *D*. If the occupant complies with her/his movement pattern with the uncertainty of u , then the movement equivalent with the expected movement to area *C* will be more likely with the chance of $1-u$. So, summation of the chance of movements to other areas will be u . In Figure 5.7, the chance of movement to either areas *A* and *D* is $u/2$. If the occupant moves to area *C*, the time spent by the occupant in this area will be calculated using a normally distributed random variable calculated from Equation 5.2. The uncertainty in duration (σ) is representing the flexibility of the time that an occupant can spend in this state (area *C*).

The transition between different areas of a single-occupant environment is also dependent on the profile of the occupant. If it is assumed that there is a daily pattern of occupancy in the proposed environment, then the impact of this pattern should be considered in the modelling of the occupancy signal. As an example, in the daily occupancy pattern of the occupancy signal shown in Figure 5.8, the probability of the transition from state *B* to other states in different points of the pattern is not identical. In state *B*, the first, third, sixth, and ninth transitions are to state *D* but the second, fourth, seventh, and eighth transitions are to state *C* and a transition from *B* to *A* occurs as the fifth transition of state *B* in the daily pattern. Therefore, the probabilities *p1*, *p2*, and *p3* should be changed based on where in the pattern they are. In other words, three transitions probability matrices are needed to model the transitions in the occupancy signal of the pattern shown in Figure 5.8.

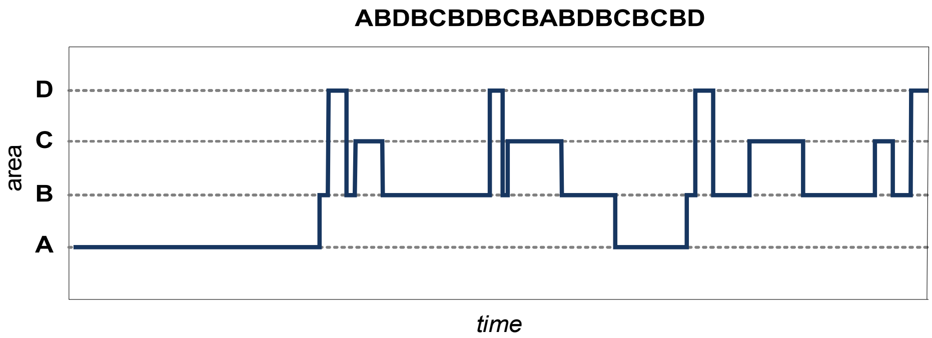


Figure 5.8 - Daily occupancy pattern in a single-occupant environment.

A pattern detector [125] is used to choose amongst the transitions probability matrices by finding out where in the pattern the occupancy signal is. The expected occupancy pattern in the simulator can be set manually. The best way to find out this expected pattern of occupancy is to monitor the actual equivalent environment by sensory agents for couple of days which was explained in Chapter 4.

5.2.3 Formulation of the Model

The scenario explained in Sections 5.2.1 and 5.2.2 is a statistical model. Formulation of a statistical model is quite complicated. However, following mathematical equations can provide an analytical understanding of the occupancy signal modelling.

As it was mentioned earlier in this chapter, an occupancy signal which is a time-series can be represented by a number of transitions T_i and durations D_i such that:

$$signal(t)=\{T_i, D_i\} \tag{5.4}$$

Assuming A as the level in the occupancy signal (occupied area) and D as the durations (time spent in occupied area), if there is no uncertainty in the movements then a signal which follows the expected daily pattern can be generated as follows:

$$Expected\ Daily\ Pattern=\{\bar{A}(1), \bar{A}(2), \bar{A}(3), \bar{A}(4), ...\} \tag{5.5}$$

$$Expected\ Durations=\{\bar{D}(1), \bar{D}(2), \bar{D}(3), \bar{D}(4), ...\} \tag{5.6}$$

where indices $1, 2, 3, ...$ in Equations 5.5 and 5.6 represent the consecutive visited areas in the expected daily pattern. In this situation, $D(i)$ is calculated using normal distribution modelling with expected duration $\bar{D}(i)$ and variance σ which represents the uncertainty in the time spent in an area.

Generating an occupancy signal in presence of movement uncertainty, u , is more complicated and can be formulated as:

$$A=\begin{cases} A(i) & 0<R_i\leq(1-u)*100 \\ \hat{A}(i) & (1-u)*100<R_i\leq 100 \end{cases} \tag{5.7}$$

In this model, if an expected transition takes place then the duration of the current level (occupied area) will be calculated from the mean duration in the expected pattern and an uncertainty factor in the time spent in the area. On the other hand, if an unexpected transition takes place then the duration of that unexpected movement will be calculated from the unexpected duration time and an uncertainty factor. This is shown as:

$$D=\begin{cases} \bar{D}(i)+\sqrt{\sigma^2}(R_i-6) & \textit{if expected transition met} \\ \bar{\hat{D}}(i)+\sqrt{\hat{\sigma}^2}(R_i-6) & \textit{if unexpected transition met} \end{cases} \tag{5.8}$$

where R_i is a random number.

Transitions in the model as described before are calculated using a uniform distribution. The movement uncertainty parameter, u , is the chance of the movement to different connected areas rather than the expected area. Hence, $1-u$, would be the chance of that the next movement follows the expected daily pattern.

$$Signal(t)=\begin{cases} \bar{A}(1) & 0<t\leq D(1) \\ \bar{A}(2) & D(1)<t\leq D(1)+D(2) \\ \bar{A}(3) & D(1)+D(2)<t\leq D(1)+D(2)+D(3) \\ & \ldots \\ & \ldots \end{cases} \tag{5.9}$$

$D(i)$ is expressed as:

$$D(i)=\bar{D}(i)+\sqrt{\sigma^2}\left(\sum_{i=1}^{12} R_i-6\right) \tag{5.10}$$

where R_i is a uniformly distributed random number.

5.3 Simulation Algorithm

In order to generate a software programming code for the occupancy signal model proposed in Section 5.2, an algorithm is designed and implemented to simulate the behaviour of an occupant in a single-occupant environment. The code of this algorithm as a signal generator for daily activity is flexible enough to accept different environmental profiles as well as variety of occupant's profiles of behaviour. The simulation algorithm is created by considering following criteria:

- Each daily occupancy signal can affect the occupancy signal on next day. For instance, a next day activity cannot start in bedroom (A) if the previous day activity is not finished in lounge (B) or bedroom (A),
- Daily observed occupancy pattern can become longer than an expected occupancy pattern,
- The design of the environment is represented by transitions possibility matrix as well as probably the type of each area (bedroom, kitchen, lounge, bathroom …),
- The occupant's behaviour profile is represented by his/her expected occupancy pattern, his/her transitions probability matrices, his/her expected duration matrices in each area, as well as his/her unexpected duration,
- The first area met on the first day of activity simulation would be the first area of the expected occupancy pattern in the occupant's profile,
- In the case of unexpected transition, it is proposed that a return to the previous state be the most probable action happening next. A return procedure should lead to expected state,
- It is possible for the occupant to find another way to follow the pattern instead of returning to previous passed states.

In the flowchart of the algorithm depicted in Figure 5.9, there are some parameters that should be assigned at the beginning of simulation including environmental parameters (e.g. design and number of areas) and behavioural profile of the occupant (e.g. expected pattern of occupancy, mean durations for the expected pattern of occupancy, uncertainty in the expected pattern of occupancy, and the mean duration for unexpected transitions).

The algorithm starts from the first state of the expected pattern (solid lines, white boxes). If the expected state is met by the algorithm as it might not met due to the uncertainty of the behaviour, then a normal procedure determines the next state of the

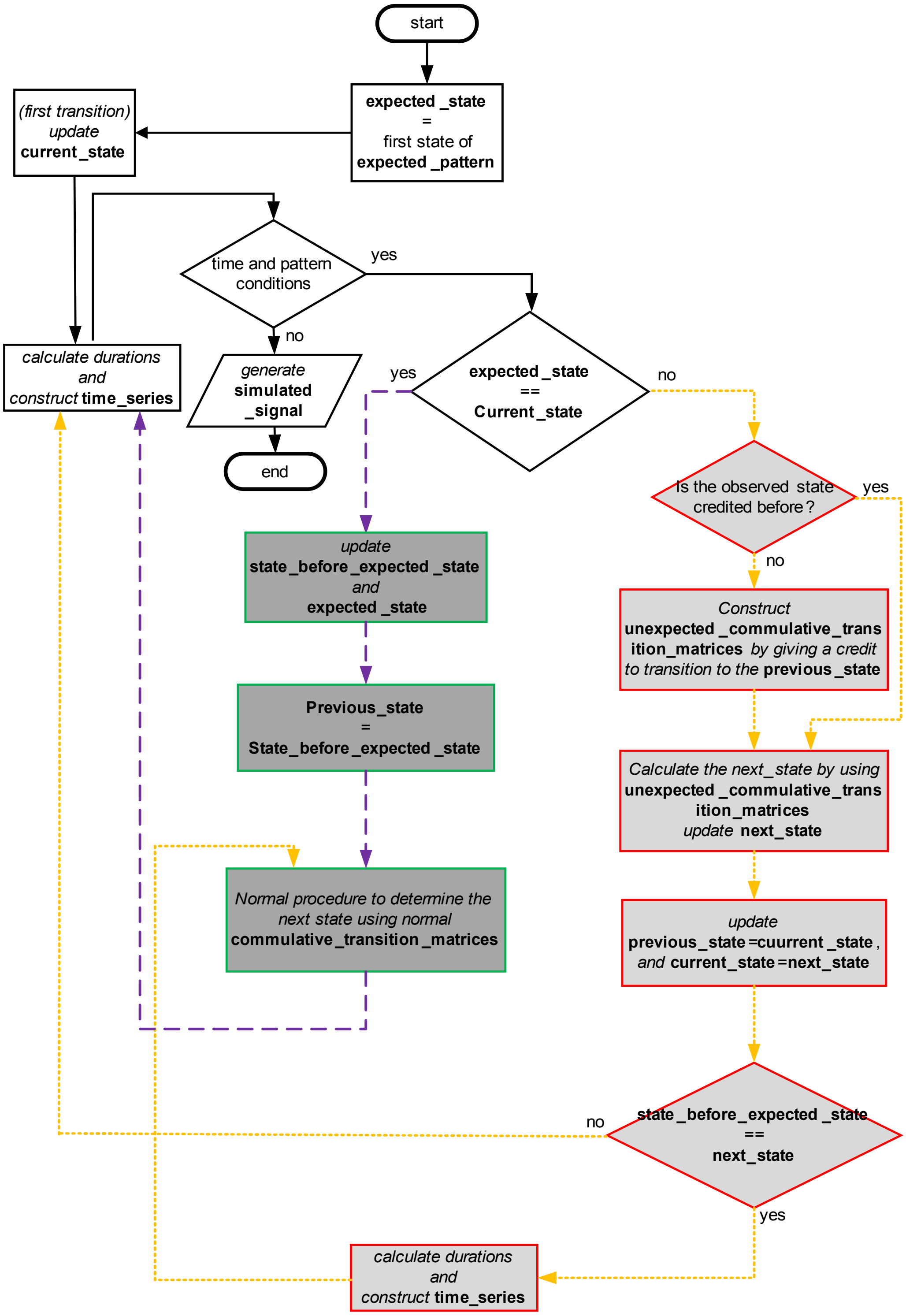


Figure 5.9 - Simulation Algorithm Flowchart for Generating Occupancy Signal.

pattern and the duration of the current state will be calculated based on the mean and variance defined for the normal distribution of the duration in the state which is met (dashed lines, dark grey boxes). On the other hand, if the state met is an unexpected state, then responsibility will be given to unexpected part of the algorithm to generate unexpected duration for the state met (dotted lines, light grey boxes).

If unexpected states are met continuously, then the algorithm keeps on in unexpected section until an expected state is met and the responsibility is given to the expected section in the algorithm. The algorithm ends if the time and pattern conditions (either the expected pattern is recognized or time goes beyond the simulation number of days) are not satisfied anymore. Finally an occupancy signal will be constructed from the states and durations generated by the algorithm.

5.4 Evaluation of the Model

Creating a model of a real system is advantageous in terms of flexibility and expandability. In the case of occupancy signal modelling, the model can reduce data collection efforts significantly. However, whether a model is created well is a question should be answered by evaluating that model. To measure the Simulator's degree of the validity, it is proposed to create a validation test scheme to evaluate the signal generated by the model against a real occupancy signal collected from an elderly-living apartment.

5.4.1 Validation Scheme

A schematic diagram of the simulator validation scheme is shown in Figure 5.10. In this scheme, real data as a reference collected from an elderly-living flat is used in a validation scheme. The reference data is compared with the simulator's generated data and subsequently parameters of the simulator are adjusted to minimise the error.

The final parameters found by the optimizer should result in the best fit of the generated signal with the reference data.

In the validation scheme, a set of statistical parameters $(\mu, \sigma, u, \nu, \pi)$ are found to result in the best match with the reference data. These parameters are explained as:

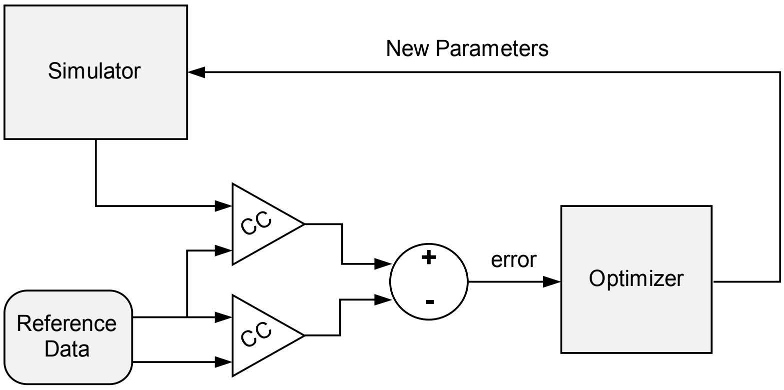


Figure 5.10 - Simulator Validation Scheme.

- μ as the mean and σ as the variance (uncertainty) divisor of the expected occupancy pattern,
- u as the uncertainty probability in the occupant movements,
- v as the return factor or the force of returning to comply with the expected pattern when an unexpected movement takes place, and,
- π as the unexpected movement mean time.

5.4.2 Similarity Factor

In the validation scheme, in order to examine the similarity, a cross correlation of two time-series is calculated. Cross correlation of two signals involves multiplying them while one of them is shifting. i.e.

$$(gen_{sig} * ref_{sig})[n] = \sum_{m=-k}^{k} gen_{sig}[m]\ ref_{sig}[n+m] \qquad \textbf{\textit{(5.11)}}$$

where gen_{sig} is the occupancy signal generated by the simulator for an equivalent layout with the real environment, ref_{sig} is the occupancy signal shaped for the real data collected from the real environment, n and m are cross-correlation indices. Cross-correlation can provide a very good similarity measure between two time-series [126].

To minimise the difference between two signals, an error function as an objective

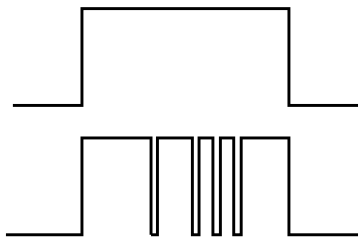


Figure 5.11 - Fake-Weight Effect.

function is suggested which should be minimised by optimisation techniques i.e.

$$error = |(gen_{sig} * ref_{sig} - ref_{sig} * ref_{sig})| \quad \textbf{(5.12)}$$

The error function explained above can work fine for continuous signals, but in the case of discrete signals including digital signals like the occupancy signal, the accuracy of the error optimisation can be affected by fake-weight effect.

The fake-weight is the similarity of a high frequency signal with a very low frequency signal in which the high frequency signal durations are very narrow in the levels causing difference with the low frequency signal (see Figure 5.11). Fake-weight effect can cause invalid return of the cross-correlation measures. In order to take into account the fake-weight effect in error function, it is proposed to add a penalty part in the error function which is the difference between the simulated occupancy signal and test signal derivatives i.e. $(der_{num}(gen_{sig}), der_{num}(ref_{sig}))$. Hence, Equation 5.13 is the final error function which should be minimised by optimisation techniques as:

$$error = |(gen_{sig} * ref_{sig} - ref_{sig} * ref_{sig})| + C * |(der_{num}(gen_{sig}) - der_{num}(ref_{sig}))| \quad \textbf{(5.13)}$$

where C is a coefficient representing the number of days.

5.4.3 Applied Optimisation Techniques

Minimising the error function in simulator evaluation can be performed by optimisation techniques. There are a number of computational optimisers with different features. Some of these techniques try to optimise functions by taking the derivatives of the error function and returning optimising inputs or parameters [127]. Artificial Neural

Networks (ANN) and Steepest Descent are some of the well-known derivative-based optimisers. Although the differential optimising techniques such as steepest descent are very efficient in some applications, the calculation of error function derivatives can be very difficult or even impossible in complicated systems or statistical models. Alternative derivative-free optimisation techniques are applicable when the derivatives of the error function are not easy to calculate. Tabu Search, Simulated Annealing (SA), and Genetic Algorithm (GA) are amongst derivative-free optimisers which are basically search techniques for finding exact or approximate solution for minimising an error function.

Due to the statistical nature of the simulated occupancy signal modelling explained in this chapter and impossibility of using derivative-based optimisers, derivative-free techniques including simulated annealing and genetic algorithm explained below are suggested and applied for the evaluation of the simulator model.

5.4.3.1 Simulated Annealing Optimisation

The task of Simulated Annealing (SA) is to sample the input space effectively to find an input that minimises an objective function [114]. SA algorithm is derived from the energy in thermodynamic systems. The algorithm is performed in the following steps:

- **Step 1:** A start point x is chosen and the temperature T which is the diversity of the choice domain is set to high,
- **Step 2:** Objective function is evaluated for x,
- **Step 3:** Algorithm chooses a new point based on the difference determined by the generating function,
- **Step 4:** The new value of the objective function in new point is calculated,
- **Step 5:** Algorithm sets x to the new point with probability determined by an acceptance function,
- **Step 6:** The temperature reduces according to the annealing schedule,
- **Step 7:** The algorithm continues above steps until reaches a stop criterion.

By reducing the temperature, the set of points in SA get restricted to approach the best point with the minimum objective value.

5.4.3.2 Genetic Algorithm Optimisation

Genetic Algorithm (GA) is based loosely to the concepts of natural selection and evolutionary process and is known as a population-based optimisation that improves performance by upgrading entire populations rather than individual members. Major components of GA include encoding scheme, fitness evaluations, parent selection, crossover operators, and mutation operators [114].

- **Encoding scheme** transform points in parameter space into bit string e.g. parameter space (*10,5,9*) to *1010 0101 1001* which is encoded as a gene,
- **Fitness evaluation** is the first step after creating a generation by which the fitness value of each member in the population is calculated in the objective function,
- **Selection** takes place after evaluation that determines which parents participate in producing offspring for the next generation known as survival of the fittest,
- **Crossover** is usually applied to selected pairs of parents with a probability equal to a given crossover rate. Crossover exploits the potential of the current gene pool by crossover operators to generate new chromosomes that will hopefully retain good features from the previous generation. Therefore, some children are able to outperform their parents if they get "good" genes or genetic traits from both parents,
- **Mutation** operators can generate new chromosomes if no amount of crossover can produce a satisfactory solution. The most common way of implementing mutation is to flip a bit with a probability equal to a very low given mutation rate.

Hence, for producing a next generation of parameters with a better fitness compared with current generation, three processes of selection, crossover, and mutation should take place over the current population.

5.5 Generated Signal Specifications

This section illustrates the capability of the signal generator in generating occupancy signals with different specifications; in other words, simulator's approach to cope with a real occupancy signal.

Four signals with different duration and transition uncertainties are generated. In Figure 5.12, first occupancy signal generated (solid blue) has no uncertainty for both transition and duration. Therefore, this signal matches the expected occupancy signal (dashed red) completely. In the same illustration, the second occupancy signal generated has 12.5% of duration uncertainty which results in different durations with 12.5% variance compared with the expected occupancy signal.

In Figure 5.13, the first occupancy signal generated has no duration uncertainty and 10% transition uncertainty. Hence, the generated signal (solid blue) can match the expected signal (dashed red) in terms of durations but some unexpected transitions can be observed in the generated signal. The second occupancy signal generated in the illustration is with 12.5% of duration uncertainty and 10% transition uncertainty. So, as it is apparent from the illustration, the generated occupancy signal (solid blue) looks like a little different signal of the expected signal (dashed red) but still has an expected pattern in its nature.

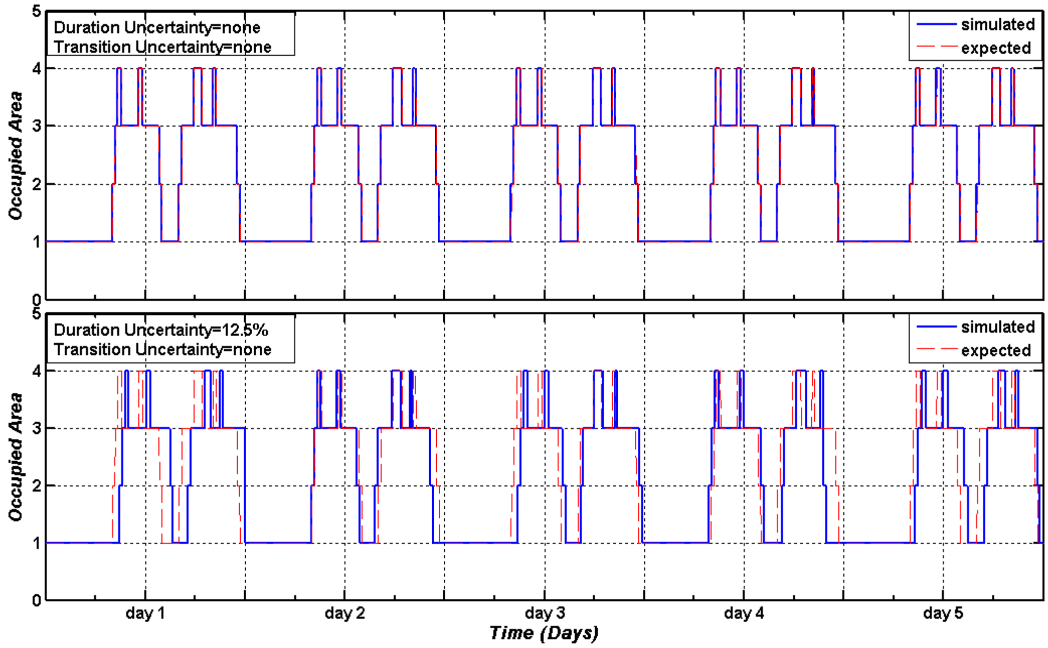


Figure 5.12 - Generated Occupancy Signals without Transition Uncertainty.

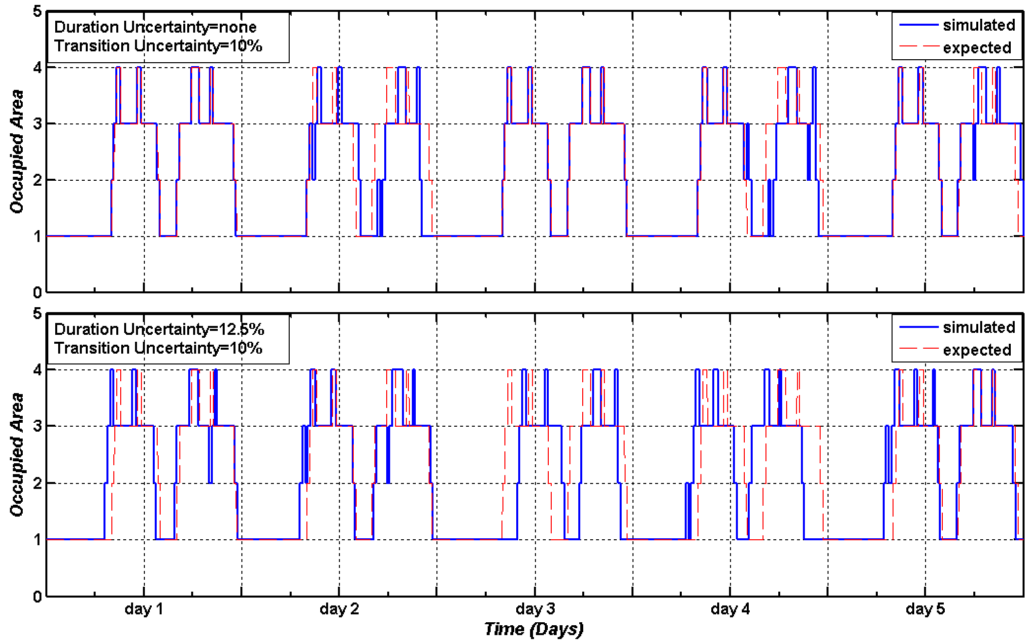


Figure 5.13 - Generated Occupancy Signals with Transition Uncertainty.

5.6 Simulator Validation Results

To validate the occupancy signal modelling, it is proposed to generate signals by initialising the simulator with a set of known parameters i.e. $(\mu, \sigma, u, \nu, \pi)$.

The generated occupancy signal is then used as a reference data in the validation scheme explained earlier in this chapter. If optimisation techniques were able to converge to the known signal parameters, then it is possible to claim the validity of the occupancy simulator.

To validate the simulator, first of all, a 15-day occupancy signal with the following test parameter values is generated:

$$\begin{cases} \sigma = 0.125 \\ u = 0.15 \\ \nu = 0 \\ \pi = 5 \end{cases}$$

Using a 15-day generated occupancy signal as the reference data in the validation scheme, the objective function is minimised by optimisation techniques including Simulated Annealing and Genetic Algorithm. The parameters of these techniques are set appropriately to make them converge to the solution effectively. The values of these parameter and the justification for them are discussed in the following section:

Table 5.1 - Chosen Values for SA Parameters.

Optimiser	*Initial Temperature (T1)*	*Function*	*Temperature Update Function*	*Re-annealing Intervals (Epochs)*	*Stopping Criteria*
SA	100	Fast Annealing	Exponential Temperature Update	100	200 Iterations

5.6.1 Setting the Parameters for SA and GA

Prior to the optimisations by Simulated Annealing (SA), the parameters of SA, including Initial Temperature (T1), Annealing Function, Temperature Update Function, and Annealing Intervals should be set. These decisions may differ if problems are different, that is, these decisions are problem specific [144]. The value of initial temperature is recommended to be set large enough to make the initial probability of accepting transitions be closed to 1. On the other hand, too high initial temperature may cause a long computation or a bad performance. In simulated annealing, the value of temperature is updated by the temperature update function which is also called proportional cooling function as follows:

$$T_k = \alpha T_{[k-1]} \qquad where \qquad (0 < \alpha < 1) \tag{5.14}$$

where α is calculated by an exponential, a logarithmic, or a linear function. For instance, the exponential temperature update function is as follows:

$$\alpha = (T_M / T_1)^{[1/(M-1)]} \tag{5.15}$$

where T_1 is the initial temperature, T_M is the temperature at the final epoch, and M is the total number of epochs. The total number of epochs in SA can be set proportional to the size of problem instance. In the experiment for finding the uncertainty parameters of the simulator, the value of SA parameters are chosen as shown in Table 5.1. These values are calculated and tuned to result in the best performance by a number of algorithm runs.

For the optimisation by Genetic Algorithm (GA), values for the following parameters should be set:

Table 5.2 - Chosen Values for GA Parameters.

Optimiser	*Population Type (Encoding)*	*Population Size*	*Crossover Function*	*Mutation Function*	*Selection Function*	*Stopping Criteria (Generations)*
GA	Double Vector	20	Scattered	Uniform Probability = 0.01	Stochastic Uniform	20 Generations

- **Population type (**Gene type or encoding**):** Encoding depends on the problem and also on the size of instance of the problem.
- **Population size:** Very big population size usually does not improve performance of GA (i.e. the speed of finding solution). Good population size is about 20-30.
- **Crossover function:** Crossover rate generally should be high, about 80%-95%.
- **Mutation function:** On the other side, mutation rate should be very low. Best rates reported are about 0.5%-1%.
- **Selection function:** Stochastic uniform, uniform, remainder, roulette, or tournament can be used.

Decisions on these parameters are problem specific. However, to choose the best set of parameters, different sets of them can be applied to the optimisation problem. Therefore, the best parameter set is the one with the best performance. In the experiment for finding the uncertainty parameters of the simulator, the value of SA parameters are chosen as shown in Table 5.2.

The graphs in Figure 5.14 and Figure 5.15 illustrate the convergence of SA and GA to the movement and duration uncertainties respectively.

5.6.2 SA and GA Convergence to Movement Uncertainty

For finding the movement uncertainty by optimising the error function in Equation 5.13, a Simulated Annealing algorithm was applied. SA was able to converge to the test movement uncertainty (0.125) after 200 iterations (Figure 5.14-A).

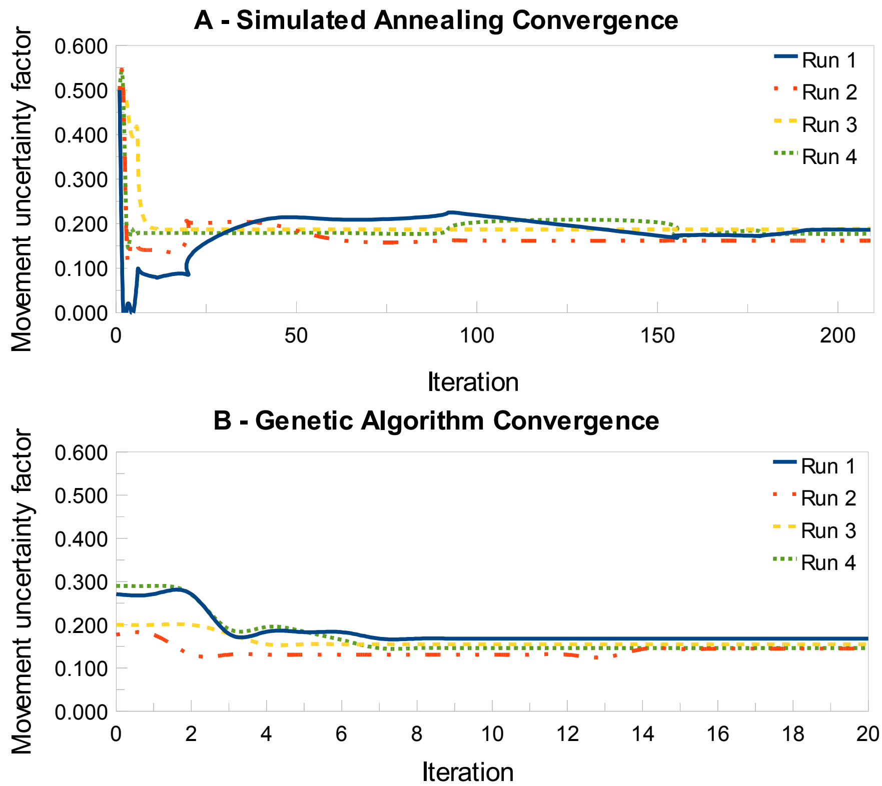


Figure 5.14 - SA and GA search for movement uncertainty value.

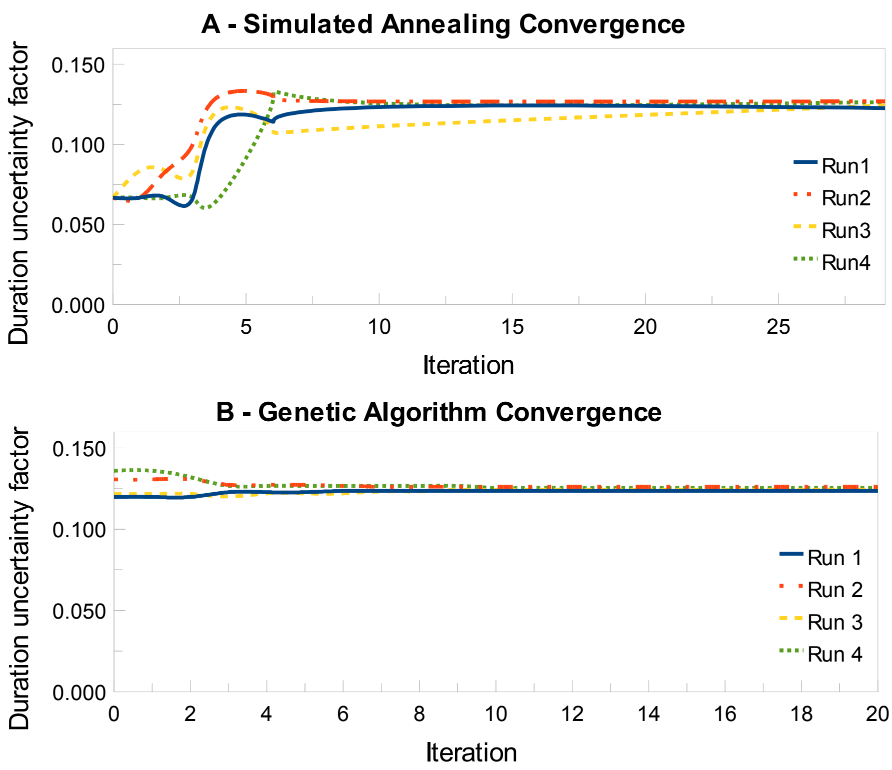


Figure 5.15 - SA and GA search for duration uncertainty value.

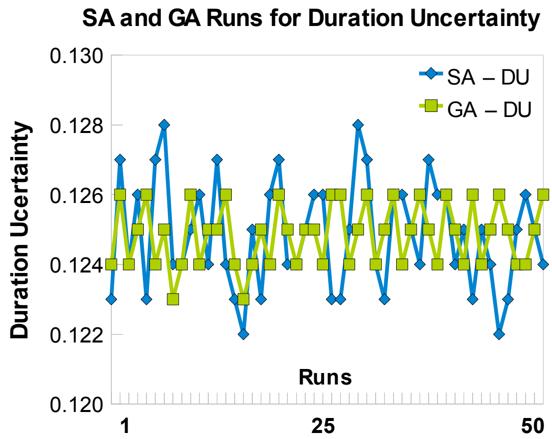


Figure 5.16 - Duration Uncertainty: SA and GA results after in 50 runs.

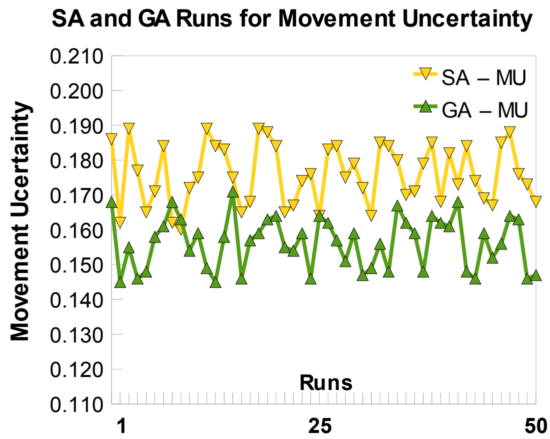


Figure 5.17 - Movement Uncertainty: SA and GA results in 50 runs.

A Genetic Algorithm optimiser with the population size of 20 for 20 generation was also applied for optimising to the movement uncertainty (Figure 5.14-B). The performance of SA and GA was examined for 50 runs which is depicted in Figure 5.16. The mean of results for both SA and GA was 0.1248 with standard deviation of 0.0015 for SA and 0.0008 for GA.

5.6.3 SA and GA Convergence to Duration Uncertainty

In order to find the duration uncertainty by optimising the error function in Equation 5.13, a Simulated Annealing algorithm was applied. SA was able to converge to the test duration uncertainty (0.15) after 30 iterations (Figure 5.15-A). A Genetic Algorithm optimiser with the population size of 20 for 20 generation was also applied for optimising to the duration uncertainty (Figure 5.15-B). The performance of SA and GA was examined for 50 runs which is depicted in Figure 5.17. The mean of results for SA and GA was 0.1758 and 0.1563 respectively with standard deviation of 0.0084 for SA and 0.0074 for GA.

5.7 Simulator Evaluation Results

The applied validation method can give a good understanding of the simulator's degree of validity. However, for the evaluation of occupancy signal modelling, the performance of the model should be experimented against a real occupancy signal. Therefore, the real occupancy signal collected from the elderly lady's apartment mentioned in Chapter 4 is used as the reference in the validation scheme. 10 days of this occupancy data is used to find the parameters of the model. Parameters found by optimisation techniques are then used as the modeller for the real data. In other words an occupancy model is created which is expected to be equivalent to how the elderly lady occupies different areas in her apartment. Comparing remaining real data (3 days) with the data generated by the modeller can give the understanding of how good the model can converge to a real single-occupant data. If the model converges well to the real data, then it is possible to claim that the model can generate the occupancy signal with a degree of similarity to the movements of a monitored occupant. Hence, the simulator can be used to generate a signal similar to the profile of the monitored occupant in the monitored environment.

Using the real occupancy signal in the validation scheme, the profile of the occupant was found with 4.33% uncertainty in her movements, 8.77% uncertainty in the time she spends in different areas, 9.2% uncertainty in following the daily movement pattern, and 187 second of the average time she spends in the areas not followed by the movement pattern i.e.

$$\begin{cases} \sigma = 0.0877 \\ u = 0.0433 \\ \nu = 0.092 \\ \pi = 187\,sec \end{cases}$$

After the value of parameters were found, a model was created using these values. The cross correlation of the test data (3 days) with the occupancy signal generated by the

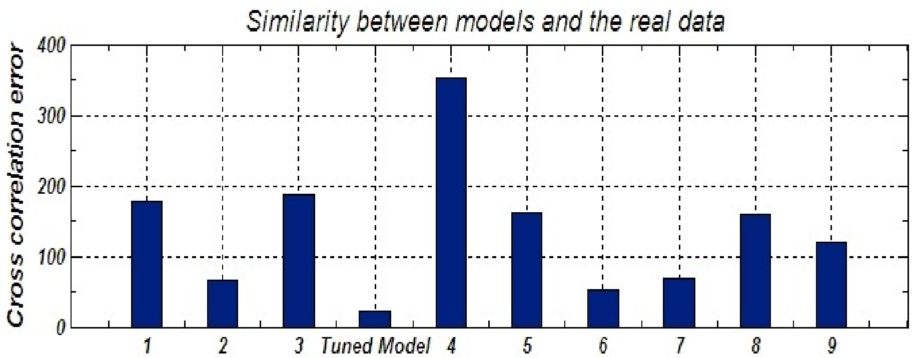


Figure 5.18 - Similarity error of the tuned model compared with other models.

model was then used as the similarity factor. The results in Figure 5.18 illustrates that the model tuned with found parameter values can be a good representation of the real data. In Figure 5.18, the output of the simulator with 8 different set of parameters is cross correlated with the real data and compared with cross correlation of the tuned model and the real data. The cross correlation with tuned model is the smallest compared with other models which means the tuned model is behaving more similar to the real occupancy data.

Although it was shown that the tuning of the model to the occupancy behaviour of residents by using a small data set is not impossible. However, to find a better fit of the model to the occupant behaviour, using larger occupancy data set is essential. For instance, to model an occupancy signal for long-term occupancy i.e. monthly or annually instead of daily occupancy, the model should be tuned with large data set i.e. couple of months or years.

5.8 Summary and Discussions

Different factors in human behaviour have made it very challenging to model and simulate. It was shown in this chapter, it is possible to approach modelling if the problem is simplified with two conditions. The first condition is to focus on a particular behaviour modelling such as modelling the movements of the occupant in different areas instead of modelling every aspect of an occupant's life. The second condition is to model the behaviour of persons with less uncertain behaviours like modelling the behaviour of occupants who follow a daily pattern in their life e.g. elderly people.

Applying these conditions, a single occupancy model was created by using statistical methods. The simulator created based on this model is very useful for generating as much as data needed for simulating the pattern of occupancy for different profiles of any occupant in any environment with different layouts. The statistical modelling for the simulator has taken into account a number of uncertainty factors related to both modelled occupant as well as modelled environment including the movement and duration uncertainties.

Using the validation scheme proposed in the chapter, the simulator was tested and validated against a number of data sets generated by the model. The experimental results showed that the model can approach uncertainty parameters of the generated data successfully.

The simulator was evaluated using a set of real data collected from an elderly-living apartment. The evaluation results showed that the simulator can find a set of values for the parameters of the model to make the model generating a very similar occupancy data to the real data set. In order to find a better fit, the model should be tuned with sufficient occupancy data. For example, if the performance of the model for monthly or annual outcomes are concerned, then a data set for couple of months or years should be applied to the validation scheme. Besides, to understand the trends in the occupancy, this behaviour should be monitored and its data should be collected in a long-term manner. However, the small occupancy data used in this chapter was used to find daily occupancy pattern instead of the trends in long-term occupancy situations.

Although the occupancy model created in this chapter can be a good simulator of occupancy signal in a single-occupant environment, it is not claimed that the simulator explained in this chapter can be a perfect model for the occupancy behaviour of any person with any profile. However, the simulator can give a good understanding of the occupancy and generate as much as data required to test and verify time-series prediction techniques for the prediction of the occupancy signal explained in Chapter 4.

Chapter 6

Occupancy Monitoring and Prediction in Multiple-Occupant PaIE

6.1 Chapter Overview

In Chapter 4, the occupancy detection and consequently prediction were addressed when an environment is assumed to be primarily single-occupant. The existence of a single-occupant environment is not far from reality nowadays. However, the situation in which an environment remains absolute single-occupant permanently seems to be unlikely in reality. For instance, a situation in which a single person lives in an apartment without having visitors for a long time is not very likely to happen in reality.

The multiple-occupant situation refers to an environment where more than one person is living or working. This situation also takes place in single-occupant PaIEs when other persons such as visitors are present in the environment which is primarily assumed to be single-occupant.

Monitoring the occupancy of different areas in an absolute single-occupant environment was shown feasible by implementing a WSN of PIR and door contact sensors which was explained in details in Chapter 4. But, in a multiple-occupant environment, PIR signals cannot identify a monitored person in different areas due to the sensitivity of PIRs to the motion of every living objects. This situation is equivalent for both a multiple-occupant environment and a single-occupant environment in the presence of visitors. The challenge of dealing with multiple-occupant PaIEs is not only limited to the occupancy detection, but also the other issues related to AmI in such environments. This is due to the problem of identifying inhabitants involved in actions or movements in PaIEs.

As a solution, it will be shown in this chapter that for the occupancy detection and prediction, a multiple-occupant PaIE can be considered as a number of single-occupant scenarios (see Figure 6.1). Therefore the solution proposed in Chapter 4 for a single-occupant environment will be a relevant approach and can be extended towards finding a solution for an environment with a more complicated situation. This solution can help to distinguish the occupancy of for example the elderly people with dementia or Alzheimer disease when he/she is being visited by relatives, carer, or other visitors.

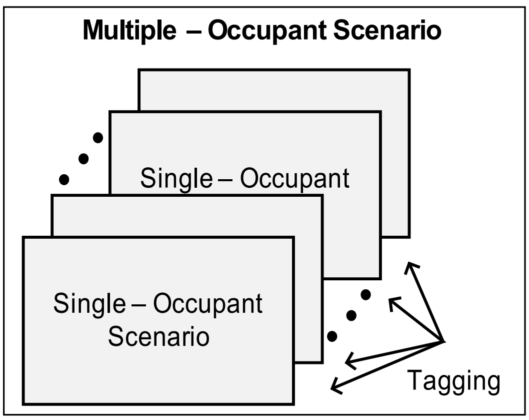


Figure 6.1 - A Multiple Occupancy Scenario derived from Single-Occupancy Scenarios.

In this chapter, the challenge of occupancy detection when an environment cannot be categorised as a single-occupant is explained in Section 6.2. In Section 6.3, as a solution a tagging mechanism is proposed; hence, a number of tagging technologies are investigated through a series of comprehensive measurements. In this section, it is also proposed to integrate a tagging mechanism to the previously reported occupancy detection of the single-occupant scenario to identify an occupant in his/her living/working environment even in the presence of other persons e.g. visitors. These tagging mechanisms are employed to address the occupancy detection in a multiple-occupant scenario and assist to properly separate the occupancy signal associated to tagged inhabitants for occupancy prediction purposes. The problems associated with tagging technologies such as uncertainties are explained and the solutions are proposed in Sections 6.4. Finally, the experimental results are presented with a comparative discussion at the end.

6.2 Occupancy Signal Representation Challenge in the Presence of Visitors

In an absolute single-occupant situation, a data acquisition system of wireless sensory agents explained in Chapter 4 can properly monitor the occupancy of different areas in the environment. For instance, for the occupancy detection of a proposed single-occupant environment with the layout shown in Figure 6.2, WSAs of four PIRs and a door contact sensor can be employed. In this scenario, the sensory data collected in a

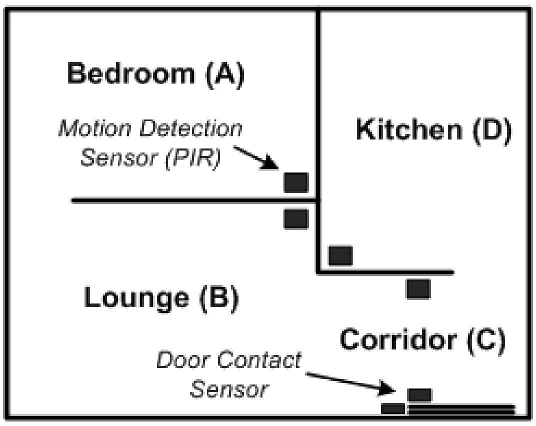


Figure 6.2 - Proposed single-occupant environment.

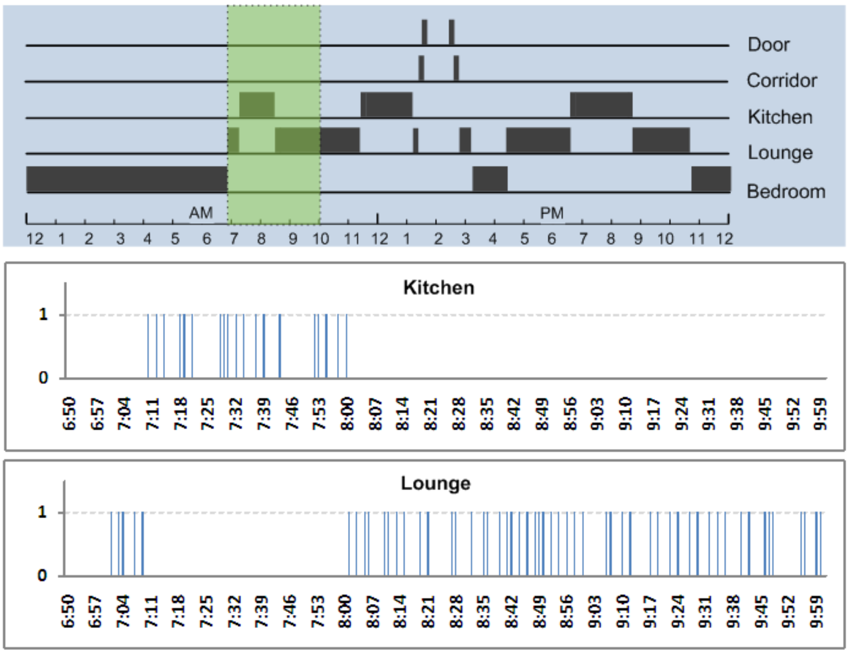


Figure 6.3 - Daily data collected by sensory devices.

base station can be used to shape an occupancy signal for a single person living/working in the single-occupant PaIE. Then, the occupancy signal can be used for prediction purposes as described in Chapter 4.

A snapshot of the data collected from WSAs of this environment in the base station is illustrated in Figure 6.3. In this figure, the PIR activities show that due to the presence of only one occupant in the monitored environment, no parallel activities in different areas are detected. For example, for the duration of *7:00 AM-10:00 AM*, the lounge and kitchen are not occupied at the same time as extracted from the marked area of the PIRs activity signal in Figure 6.3. In an absolute single-occupant environment, as there is no parallel activity of PIRs in different areas, the activity in one area can ensure the occupancy of that area by the monitored occupant. Hence, by using solutions proposed in Chapter 4, the occupancy detection of the monitored occupant in an absolute occupancy scenario becomes possible.

By assuming different levels for the PIR activities, $P_i(t)$, in each area or the occupancy of each area expressed as:

$$P_i(t)=\begin{cases} i & PIR\ activity\ \ for\ area\ i \\ 0 & PIR\ activity\ \ for\ other\ areas \end{cases} \tag{6.1}$$

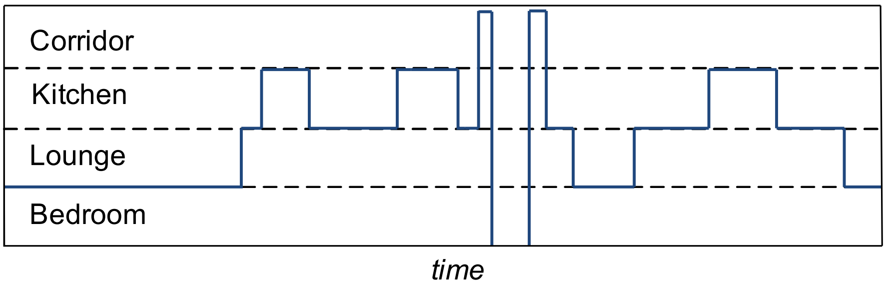


Figure 6.4 - Occupancy signal as a time-series.

A time-series signal can be formulated.

$$TS(t)=\sum_{i=1}^{N} P_i(t) \tag{6.2}$$

In Equations 6.1 and 6.2, i is a label representing each area and N is the number of monitored areas in a PaIE.

A simple occupancy time-series is depicted in Figure 6.4. Such a time-series can then be used in prediction techniques for the prediction of occupancy in an ambient intelligent environment. This was discussed in details in Chapter 4.

For a single-occupant scenario with visitors or in a multiple-occupant environment, it seems almost impossible to shape an occupancy signal like the occupancy signal in an absolute single-occupant environment. In other words, in a more realistic situation, the occupancy detection mechanism should consider the presence of other occupants or visitors in an ambient intelligent environment. In multiple occupancy situation, due to

Figure 6.5 - Kitchen and Lounge PIRs' activity in the presence of a visitor.

the presence of other persons, the occupancy signal shown in Figure 6.3 will change according to the following situations:

1. Parallel activities in different areas can be detected by WSAs of motion detection sensors,
2. The activity in one area cannot guarantee the presence of only one person in that area.

For instance, the marked areas in Figure 6.5 show the parallel PIRs' activity for lounge and kitchen in the presence of a visitor where $P_2(t)\neq 0$ and $P_3(t)\neq 0$ at the same time. Therefore, it becomes almost impossible to create an occupancy signal like Figure 6.4 from PIRs' activity in a multiple-occupant scenario or a single-occupant scenario in the presence of visitors. Some of techniques reviewed in literature ([57] and [59]) suggest tagging technologies such as RFID to track inhabitants. In the next section, it is proposed to integrate tagging technology with the data acquisition system proposed in Chapter 4 in order to reduce the problems associated with multiple-occupant monitoring.

6.3 Integration of Tagging Mechanism

As it was introduced in Chapter 3, the signal strength or RSSI can be used to approximate the distance between radio transmitter and receiver. This feature has been used by different approaches such as LANDMARC [57] and Fingerprinting [59] to track objects in environments. RSSI distance approximation despite its capabilities in perfect conditions is highly potential for uncertainties due to the characteristics of the radio signal propagation. These limitations were explained in details in Chapter 3. However, as a solution, to reduce the problem of parallel PIRs' activity in single-occupant environment in the presence of visitors or a multiple-occupant environment, it is proposed to integrate a tagging mechanism to switch from the single-occupant scenario to a multiple-occupant scenario. Therefore, to choose amongst available technologies, different tagging technologies will be experimented in a series of comprehensive measurement in Sections 6.3.1 and 6.3.2. So, two active RFID products from two different companies, namely, WaveTrend [128] and Syris [129] were chosen and compared with the already available ZigBee product (XBee) on the wireless sensory agents. To test the RSSI capability and accuracy of XBee, WaveTrend, and Syris tags and readers in approximating the distance, they were compared in two series of measurements as follow:

1. Distance-based measurement with no obstacles between tag and reader (Line of sight between tag and reader),
2. Distance-based with an obstacle between tag and reader.

6.3.1 Distance-based Measurements without obstacle

The RSSI measurement was conducted in a basketball pitch located in the Nottingham Trent University without any obstacles between the reader and the tag. This measurement reveals how the RSSI in the experimented products is affected by the tag's distance from the reader.

In this measurement, for the accuracy of data, fifty readings were taken at every meter distance between the tag and the reader. The measurement results are illustrated in Figure 6.6. In this figure, the vertical axis shows the radio signal strength in a digital universe of [0 255] detected by the reader when a tag broadcasts a beacon. The data points in the graph are the average of the readings, the bars are the standard deviation of the readings, and the curve is the trend of the signal drawn for a two degree moving average estimator. Depicted in Figure 6.6-A, the WaveTrend product follows the RSSI-distance equation for the first five meters where the signal strength decreases as the distance between tags and RFID reader increases. After five meters the product shows unreliable RSSI behaviour and it is not suggested to be used for measuring the distances of more than five meters. In Figure 6.6-B, signal strength of the Syris product follows the RSSI-distance equation for the first three meters but further distances cannot be measured by this product. Illustrated in Figure 6.6-C, the XBee product follows the RSSI-distance equation as far as six meters. After six meters the product shows a little rise in signal strength and cannot be used for measuring further distances.

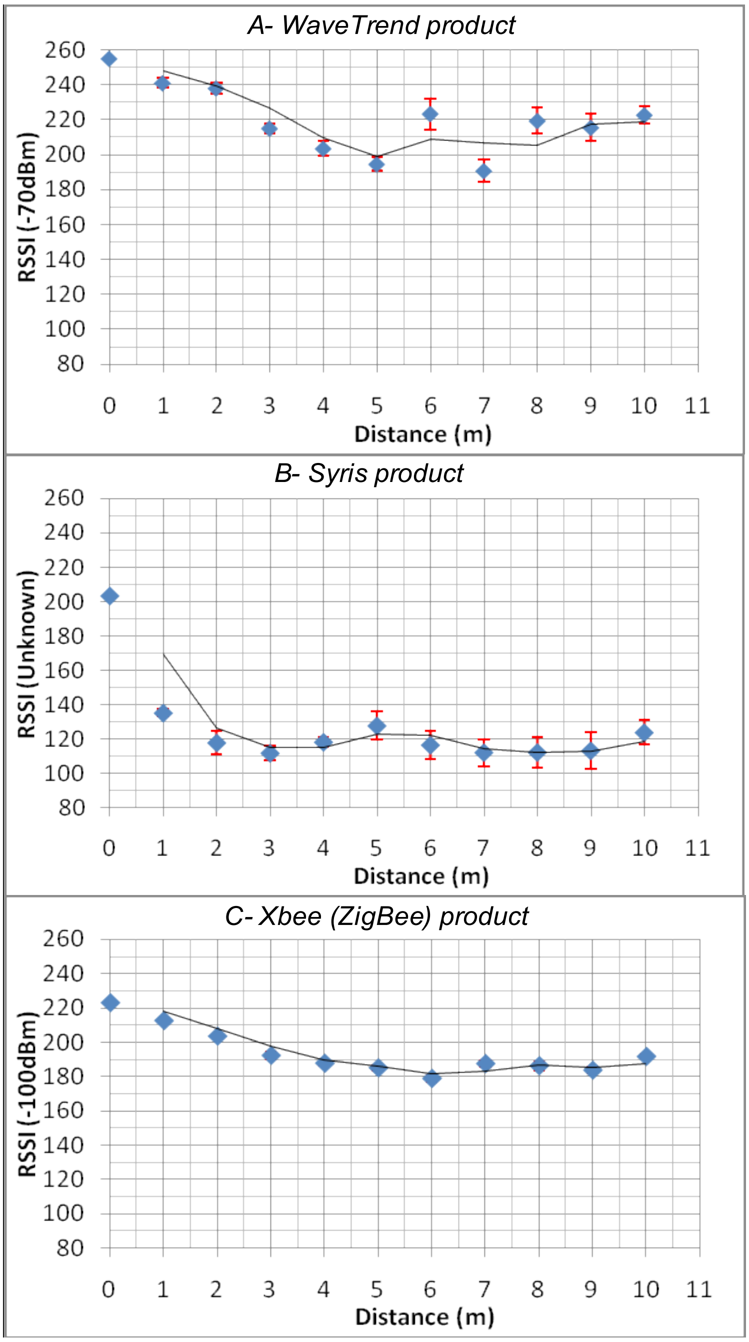


Figure 6.6 - RSSI-distance graphs with no obstacles between reader ad tag for RFID and XBee products.

6.3.2 Distance-based Measurements with obstacle

These measurements were taken in the same location of the first experiment with an obstacle between a mobile tag and the reader. The obstacle contained metal, plastic, and wood materials with a thickness of 40 centimetres. For accuracy, fifty readings were

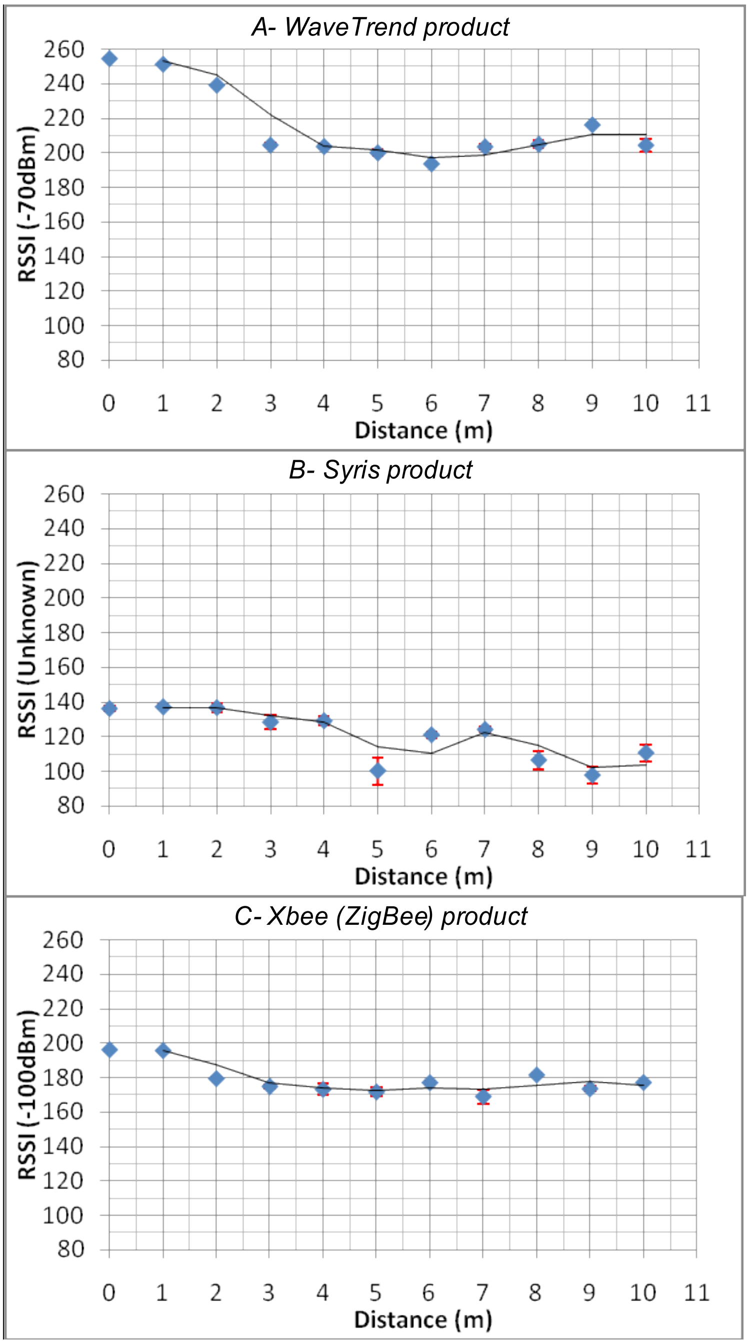


Figure 6.7 - RSSI-distance graphs with obstacle between reader and tag for RFID and XBee products.

taken at each reading point. The measurement results are illustrated in Figure 6.7. Depicted in Figure 6.7-A, the WaveTrend product follows the RSSI-Distance equation for the first six metersbut it is not suggested for further distance measurements. Figure 6.7-B shows that the signal strength of the Syris product decreases according to RSSI-distance equation for the first five meters but it does not follow the equation for longer

Table 6.1 - Summary of distance-based measurements.

Product	*Maximum Range without hindrance (m)*	*Maximum Error without hindrance (unit)*	*Maximum Range with hindrance (m)*	*Maximum Error with hindrance (unit)*
WaveTrend	5	4.24	6	1.79
Syris	3	6.68	3	3.97
XBee	6	2.18	5	3.42

distances. In the final graph (Figure 6.7-C), the signal strength of the XBee product decreases according to the RSSI-distance equation for the first five meters.

RSSI measurement results in both conditions i.e. with and without obstacle shows the uncertainty and non-linearity involved with three experimented products for approximating the distance.

A summary of the results for distance-based measurements is given in Table 6.1. It can be inferred from the table that the XBee product is a good competitor for RFID tagging. In addition, in order to keep using wireless sensory agents and also the infrastructure of single-occupant detection, it is proposed to modify WSAs to work for multiple-occupant scenario by enabling RSSI measuring for XBee chip which is already integrated to the agents. Hence, WSAs were equipped with RSSI capability, developing Wireless Localising Sensory Agents (WLSA). RSSI values received by WLSAs from an XBee tag attached to monitored occupant were displayed and logged by the modified monitoring portal (Appendix A – Figure A.3). In this approach, the XBee tag acts as a transmitter broadcasting a radio beacon every 5 seconds which is received by all WLSAs installed in the environment. At the receiver side, WLSAs receive the beacon from the tag, measuring the signal strength of the transmitter (tag), and send the RSSI information along with other sensory data to the monitoring portal for further processes.

RSSI enabled wireless localising sensory agent in each area is primarily proposed to be fixed in the centre of the ceiling. In this scenario depicted in Figure 6.8, the tagged occupant beacon is received by WLSAs by which the sensory data, tag id, and the RSSI

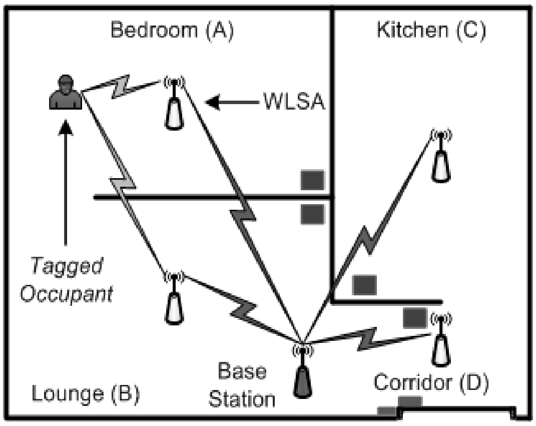


Figure 6.8 - Tagging a person in an Ambient Intelligent Environment.

of the received beacon are transmitted to the base station. In the base station all RSSI levels detected and transmitted from wireless localising sensory agents are compared with one another and sorted accordingly. Hence, the higher level of RSSI in the base station should represent the closest localising agent to the mobile node. For example, if at a specific time the RSSI received from the bedroom's localising agent is larger than the RSSI received from agents located in other areas, then it is more likely that the tagged person is located in bedroom at that time. However, decision for identifying the occupied area is highly potential of uncertainty due to the characteristics of the radio signal as explained in Chapter 3. This issue will be addressed in the next section.

6.4 Reducing the Uncertainty involved in WLSAs

Despite the benefits of the applied RSSI technology, due to the nature of wireless signals, it brings uncertainty in the occupancy detection mechanism. Therefore, in order to reduce the uncertainty, a number of approaches are proposed as follow:

1. To keep the single-occupancy detection in WLSAs and switch between single-occupant and multiple-occupant scenarios when appropriate,
2. Installation of WLSA readers in a way that covers all the areas and reduces the overlap in their coverage (Zoning),
3. Using clustering techniques to classify the signal strength received by WLSAs

based on the occupied area,

4. Incorporating supporting mechanisms for reducing the uncertainty.

These techniques are explained in subsequent sections.

6.4.1 WLSAs for Single and Multiple-Occupant situations

To reduce the uncertainty arising from RSSI tagging, it is preferred to keep the current PIR occupancy detection with its strength for the absolute single-occupant scenario and switch to RSSI occupancy detection in the presence of visitors.

To shape an appropriate occupancy signal for a single-occupant environment with visitors from the integrated occupancy detection system, first of all, the system chooses between occupancy signal generated by PIRs and the RSSI-based occupancy signal. To do this, the system should be able to distinguish between different situations and switch between the following conditions:

1. *Tagged occupant is alone in the environment:* Occupancy signal should be generated based on PIRs' activity,
2. *Tagged occupant is not alone in the environment:* Occupancy signal should be generated based on RSSI signals' level.

The first part of the occupancy signal is created based on the PIRs' activity whereas, due to the parallel activity of PIRs, the second part is created based on the signal strength (RSSI) of the beacon received from the tagged mobile node (see Figure 6.9). To choose between different situations either absolute single-occupant or the presence of visitors or other occupants in the environment, the following options are available:

1. Parallel activity of PIRs in different areas due to the presence of other occupants or visitors,
2. Increased activity of PIRs due to the presence of other occupants or visitors,
3. Main door contact sensor used to recognise the entry of other persons.

By the integration mechanism explained above, in absolute single-occupant situation the

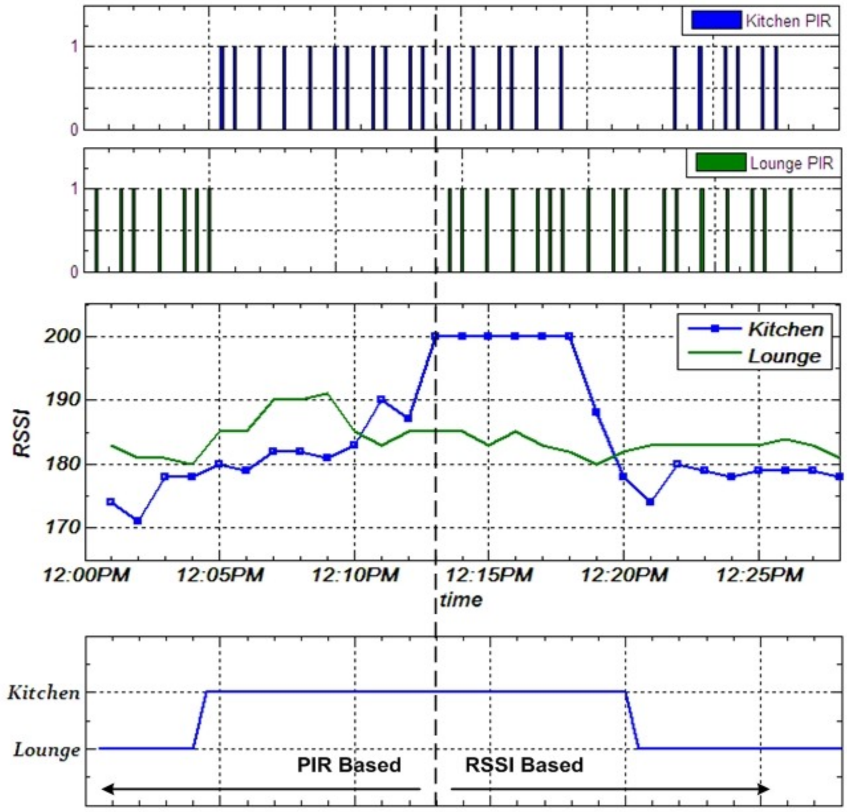


Figure 6.9 - Occupancy signal creation from the Integrated System.

integrated system is enabled to generate the occupancy signal from PIRs' activity, and in a single-occupant environment with visitors or a multiple-occupant it can tackle the inadequacy of the PIRs by generating the occupancy signal based on RSSIs received from wireless localising agents. On the other hand, it can also reduce the uncertainty of RSSI localisation by using PIR sensors when the environment is recognised as single-occupant. However, in multiple-occupancy situation, the RSSI uncertainty would still remain problematic.

6.4.2 Zoning Approach for the Coverage Uncertainty

In the proposed tagging mechanism for occupancy detection, coverage uncertainty in RSSI signals can be problematic. This uncertainty is due to the coverage of wireless localising agents that can take place in two different forms:

1. *Uncovered Zone:* Uncovered zone is a zone in an area which is not covered by

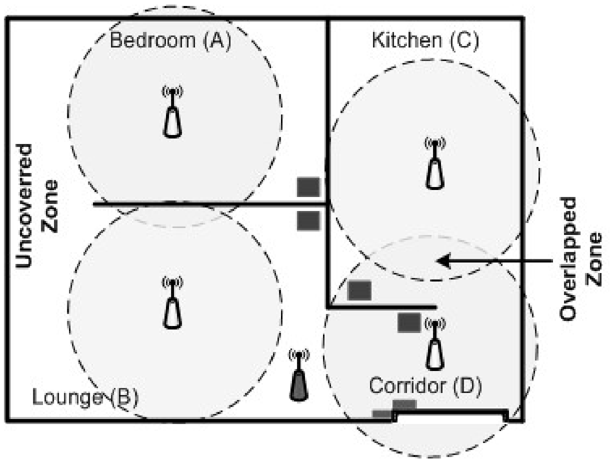


Figure 6.10 - Coverage problem with wireless agents.

the reader in the area or receives a better coverage from the agents of other areas than the agents in its area,

2. *Overlapped Zone:* Overlapped zone is a zone in an area which receives a good coverage not only from the agents in its area but also from the agents in other areas.

The above mentioned zones are illustrated in Figure 6.10

These uncertainties can cause ambiguities for identifying the location of tagged inhabitant. To overcome this coverage problem, a zoning approach is proposed with following steps:

1. *Using multiple wireless localising agents in one area:* This will result in the coverage of the whole area without leaving any uncovered zone in each area. So, the uncertainty caused by uncovered zones will be reduced,

2. *Modifying the sensitivity of wireless localising agents:* Decreasing the sensitivity of wireless localizing agents from the default sensitivity radius R to a modified sensitivity radius r reduces the coverage of unwanted zones outside the area. Therefore, the uncertainty caused by overlapped zones will be reduced.

The zoning approach is depicted in Figure 6.11 for the layout of the environment shown in Figure 6.2. In Figure 6.11, two agents are employed for kitchen and bedroom to cover the whole area. In addition, the sensitivity radii of the wireless localizing agents

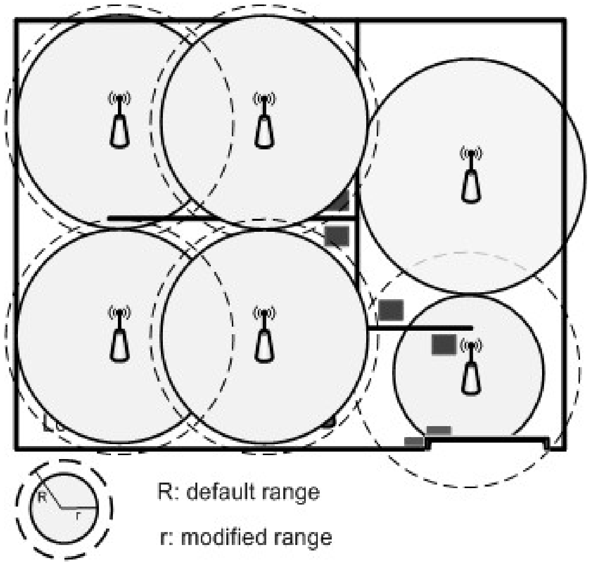


Figure 6.11 - Zoning to overcome coverage problem.

employed for bedroom, corridor and kitchen are reduced to prevent overlapped zones.

6.4.3 Regional Clustering

For occupancy detection of the tagged inhabitants in a living/working environment, as suggested, an RSSI enabled tag broadcasts a beacon every few seconds. This beacon is received by the WLSAs installed in different areas. Therefore, the signal strength of the beacon received by a WLSA should represent the distance between tag and WLSA. By measuring this distance in every WLSAs the location of tagged inhabitant can be approximated. For example, the triangulation technique can be used in three WLSAs to localise the tagged inhabitant. However, due to the possible interference in the monitored environment and the characteristics of the radio signal transmission, localising the tagged occupant can still remain potential for uncertainty.

Suppose that the WLSAs are installed in a prototype environment as shown in Figure 6.12. In order to reduce their error effects and therefore the uncertainty in RSSI signals, a regional clustering scheme is proposed as follow:

1. Installation of each WLSA in the centre of correspondent area for a balanced coverage of the whole area,

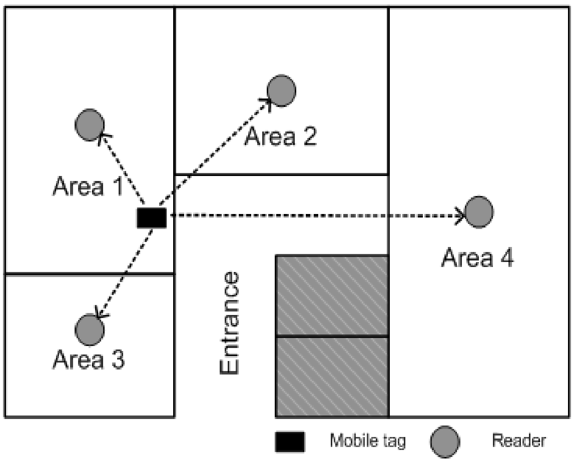


Figure 6.12 - Readers and a mobile tag in a prototype environment.

2. Installation of WLSAs based on the regions instead of areas in the case of imbalanced coverage,
3. Clustering monitored areas to reduce the occupancy detection error.

Using regional clustering scheme and incorporating intelligent clustering techniques such as K-Means and Fuzzy C-Means clustering [60], a number of clusters equivalent to the number of monitored areas will be found. This approach is called a regional approach which is explained below:

Suppose that the tagged inhabitant is present or moving in Area 1 in an environment with the layout shown in Figure 6.12. A statistically reasonable number of RSSI readings will be taken when the occupant is moving in Area 1. These readings are then taken by the WLSAs installed in all other areas. Readings from WLSA in *Area1*, *Area2*, *Area3*, and *Area4* are respectively presented as:

$$[r_{11} \;\; r_{12} \;\; r_{13} \;\; r_{14}] \tag{6.3}$$

In Expression 6.3, the first index shows the area occupied by the tagged inhabitant and the second index is the WLSA index. So, for a four area layout similar to Figure 6.12, an RSSI readings matrix can be created as:

$$R_{ij} = \begin{bmatrix} r_{11} & r_{12} & r_{13} & r_{14} \\ r_{21} & r_{22} & r_{23} & r_{24} \\ r_{31} & r_{32} & r_{33} & r_{34} \\ r_{41} & r_{42} & r_{43} & r_{44} \end{bmatrix} \tag{6.4}$$

Each element in the reading matrix can contain a number of readings but in different locations of the same area.

In regional clustering, an intelligent clustering technique such as Fuzzy C-Means clustering, K-Means, SOM, PCA, and SVM can be applied to the RSSI readings matrix resulting in a number of cluster centres equivalent to the number of monitored areas. In the case of prototype environment in Figure 6.12, four clusters will be derived with the following centers:

$$C_{ij}=\begin{bmatrix} c_{11} & c_{12} & c_{13} & c_{14} \\ c_{21} & c_{22} & c_{23} & c_{24} \\ c_{31} & c_{32} & c_{33} & c_{34} \\ c_{41} & c_{42} & c_{43} & c_{44} \end{bmatrix} \tag{6.5}$$

Each of the rows in cluster centres matrix represents a cluster centre vector.

Clustering techniques try to find a distance between a new data with cluster centers. For example in Fuzzy C-Means clustering, after finding cluster centers, the distance of a new reading which is the degree of belonging to clusters (u_k) will be found. The sum of the elements in degree of belonging matrix should be 1 as shown in Expression 6.6.

$$\sum_{k=1}^{i} u_k = 1 \qquad 0 \leq u_k \leq 1 \tag{6.6}$$

The cluster centres in Expression 6.5 can be used to identify the presence of the tagged inhabitant in one of the areas. This happens by comparing the new readings with cluster centres and finding the maximum similarity between them i.e. the maximum element in membership matrix $Max[u_k]$.

6.4.4 Incorporating Supportive Technologies

Tagging technologies in some applications can incorporate other technologies to reduce RSSI uncertainty. For example, the elderly lady living in her apartment as a real environment in Chapter 4 uses a walker to move around. The walker itself can be used to be integrated with other technologies. For instance, it is proposed to integrate a

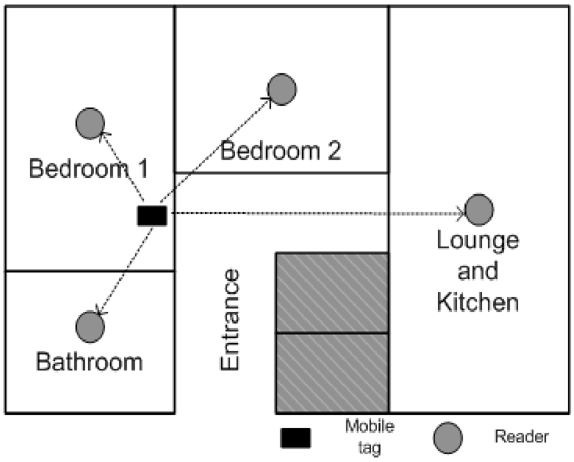


Figure 6.13 - Layout of the apartment in the third experiment.

passive RFID reader with sensory agents to support RSSI signals. Passive RFID tags will be located somewhere in the pathways between two adjacent areas. Installing the reader on the walker, when the walker is passing this zone, passive RFID reader will activate passive RFID tags. This can be a support for uncertainty reduction. For instance, if passive RFID tags are installed on the door frame between bedroom and corridor, when the occupant passes between two areas the reader will identify these tags. Therefore, the system will know that the occupant is in one of the two areas even in presence of visitors. This idea is suggested for future work in the field.

6.5 Experimental Results and Validation

In order to test the capability of WLSAs in localising tagged occupants, a number of experiments were conducted. A 4-area double-bedroom apartment located in Nottingham with the layout of Figure 6.13 was chosen for these experiments. The chosen apartment is a multiple-occupant environment with three occupants living in it.

WLSAs were installed in bedrooms 1 and 2, lounge, and bathroom in the centre of ceilings. One of the occupants was asked to carry the XBee tag as the tagged person in this multiple-occupant environment.

Experiment 1: RSSI tagging without uncertainty reduction

In this experiment, the tagged occupant moves amongst four areas with the pattern of

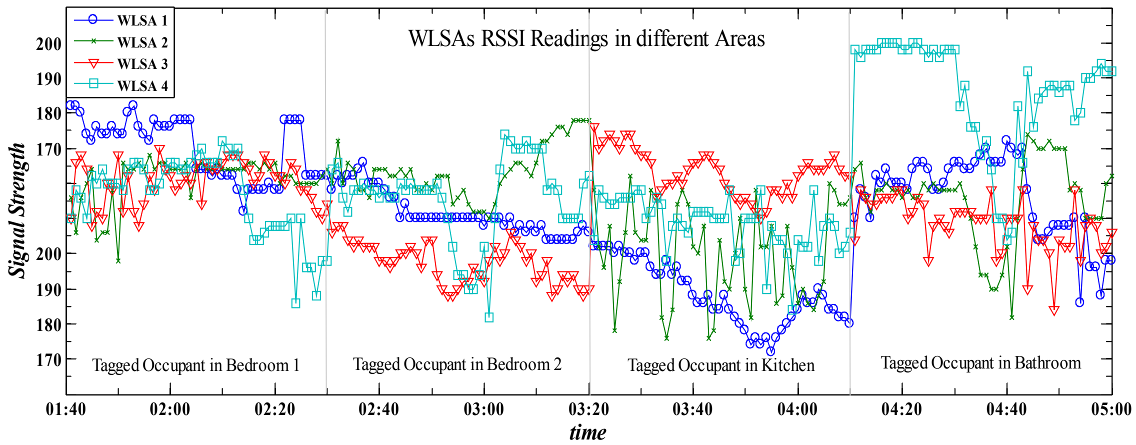


Figure 6.14 - WLSAs RSSI readings in different areas.

Bedroom 1, *Bedroom 2*, *Kitchen*, and *Bathroom* (*B1*, *B2*, *K*, *BT*). Fifty RSSI readings are recorded for each area. The graphs of signal strength received by WLSA are illustrated in Figure 6.14 in which WLSA 1, 2, 3, and 4 are located in the center of the ceilings in areas *bedroom 1*, *2*, *kitchen*, and *bathroom* respectively.

In this experiment, it is assumed that the highest RSSI reported should represent the occupied area by the tagged inhabitant. However, due to the uncertainty in the nature of radio signals, these readings sometimes cannot represent occupied area successfully. In this experiment, 18 out of 50, 14 out of 50, 4 out of 50, and 7 out of 50 reading could not represent the occupancy of bedroom 1, bedroom 2, kitchen, and bathroom respectively. Therefore, this experiment shows that 43 out of 200 readings could not represent right occupied area causing 21.5% uncertainty in the tagging technology integrated as wireless localising sensory agents.

Experiment 2: RSSI tagging with zoning

In this experiment, the sensitivity of WLSA 1 and WLSA 2 in Bedroom 1 and 2 was modified (zoning) to become less sensitive to the RSSI received when the tagged occupant is present in other areas and avoid overlapping. In addition, a WLSA 5 was installed in kitchen to support WLSA 3 preventing uncovered zones. Sensitivity of WLSA 3 and 5 were also decreased to avoid overlapping.

In this experiment, 15 out of 50, 10 out of 50, 6 out of 50, and 8 out of 50 reading could not represent the occupancy of bedroom 1, bedroom 2, kitchen, and bathroom respectively. Therefore, this experiment shows 39 out of 200 readings could not represent right occupied area causing 19.5% uncertainty in the tagging technology supported by zoning approach.

Experiment 3: RSSI tagging with clustering

In this experiment, after data collection, regional clustering method such as Fuzzy C-Means are applied to the collected data to group them in four clusters. These clusters should represent the presence of tagged inhabitant in each area (*Bedroom 1*, *Bedroom2*, *Bathroom*, and *Kitchen*).

Fuzzy C-Means

Using Fuzzy C-Means clustering technique, the clusters found for the XBee tag's RSSI readings are shown in Figure 6.15. In this figure, a 4-dimensional data from four WLSAs is represented in 2-dimensional plots. Data points on the plot area show the readings and the numbers on the plot are cluster centres in a binary range of [0 255]. The cluster centres found for the XBee tag's RSSI readings are shown in Table 6.2.

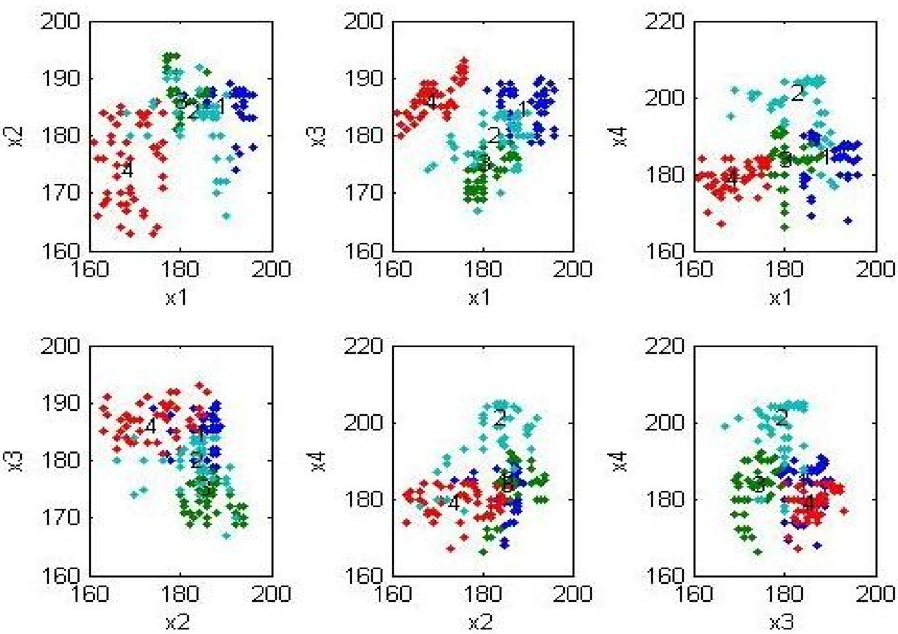


Figure 6.15 - ZigBee readings and cluster centre (x1: bedroom1 reader, x2: bedroom2 reader, x3: kitchen reader, and x4: bathroom reader).

Table 6.2 - Fuzzy C-Means cluster centres.

Clusters	*Reader 1 (Bedroom 1)*	*Reader 2 (Bedroom 2)*	*Reader 3 (Kitchen)*	*Reader 4 (Bathroom)*
1- Tag in Bedroom 1	189.71	185.11	184.42	184.34
4- Tag in Bedroom 2	180.85	186.06	175.04	183.46
3- Tag in Kitchen	169.04	174.12	185.85	178.99
4- Tag in Bathroom	183.18	184.33	180.02	201.11

In a Silhouette diagram like Figure 6.16, the surface of each cluster shows the number of data points in that cluster. So, more data points in a cluster, bigger surface the cluster will have in the diagram. In a Silhouette diagram a data point's degree of belonging to a cluster can be negative or positive. If a data point is more positive, then the data belongs to its cluster with more confidence. On the other hand, data points with negative degree of belonging would be known as a data point with no cluster. After finding cluster centres, 200 test data points with known areas associated with them collected from four areas were classified to the found clusters.

The test data was successfully classified with 86.5% of accuracy for finding the

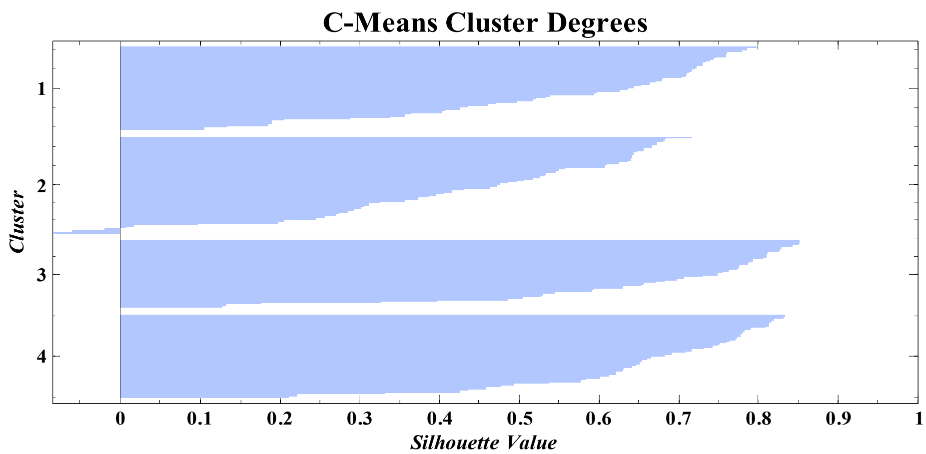


Figure 6.16 - Fuzzy C-Means Cluster Degrees.

occupied area. Hence, the uncertainty was reduced to 13.5% by applying the regional clustering explained in Section 6.4.3.

6.6 Summary and Discussions

The idea of occupancy detection in the environments with more complicated situation compared with single-occupant environment was addressed in this chapter. It was proposed to use RSSI-based tagging technologies such as active RFID and WSN to reduce the problem of occupancy detection in multiple-occupancy situation. Hence, a number of tagging technologies were tested in a series of measurements. It can be summarized from the distance-based measurements that the accuracy and reliability of the RSSI-distance measuring varies over the distance between tag and reader and is affected by many interfering factors. It was also suggested that by using tagging technologies and separating the occupancy signal derived for each tagged inhabitant, their occupancy signal as time-series can be analysed and predicted by time-series prediction techniques. The tagging technologies using RSSI were shown to be potential for uncertainties due to the nature of radio signal strength measures used for tagging. So, a number of resolutions to reduce this problem was suggested, their theories were explained and experimented and the results were reported.

The integration of tagging technology with wireless sensory agents for creating wireless localising sensory agents reported in this chapter is a simple way of equipping the data acquisition system explained in Chapter 4 with the tools required to deal with more complicated situation in PaIEs. The importance of such data acquisition system i.e. WLSAs is more highlighted when for example the monitored elderly lady's apartment is occupied by other people such as visitors where WSAs are not able to separate elderly lady's occupancy signal from others' activities.

The solutions proposed in this chapter for reducing the uncertainty in tracking the tagged inhabitant such as zoning and regional clustering were able to reduce the uncertainty of RSSI occupancy detection by WLSAs from 21.5% down to 13.5%. Despite the performance of these solutions the uncertainty remains a problem which degrades the accuracy of the data acquisition system. It is also proposed to support

WLSAs for RSSI occupancy detection with other signals such as passive RFID signals which can be explored as a future work in the field.

In the multiple-occupancy monitoring proposed in this chapter is independent of the number of occupants or visitors. It can be inferred from the application purpose of this thesis, which is to monitor people who live alone, by tagging the monitored elderly his/her occupancy signal can be separated from others.

Chapter 7

CONCLUSIONS

7.1 Summary

The research was conducted to enhance the efforts for the development of ambient intelligent environments. It was focused on a particular aspect in smart environments which can assist intelligent techniques to discover the pattern of behaviours for residents living or working in the environment i.e. occupancy monitoring and prediction in ambient intelligent environment. It was shown that the occupancy monitoring can play an important role for extracting the behavioural pattern of occupants. In addition to pattern extraction, the occupancy monitoring and prediction can assist in predicting not only the occupancy of the environment but also the behavioural pattern of the occupants. Therefore, in this research, it was aimed to produce a proper occupancy signal for prediction by investigating data collection mechanism, signal analysis and prediction techniques.

This was achieved by initially proposing a data acquisition system for collecting occupancy data from real environments. In the data acquisition system, simple sensory devices were interconnected in a wireless sensor network as wireless sensory agents. Collected occupancy data from single-occupant environments was represented in binary format. The digital characteristics of the collected data were a challenge for the prediction, therefore, a new data representation by combining separate sensory readings and filtering the combined signal was proposed. It was shown that the final signal is a time-series which incorporates both the location and the time in a spatio-temporal manner. The significance of the technique was shown to be highlighted by the capability of applying powerful time-series prediction techniques for the application of occupancy prediction.

Secondly, the characteristics of the occupancy signal were considered to create a model of occupancy using statistical modelling. The model was created based on the occupant's movements in the environment and the time spent in each area. The daily movement pattern of the occupant, the layout of the environment, and the uncertainties in her/his movements pattern including movement and duration uncertainties were incorporated in the occupancy model. Hence, a signal generator was created to produce sufficient amount of occupancy data needed for test and comparison amongst time-series prediction techniques.

Thirdly, the problem of creating an occupancy signal in a multiple-occupant environment or in a single-occupant environment in presence of visitors was addressed to make the occupancy detection and prediction more generalised. Tagging technologies were compared to measure the accuracy of occupants' identification in the environment. The ideas of area occupancy detection, zoning, and regional clustering were incorporated to tackle the uncertainty in the tagging mechanisms. Hence, the data acquisition system proposed for single-occupant environments i.e. wireless sensor agents was modified to wireless localising sensory agents capable of identifying occupants and distinguishing amongst them. As a result, a separate occupancy signal was extracted for each occupant.

7.2 Concluding Remarks

The proposed solutions for occupancy detection, prediction, and modelling in this research bring advantages to the field which are explained below:

- Firstly, the focus of the research was the area occupancy. Instead of tracking exact location of living objects, the idea of the occupancy of areas was proposed and investigated. Although dealing with exact location of objects is very interesting in the field of PaIEs, it is not required in most of the applications in PaIEs. Therefore, the idea of area occupancy proposed in this research can adequately address the requirements of the PaIE in elderly people behavioural monitoring whereas other techniques such as LANDMARC [57], [58] and Fingerprinting [59] try to find the exact location of objects. Moreover, using the techniques suggested in this research, the uncertainties arising from the techniques dealing purely with the exact location of objects in the environment (such as LANDMARC and Fingerprinting) can be reduced remarkably,

- Secondly, using simple sensory devices and communication mechanism has made the data acquisition system proposed and implemented in the research an inexpensive, unobtrusive, and expandable data collection system compared with other techniques such as those using visual equipment. These sensory devices such as PIRs which currently exist in the buildings with even a very little intelligence have not been used for occupancy detection except in a few researches such as [45] and [56]. However, this work represents an alternative approach to [45] and it deals with the location of occupant instead of number of occupants as in [56].

- Thirdly, the simple data analysis and preprocessing required for creating the occupancy signal suitable for prediction has made it a quick and less processor hungry signal reshaping technique compared to the techniques which require visual data analysis,

- Fourthly, the research was comprehensive in addressing different issues related to the occupancy of areas in an ambient intelligent environment. Considering single-occupant and multiple-occupant situations, their related issues were explained and addressed properly in the research. This separation has not been considered in the literature whereas considering it can categorise environments based on their occupancy situation. It can reduce the resources required for occupancy detection and prediction in terms of equipment for detection and tagging occupants,

- Fifthly, the multiple-occupancy monitoring proposed in Chapter 6 is independent of the number of occupants or visitors. In comparison with [67], which tries to identify and distinguish between two occupants, the number of occupants is not restricted in the solutions of this chapter,
- Moreover, the approach for the occupancy modelling was developed on the idea of occupancy signal representation for which there is not any similar work in the literature. This model can play an important role in understanding and analysis of the occupancy situation in the environment. The occupancy modelling reported in [61] lacks the requirements for occupancy modelling in different environments with a number of areas for different occupants. These issues are addressed in the occupancy model proposed in this research by which flexibility of different environments as well as different people with various behavioural parameters can be incorporated in the simulation which is a significant contribution to the field,
- Finally, the application of the research as a way to improve the life style of elderly people and the people with physical and mental impairments who want to live on their own property has always been considered. The issues and problems related to the application are addressed in this thesis.

The data acquisition system proposed and implemented in Chapter 4 is one of the approaches in the field of ambient intelligent environment which brings a number of advantages and disadvantages. Using simple sensory devices such as PIRs and door contact sensors with ZigBee wireless communication have made the data acquisition system inexpensive, simple, flexible, and expandable for occupancy data collection. The data acquisition is also unobtrusive and so does not interfere with occupants' daily life. Moreover, wireless sensory agents have been implemented in a way that integrates sensors, communication, and processing unit which makes them easy for further needed expansions. On the other hand, the data acquisition system proposed in Chapter 4 lacks the utilisation of the agents' processing capability due to the data analysis and prediction centralised more in the base station.

The data representation technique for converting digital motion signals to a continuous occupancy time-series has made it possible to apply time-series prediction techniques for occupancy prediction. One might conclude, the techniques to be a potential to information loss; however, a good interpretation of the filtered data has eliminated the loss and the wrong interpretation of occupancy signal.

Using the data representation proposed in Chapter 4, the prediction techniques including ANFIS and ARMA were shown capable of predicting the occupancy signal in a virtual environment for up to 900 second (15 minutes) ahead. The occupancy data collected from the elderly-living environment was predicted up to 510 seconds by ANFIS and up to 530 seconds by ARMA. Both predictors predicted the virtual data better than the actual collected data due to the nature of two signals. In the virtual occupancy signal, the uncertainty of occupant's movement was not considered and the signal durations involved more similarity compared with the real situation.

Due to the applications arising from the research, the prediction can be beneficial for lonely living occupants and occupants who are in the need of support and monitoring. So, duration of prediction even shorter than that achieved in Chapter 4 i.e. 530 seconds ahead can be considered vital in some applications. As an example, identification of occupancy situation in an elderly lady's apartment and comparing it with expected or predicted occupancy situation can change the level of awareness for the health of the monitored occupant; therefore, persons in charge for her/his health monitoring can be prepared for the situation.

Although several influencing factors in human behaviour have made modelling this behaviour very difficult, it was shown in Chapter 5 that the simplification of situations can make it feasible to approach. The focus on a particular behaviour such as movement pattern of persons with less uncertainty in their daily activity e.g. elderly people made the occupancy modelling more possible. The signal generator created based on the model has proved to be a good means for generating as much as occupancy signal as as required, incorporating different occupant and environmental profiles. Using a validation scheme proposed in Chapter 5, it was shown that the model can converge to the parameters of the generated data successfully. Evaluation of the simulator against the occupancy signal created from the data collected from a real environments showed that the model can find values for uncertainty parameters. Using these values, it was proved that the signal generated by the simulator has more similarity to the real data rather than other signals with different values for the uncertainty parameters.

However, although the model explained in Chapter 5 can be a good simulator of occupancy signal in a single-occupant environment, it does not bring sufficient confidence to claim that the simulator explained in the chapter can be a perfect model for the occupancy behaviour of any person with any profile. However, the simulator can generate sufficient occupancy data required to test and verify time-series prediction techniques for the prediction of the occupancy signal explained in Chapter 4.

The idea of occupancy detection in single-occupant environments was extended to multiple-occupant environments in Chapter 6. It was shown that tagging technologies can assist to create an occupancy signal for each person in the environment; hence, the occupancy detection and prediction in multiple-occupant environments became possible. It can be concluded from the chapter that the tagging mechanisms can bring uncertainties relevant to the characteristics of the radio signal. However, the solutions proposed and experimented in Chapter 6 have been able to reduce this problem. The installation of wireless localising sensor agents in appropriate locations in monitored areas and a regional clustering approach could identify the location of the monitored occupant with 86.5% accuracy in multiple-occupant situation. It can also be inferred from the application purpose of this thesis, which is to monitor people who live alone, by tagging the monitored elderly his/her occupancy signal can be separated from others. However, the approach reported in [67] can deal with more than one occupant simultaneously which is beneficial in several applications. On the other hand, the approach can be impractical when the number of occupants or visitors increases.

7.3 Future Works

The idea of occupancy detection and prediction in ambient intelligent environment proposed and investigated in this research can be expanded for future research investigations and technological approaches as follow:

- The occupancy pattern extraction explained can be expanded to behavioural pattern extraction. For example, monitoring other activities, and to extract the daily pattern of the activities such as activities which can be dependent on the occupancy pattern,
- It is clear that the prediction works if there is a pattern in the behaviour; therefore, the prediction of behavioural pattern is not feasible if there is not a pattern in the behaviour. In the research, the focus of the work was on monitoring and prediction of occupancy for persons with a good daily pattern with more certainty in their behaviour. However, finding solutions and expanding the work to the prediction of the behaviour for persons with less certainty can be a good direction for future work,
- The prediction time achieved in this research is also a potential for expansion using alternative prediction techniques or a fusion of data analysis and time-series prediction for future works,
- The strength of higher types of fuzzy system such as type-2 fuzzy should be considered in future works. Type-2 fuzzy can model and minimise the effect of uncertainties with more degree of freedom. Hence, it is suggested to incorporate type-2 fuzzy in the ANFIS model to create a more suitable model for single occupancy prediction,
- The data collection in the research was distributed in a wireless sensor network but the data analysis and prediction was performed in the base station as a centralised system. The distribution of data analysis using potential precessing power of WSAs or WLSAs is also a direction for future works,
- The real data used for the evaluation of the hypothesis in this thesis is not

sufficient when the long-term behaviour of the occupant is concerned. Therefore, as a future work, collecting large data sets i.e. for couple of months or years can help in understanding seasonality and trend in the occupancy data,

- Expanding the occupancy signal simulator to a model covering other activities in an ambient intelligent environment is a potential for further investigations,
- Tagging approaches investigated for tracking objects are not yet accurate and efficient enough; hence, alternative approaches in an inexpensive manner are still potential for investigations,
- Due to the potential market for elderly care, health monitoring, and similar applications, the data acquisition including the monitoring portal has potential for developing a web based portal. In addition, the system can be made to learn from daily movements in the environment and predict the occupancy pattern. So, the expected occupancy signal can be compared with the actual occupancy signal to find the abnormalities in the behaviour of the monitored occupants. Hence, the whole work has feasible potential for a reliable framework to reduce the time spent by carers, nurses, and children for monitoring the healthy conditions of their patients or parents reducing stress and concerns related to their duties,
- As a consequence of this work, the school of science and technology in the Nottingham Trent University is developing an intelligent office laboratory. This laboratory is being equipped with a WSN of different types of sensors such as motion detection, door contact, light intensity, temperature, humidity, and pressure sensors as a test-bed. In addition, other data acquisition systems are being installed to equip the test-bed with both wired and wireless technologies for data collection. Moreover, a number of controllable appliances such as electric curtains, dimmers, switches, etc. are being employed in the laboratory. The idea of automatic control in an intelligent environment by optimising the energy usage and occupants' comfort will be explored in the university's intelligent office test-bed.

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Appendix A: Data Acquisition Prototype

A.1 Wireless Sensory Agent (WSA)

For creating a data acquisition system, due to the features of wireless sensor network mentioned in Chapter 3, an XBee wireless network chip which employs ZigBee protocol was chosen. Chosen XBee wireless network module was integrated with a micro-controller to create a Wireless Sensory Agent (WSA). A connection terminal interfaced with micro-controller on the WSA is a mean to connect any type of digital and analogue sensors (Figure A.1). The micro-controller on the wireless sensory agent can be programmed to read sensory data with a complete control on sample rates and the status of the connected sensors. For instance, the micro-controllers on every WSA are programmed to trigger on the state change of digital sensory devices such as PIRs and door contact sensors. On the other hand, for analogue sensors like temperature and light intensity sensors, a sampling method is applied and there is no data transmission if there is no reading changes. Therefore, the overhead of the data transmission is reduced.

The XBee module on WSA is responsible for communication of the data read by the sensor. So, any data reported for transmission is sent to the XBee module via its serial connection with micro-controller. Then the read data is sent as a packet (using IEEE 802.11.54 standard) to a destination which can be either the base station or other WSAs. The XBee module on WSA has a unique identification address and a unique destination

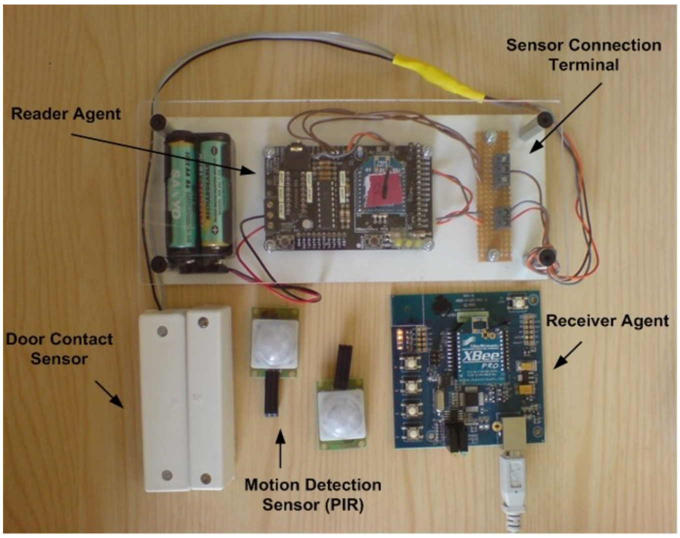

Figure A.1 - Wireless Sensory Agent.

address that enable the communication among XBee devices and consequently among WSAs possible.

In an optimum scenario, all wireless sensory agents communicate with a wireless receiver agent (Figure A.1) connected to a desktop PC or laptop as the base station (star topology, see Figure 3.2). However, in the intelligent environment, some WSAs can act as repeaters which receive messages from one agent and passes it to another wireless sensory agent (tree topology, see Figure 3.2). The need for repeater is more likely in the case of long distances or obstructions in the environment which have negative impacts on the communication among WSAs.

For power saving purposes i.e. battery life in WSAs which is a key issue for keeping the intelligent system running without interruption, every XBee module has a sleep operation mode. In the sleep mode, the XBee module's radio transmitter is switched off. In this mode, an asserted signal level can alter the mode of the XBee module from sleep to ready for communications.

The micro-controllers on WSAs are programmed to keep the XBee module in power saver (sleep) mode until a new data is available [87], [132]. Hence, the battery life of every wireless sensory agents is saved if there is nothing to transmit. This feature reduces the energy consumption; hence, the time spent for maintenance purposes.

A.2 Monitoring Portal

Using Microsoft Visual C# programming language, a monitoring software interface was developed. The monitoring portal is designed to visualise and log the raw data from the receiver agent on the base station. The raw data is sent to receiver agent by wireless sensory agents installed in a target intelligent environment. The monitoring portal is designed with flexibility for altering number and type of the sensors in any preferred configuration in which an XML file as configuration file can apply these changes.

The monitoring portal has a layout of the monitored environment with different sensors located for each area. For example, in a virtual elderly-living flat shown in Figure A.2, the occupancy of four areas namely, bedroom, corridor, lounge, and kitchen were monitored by the installed WSAs of PIR sensors. The entrance door and the bathroom

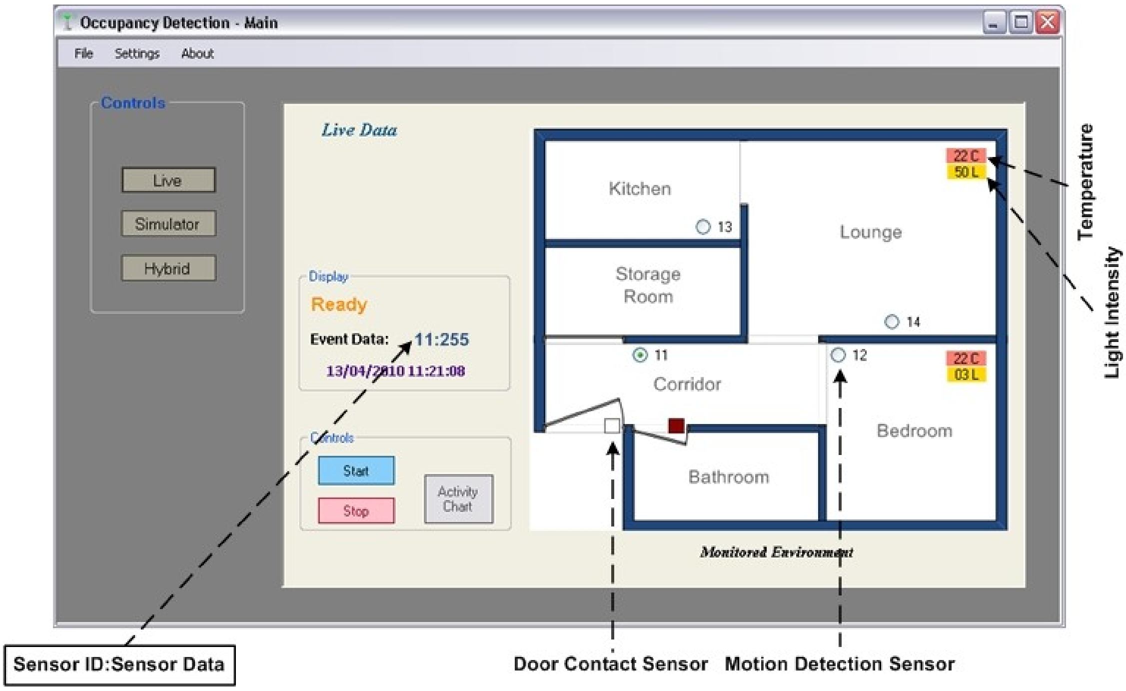

Figure A.2 - A Screen shot of the Monitoring Software Interface.

door were also monitored using WSAs of door contact sensors. In addition, a temperature and a light intensity sensors were installed in bedroom and lounge.

Any sensory data received from wireless sensory agents contains a sensor id (address) and an actual sensor value. In the monitoring portal the location and type of the sensor is identified by its address and its data is visualised in the graphic user interface of the monitoring portal and logged in a database file with the format of ***(Date, Time, Sensor Id, Sensor Data)***. Therefore, the logged data can be used by intelligent control mechanism for learning and decision making. A snapshot of the monitoring portal is depicted in Figure 2.

The WSAs along with the monitoring portal are used in as a data acquisition system for occupancy data collection described in Chapter 4.

A.3 Wireless Localising Sensory Agents (WLSA) and Monitoring Portal

WSAs are modified to create WLSAs Figure A.3 for the application of tagging occupants and localising them in their living/working environment.

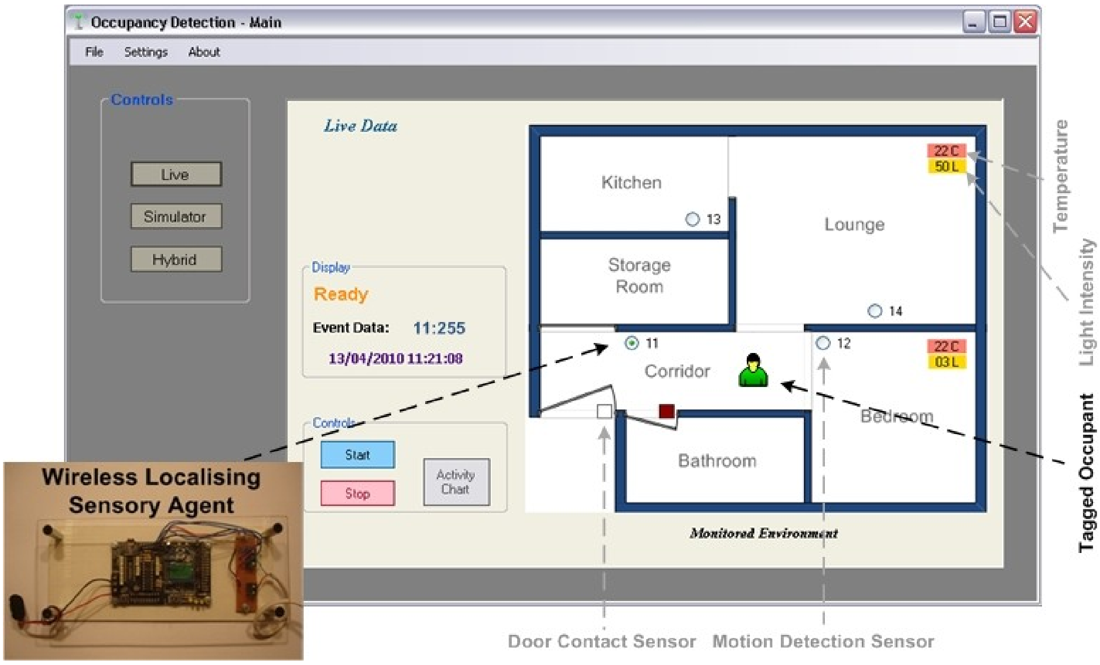

Figure A.3 - WLSA and Monitoring Interface.

The modified monitoring portal Figure A.3 compares received signal strength from the tagged occupant received by WLSAs and identifies the area occupied by the tagged person after some localising processes such as regional clustering explained in Chapter 6.

Appendix B: Simulator's User Interface

Using the behaviour modelling algorithm explained in Section 5.2 of Chapter 5, an occupancy signal generator is implemented. This application generates an occupancy signal based on different designs of the environment as well as different behaviours of occupants. A snapshot of the occupancy signal generator is shown in Figure B.1. The simulator's user interface (SUI) is a graphical interface which allows users to input desired parameters into the model.

The environment profile section in SUI accepts the number of areas in the environment and the connections amongst these areas. In the occupant profile section, users can specify expected daily pattern with the expected durations. It also accepts the movement and duration uncertainties in the occupant profile section. By setting the parameters and specifying the number of days, a blue-coloured occupancy signal will be generated along with a green-coloured dashed expected occupancy pattern. The signal generator implemented in this section can generate a simulated occupancy data for prediction if the expected pattern of behaviour, expected mean durations, and uncertainty in the pattern is assigned accurately. This is feasible if the simulated data is validated by the real data collected from the simulated environment.

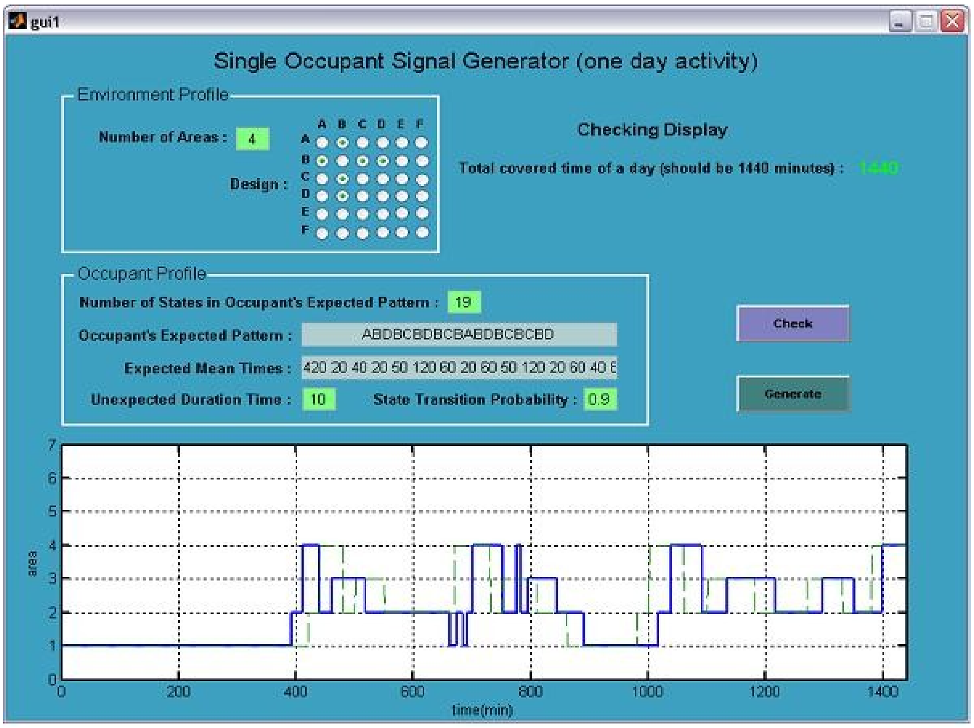

Figure B.1 - Simulator's User Interface.

Appendix C: ZigBee Wireless Technology

ZigBee is a wireless network standard which is designed to meet the requirements of sensors and control devices. These devices do not need high bandwidth but low latency and low energy consumption. ZigBee technology is also suitable for other wireless communication applications that require low cost and low energy consumption. More importantly, ZigBee as a standard can provide a unique communication standard that can realise the interoperability amongst wireless applications. In this manner, ZigBee Alliance does not push the technology, but provides a standardised base set of solutions for different wireless applications [137].

C.1 ZigBee/IEEE 802.15.4 - General Characteristics

- Dual physical layer frequency (2.4 GHz and 868/915 MHz),
- Data rates of 250 kbps (@ 2.4 GHz), 40 kbps (@ 915 MHz), and 20 kbps (@ 868 MHz),
- Optimised for low duty-cycle applications (<0.1%),
- CSMA-CA channel access: Yields high throughput and low latency for low duty cycle devices like sensors and controls,
- Low power (battery life multi-month to years),
- Multiple topologies: star, peer-to-peer, mesh,
- Addressing space of up to: 18,450,000,000,000,000,000 devices (64 bit IEEE address) 65,535 networks,
- Optional guaranteed time slot for applications requiring low latency,
- Fully handshaking protocol for transfer reliability,
- Range: 50m typical (5-500m based on environment).

C.2 ZigBee Supported Network Topologies

In order to allow producers to supply the lowest possible cost devices, the IEEE standard defines two types of devices namely, Full Function Devices (FFD) and Reduced Function Devices (RFD) for three network topologies including star, peer-to-peer and cluster tree.(Figure C.1)

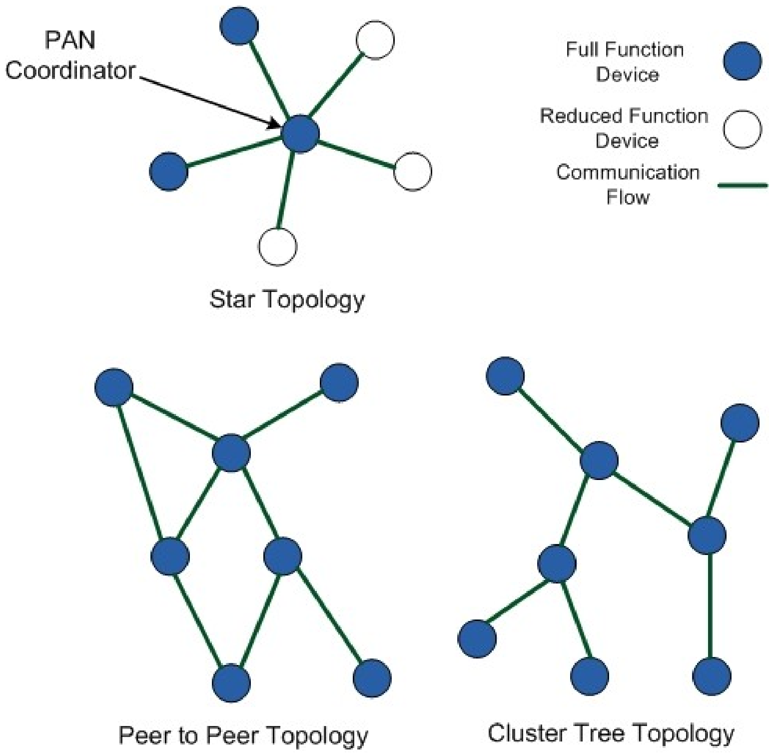

Figure C.1 - ZigBee network topologies.[137]

Full function device (FFD)

- Can function in any topology,
- Capable of being the Network coordinator,
- Capable of being a coordinator,
- Can talk to any other device.

Reduced function device (RFD)

- Limited to star topology,
- Cannot become a network coordinator,
- Talks only to a network coordinator,
- Very simple implementation.

C.3 ZigBee Addressing Modes

- Star: Network + Device Identifier (for PAN coordinator),
- Peer to peer: Source/Destination Identifier.

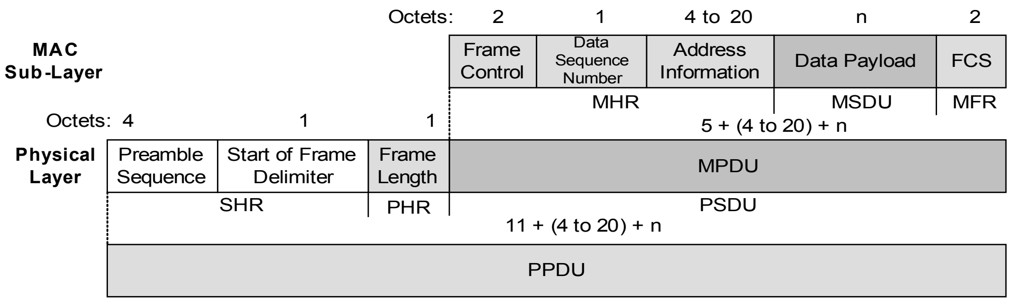

Figure C.2 - ZigBee data frame structure.[137]

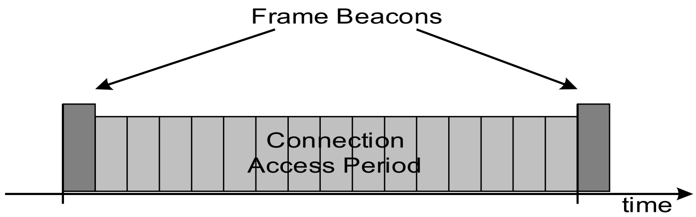

Figure C.3 - ZigBee superframe structure.[137]

C.4 Frame Structure

The IEEE 802.15.4 Media Access Control (MAC) defines four frame structures:

- A beacon frame, used by a coordinator to transmit beacons,
- A data frame, used for all transfers of data,
- An acknowledgement frame, used for confirming successful frame reception,
- A MAC command frame, used for handling all MAC peer entity control transfers.

C.5 Super Frame Structure

For low latency applications or applications requiring specific data bandwidth, the PAN coordinator may dedicate portions of the active superframe to that application. These portions are called guaranteed time slots (GTS).

C.6 ZigBee Network Model

A general architecture of ZigBee wireless network is illustrated in Figure C.4.

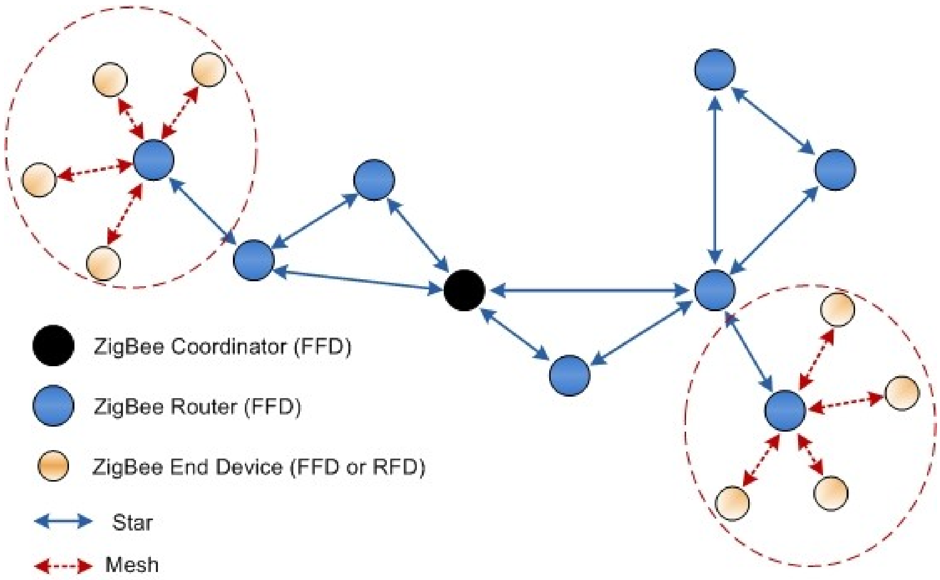

Figure C.4 - ZigBee network model.[137]

The ZigBee Network Coordinator

- Sets up a network,
- Transmits network beacons,
- Manages network nodes,
- Stores network node information,
- Routes messages between paired nodes,
- Typically operates in the receive state.

The ZigBee Network Node

- Designed for battery powered or high energy savings,
- Searches for available networks,
- Transfers data from its application as necessary,
- Determines whether data is pending,
- Requests data from the network coordinator,
- Can sleep for extended periods.

C.7 Mac Data Service Diagram

The non-beacon communication flow is shown in Figure C.5.

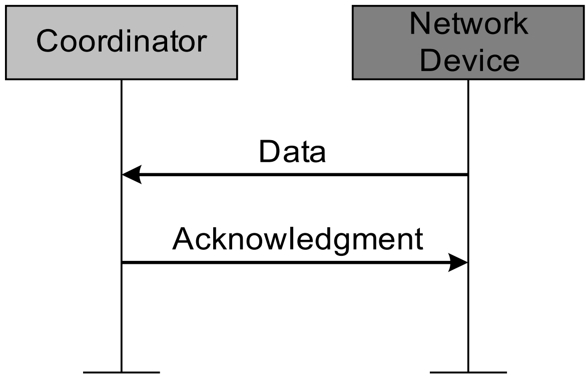

Figure C.5 - Non-beacon communication.[137]

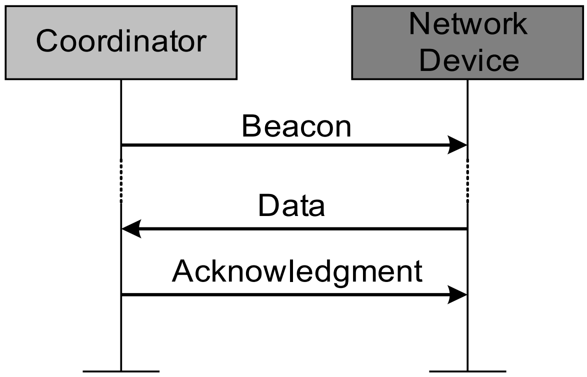

Figure C.6 - Beacon communication.[137]

The beacon communication flow is depicted in Figure C.6.

B.8 ZigBee Stack

The ZigBee network stack consists of physical, medium access control, network, and application layers. This layer stack is illustrated in Figure C.7.

ZigBee Communication Security

In its MAC layer, ZigBee uses a security mechanism to secure MAC command, beacon, and acknowledgement frames. ZigBee may secure messages transmitted over a single hop using secured MAC data frames, but for multi-hop messaging ZigBee relies upon upper layers (such as the network layer) for security [137]. In MAC layer, ZigBee uses the Advanced Encryption Standard (AES) as its core cryptographic algorithm and describes a variety of security suites that use the AES algorithm. These suites are to

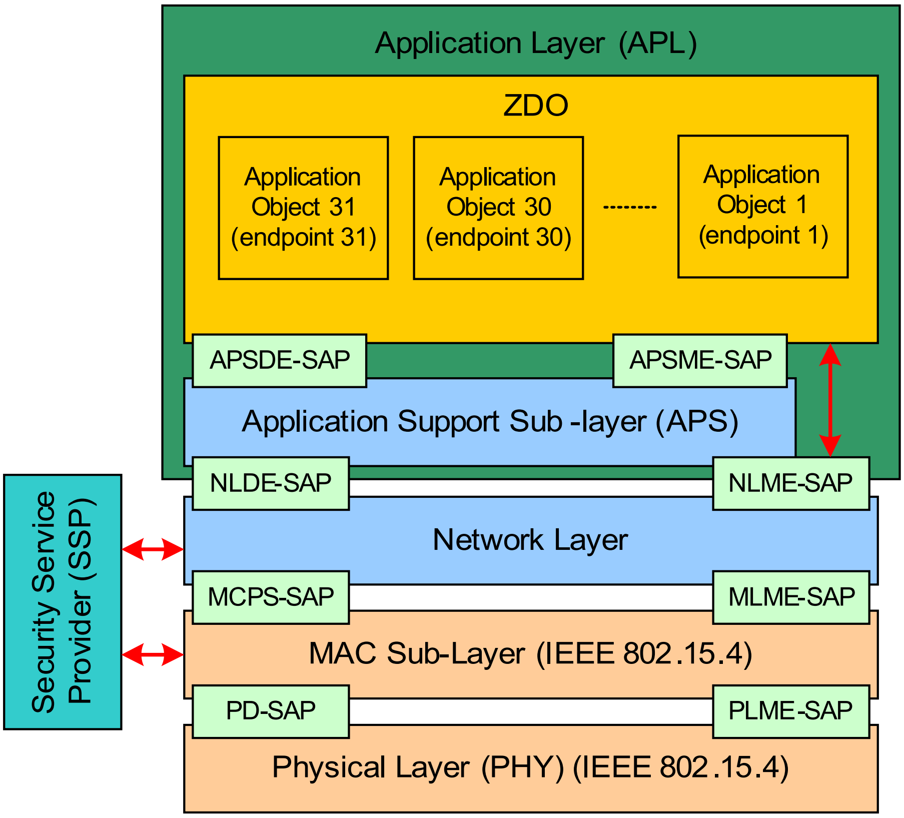

Figure C.7 - ZigBee stack.[137]

protect the confidentiality, integrity, and authenticity of frames.

Network Layer

The ZigBee network layer is responsible for:

- Starting a network,
- Joining and leaving a network,
- Configuring a new device,
- Addressing,
- Synchronisation within a network,
- Security, and
- Routing.

Application layer

The application layer in ZigBee stack consists of APS sub-layer, ZigBee Device Object

(ZDO), and the manufacturer-defined application objects. The APS sub-layer maintains tables for binding, which is for matching two devices together based on their services and their needs, and forwarding messages between devices. In addition, the APS sub-layer is responsible for the discovery of other devices operating in the personal operating space of a device. In the application layer, ZDO is the responsible for defining the role of the device within the network (e.g., ZigBee coordinator or end device). It also initiates and/or respond to binding requests and establish a secure relationship between network devices. The manufacturer-defined application objects implement the actual applications according to the ZigBee - defined application descriptions [137].

ZigBee Device Object

- Defines the role of the device within the network (e.g. ZigBee coordinator or end device),
- Initiates and/or responds to binding requests,
- Establishes a secure relationship between network devices selecting one of ZigBee's security methods such as public key, symmetric key, etc.

Application Support Layer

This layer provides the following services:

- **Discovery:** The ability to determine which other devices are operating in the personal operating space of a device,
- **Binding:** The ability to match two or more devices together based on their services and their needs and forwarding messages between bound devices.