An Intelligent Mobility Prediction Scheme for Location-Based Service over Cellular Communications Network

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Dedication

I lovingly dedicate this thesis to my respective parents who have been my constant source of inspiration. They have given me the power and discipline to tackle any task with enthusiasm and determination. I dedicate this thesis to my lovely wife who gave me endless love, trust, constant encouragement over the years and supported me each step of the way. I would like to dedicate this thesis to my brothers and sisters, their cares and prayers helped me to get over difficulties during this work. I also dedicate this work to my tutor who never failed to teach and guide me throughout my study. Without their love and support, this thesis would not have been made possible.

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Abstract

One of the trickiest challenges introduced by cellular communications networks is mobility prediction for Location Based-Services (LBSs). Hence, an accurate and efficient mobility prediction technique is particularly needed for these networks. The mobility prediction technique incurs overheads on the transmission process. These overheads affect properties of the cellular communications network such as delay, denial of services, manual filtering and bandwidth.

The main goal of this research is to enhance a mobility prediction scheme in cellular communications networks through three phases. Firstly, current mobility prediction techniques will be investigated. Secondly, innovation and examination of new mobility prediction techniques will be based on three hypothesises that are suitable for cellular communications network and mobile user (MU) resources with low computation cost and high prediction success rate without using MU resources in the prediction process. Thirdly, a new mobility prediction scheme will be generated that is based on different levels of mobility prediction.

In this thesis, a new mobility prediction scheme for LBSs is proposed. It could be considered as a combination of the cell and routing area (RA) prediction levels. For cell level prediction, most of the current location prediction research is focused on generalized location models, where the geographic extent is divided into regular-shape cells. These models are not suitable for certain LBSs where the objectives are to compute and present on-road services. Such techniques are the New Markov-Based Mobility Prediction (NMMP) and Prediction Location Model (PLM) that deal with inner cell structure and different levels of prediction, respectively. The NMMP and PLM techniques suffer from complex computation, accuracy rate regression and insufficient accuracy.

In this thesis, Location Prediction based on a Sector Snapshot (LPSS) is introduced, which is based on a Novel Cell Splitting Algorithm (NCPA). This algorithm is implemented in a micro cell in parallel with the new prediction technique. The LPSS technique, compared with two classic prediction techniques and the experimental results, shows the effectiveness and robustness of the new splitting algorithm and prediction technique.

In the cell side, the proposed approach reduces the complexity cost and prevents the cell level prediction technique from performing in time slots that are too close. For these reasons, the RA avoids cell-side problems. This research discusses a New Routing Area Displacement Prediction for Location-Based Services (NRADP) which is based on developed Ant Colony Optimization (ACO). The NRADP, compared with Mobility Prediction based on an Ant System (MPAS) and the experimental results, shows the effectiveness, higher prediction rate, reduced search stagnation ratio, and reduced computation cost of the new prediction technique.

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List of Abbreviations

1G First Generation

2G Second Generation

3G Third Generation

3GPP Third Generation Partnership Project

4G Fourth Generation

AC Authentication Center

ACO Ant Colony Optimisation

A-GPS Assisted GPS

AMPS Advanced Mobile Phone System

AOA Angel of Arrival

AS Ant System

BS Base Station

BSC Base Station Controllers

BSS Base Station Subsystem

BTS Base Transceiver Station

CDMA Code Division Multiple Access

CN Core Network

DCW Dynamic Computational Window

DRNC Drifting RNC

DS-CDMA Direct Sequence CDMA

EBSs Enhanced Base Stations

EGW Enhanced Gateway

EIR Equipment Identity Register

ETSI European Telecommunication Standard Institute

FCC US Federal Communications Commission

GGSN Gateway GPRS Support Node

GIS Geographic Information System

GloMoSim Global Mobile Information Systems Simulation Library

GMSC Gateway MSC

GPA Global Prediction Algorithm

GPRS General Packet Radio Service

GPS Global Position System

GSM Global System for Mobile

HLR Home Location Register

HMMs Hidden Markov Models

HSDPA High-Speed Downlink Packet Access

IMT-2000 International Mobile Telecommunication for the year 2000

ITU International Telecommunication Union

JDC Japanese Digital Cellular

KB Kilobyte

Kbps Killobit per Second

LA Location Area

LAN Local Area Network

LBSs Location Based-Services

LCS Location Collection Services

LPA Local Prediction Algorithm

LPSS Location Prediction based on a Sector Snapshot

LTE Long Term Evolution

Mbps Megabit per Second

MCM Markov Chain Model

MHz Megahertz

MIMO Multiple-Input Multiple-Output Communications

MMAS MAX-MIN Ant System

MPAS Mobility Prediction based on an Ant System

MPTS Minimum Pheromone Threshold Strategy

ms Milli Second

MSC Mobile Switching Center

MU Mobile User

NCPA Novel Cell Splitting Algorithm

NMMP New Markov-Based Mobility Prediction

NRADP New Routing Area Displacement Prediction for Location-Based Services

NS-2 The Network Simulator

NSS Network Switching Subsystem

NTT Nippon Telephone and Telegraph Corporation

OPNET Optimal Network Simulator

PCS Personal Communications Service

PDC Personal Digital Cellular

PLM Prediction Location Model

PSO Particle Swarm Optimiser

PTC Pheromone Trail Centralization

PTS Pheromone Trail Smoothing

QAP Quadratic Assignment Problems

RA Routing Area

RMI Remote Method Invocation

RNC Radio Network Controller

RNS Radio Network Subsystems

RPC Remote Procedure Call

s Second

SDPA Splitting-based Displacement Prediction Approach for Location-Based Services

SGSN Serving General Packet Radio Service Node

SI Swarm Intelligence

SN Serving Network

SRNC Serving RNC

TACS Total Access Communication System

TDMA Time Division Multiple Access

TDOA Time Difference of Arrival

TMSI Temporary Mobile Subscriber Identity

TOA Time of Arrival

TSP Travelling Salesman Problem

UI User Interface

UMTS Universal Mobile Telecommunications System

USDC United States Digital Cellular

UTRAN Universal Terrestrial Radio Access Network

VLR Visitor Location Register

WCDMA Wide-CDMA

Wi-Fi Wireless Fidelity

Wi-Max Worldwide Interoperability for Microwave Access

Chapter 1

Introduction

1.1 Background and Motivation

With the advancement of wireless communication and computer technologies, cellular communication has been providing versatile, portable and affordable network services [1–3] more than ever. The number of Mobile Users (MUs) has increased worldwide and it is estimated recently to be at three billion users [4], the expected number of mobile subscribers all around the worldwide in 2013 will be 5.9 billion [5]. The third and subsequent generations of communication not only bring new technical problems, but also raise a new class of interesting applications. This is due to the change in communication from single medium oriented into multimedia oriented communication such as image, computing data, Internet services, e-commerce and video conferences [4,6]. In the last few years, the requirements of mobile usage have changed. Thus, the growth in wireless and cellular communication technology has been dramatic as it continually expands to satisfy the MUs' requirements.

As shown in the figure 1.1 there is a clear shift from landlines to mobile phones; this started to appear from the beginning of the century. By the end of 2012, the number of MU holders will be five times more than landline subscribers [5]. Cellular communication planning and optimisation services which are related to the subscribers are addressed as the main important area of research for cellular network companies and vendors, too.

The rapid technological development in wireless networks and cellular commu-

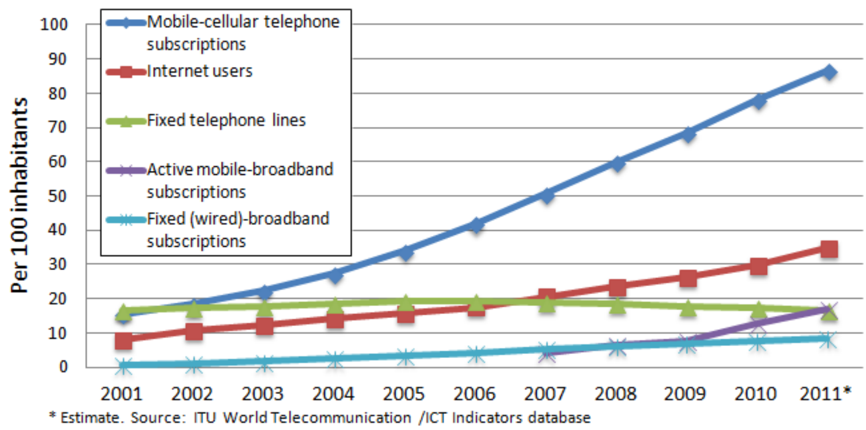

Figure 1.1: Global ICT Developments, [5].

nication has led to the emergence of the mobile computing paradigm, where information is accessible anywhere and anytime. This new paradigm enables almost unrestricted mobility to the users. This poses a new set of constraints and new kinds of challenges that need to be considered in the design of network protocols and information services. At the same time there is the challenge of decreasing the network resources that are used to deliver the target information to the MU and avoiding delay time between requesting a service and delivery of the service.

Since the service's validity that is requested by the MU is based on the time of requesting, LBSs is one of the most important requirements for guaranteeing the service's delivery on-time. This is because any service request may obtain a different result, depending on the location of MU. Therefore, mobility prediction for mobile communication systems has been suggested as a solution to anticipate the next movement of MU, for providing the time required to prepare the proper services that may be requested by the MU before requesting it.

In a cellular communications network, entities of a cellular communications system include:

1. An MU, which is on behalf of a user.

2. A Serving Network (SN), with which the MU contacts.

In 1980 the commercial cellular communications network started, after that the cellular communication era has undergone major changes according the extraordinary growth in the cellular industry. Today, the evolution of the cellular communications era is mainly divided into three generations, which are First (1G), Second (2G) and Third (3G) generations. Now, the 3G system is deployed in many countries and researchers are working on it. They seek to produce a generation of cellular networking which will be heterogeneous and integrate a number of technologies to a single global paradigm named "Fourth" generation cellular communications network (4G). The taxonomy of generations is based on fundamental technology (analogue or digital) and the services they provide. The evolution of the cellular communications network is shown in figure 1.2.

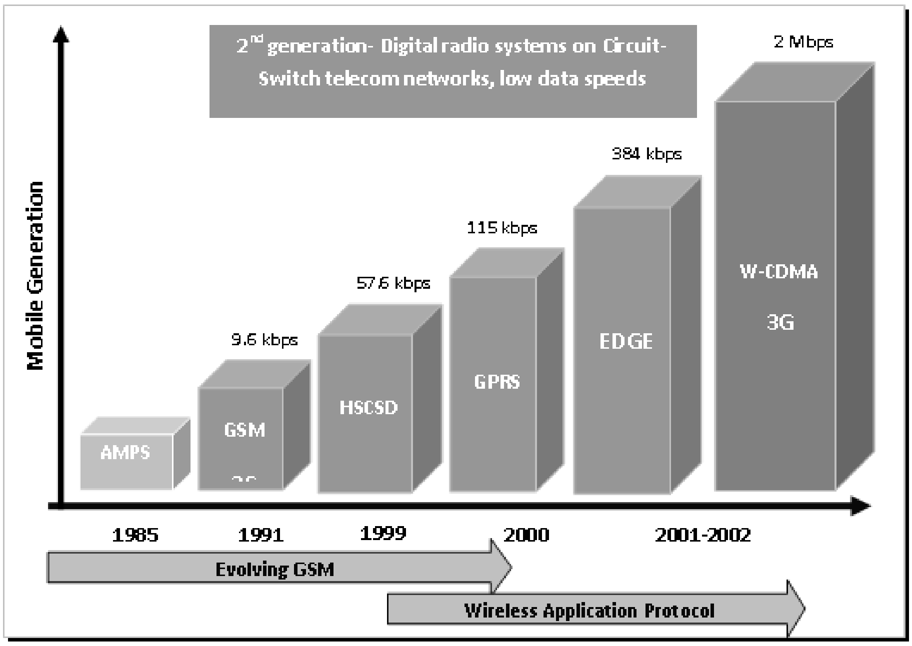

Figure 1.2: Evolution of Cellular Communications Network, [23].

Cellular 1G was introduced around 1980. The fundamental technology used in this generation is an analogue system, which transited directly from original wire-based telephone systems into cellular systems. In this generation, there were a number of examples for such systems: Nippon Telephone and Telegraph Corporation (NTT), Total Access Communication System (TACS) and Advanced Mobile Phone System (AMPS). In this generation, with low cost of equipment, speech voice services were targeted by this generation.

Taking into consideration the increase of mobile subscribers and the need for raising the network capacity, the 2G cellular communication was introduced at the end of 1980s. The basic technologies of digital systems are used in the 2G cellular system. The 2G provided low bit rate services supported - text messaging - and reliable voice communication. The main technology that 2G added compared with 1G is digital multiple access technology, such as Time Division Multiple Access (TDMA) and Code Division Multiple Access (CDMA), which changed the communication from analogue to digital channels, higher spectrum performance, and better data service. Roaming was introduced with 2G systems.

However, in this generation there are multiple systems: United States Digital Cellular (USDC) based TDMA, IS-95 CDMA based on Direct Sequence CDMA (DS-CDMA) and Global System for Mobile (GSM). The GSM was introduced in 1990 by the European Telecommunication Standard Institute (ETSI) [7].

The 3G standardisation protocol process started in 1995 when the International Telecommunication Union (ITU) began developing International Mobile Telecommunication for the year 2000 (IMT-2000). The main requirements of the IMT-2000 include support for a data rate of 144 Kbps for users in fast-moving vehicles over large areas and for pedestrians at a rate of 384 Kbps and 2.048 Mbps operations for office use [8].

The numbers of mobile subscribers has dramatically increased and there is an urgent need for mobile broadband. The 4G cellular communications network is developing. The main discussion about 4G systems was in the European Union and has taken place mostly within the context of the IST Framework Programme activities [9, 10]. The 4G systems will try to increase the data rate to fulfil the wide demand of MU and multi services. The research community has been changing its focus in the paradigm of 4G systems to be All-IP [11]. The main motivation for the changeover to All-IP is to satisfy the transparency between MU and all the technologies that have been introduced so far (e.g. GSM, General Packet Radio Service (GPRS), IMT-2000, Wireless Fidelity (Wi-Fi), Worldwide Interoperability for Microwave Access (Wi-Max) and Bluetooth). Since the cellular systems based on Wide CDMA (W-CDMA) have a high bit rate and the availability to offer services, the LBSs is addressed whereas subscribers can access numerous services through a single medium.

This proliferation in mobile devices and users' demands gives rise to LBSs. They deliver dependent and suitable information relevant to a client's location which reduces redundancy in information. A key feature of LBSs is that any service requested may need to be offered with different results, depending on the location of the MU. Location prediction provides time to prepare services that may be needed by the MU in anticipation of requesting them. Most especially, the services involved with complex computation may need to extract data and to save time, to ensure that only desired services are available when requested. The cellular communications environment is considered as a restricted dynamic environment [12, 13]. The restriction in such environments is due to the limitations of the MU in terms of processing power, memory, storage, capacity, screen resolution and battery performance.

The two key issues that affect network protocols are mobility and wireless link characteristics. Since mobility has become the norm rather than the exception, a user's location information is an additional parameter that needs to be taken into consideration in protocol design. A cost-effective technique should be deployed to locate a certain user as well as efficient data structures and algorithms to manage this fast-changing data.

A practical LBS should provide the mechanism for balancing between accuracy success rates that are offered for the target services, smallest possible cost and minimal usage of network resources. The most widely used mobility prediction techniques today deal with either Markov Chain Model (MCM) or Ant Colony Optimisation (ACO) to enhance mobility prediction success rate. Examples are the (PLM [14], NMMP) [15] plus MPAS [16] techniques respectively. Many techniques have been developed to enhance these techniques. Even with this improvement, the current MCM and ACO techniques do not meet the requirements for future generations of LBSs.

The MCMs are used for analysing complex systems and predicting behaviour under uncertain dynamic conditions. Furthermore, they can yield present and future states independently of the past states [17, 18].

The first ACO algorithm, called the Ant System (AS) [19–22], Dorigo et al., in [19] was proposed to solve the Travelling Salesman Problem (TSP). It was also proposed to a new model; namely, to combinative stochastic optimisation that is based on the ants' behaviour. This model is useful when it is used in greedy heuristics to find acceptable results in the early processing and for complex system which needs to use the distributed computational to deal with the random space variable.

According to these techniques and the increasing requirement for cellular network services, LBSs for next generation cellular systems is increasingly significantly. Thus, LBSs techniques are proposed to utilise bandwidth, while putting more computation on the network. One of the most important mechanisms used in LBSs, employs mobility prediction to anticipate the next displacement for an MU. Mobility prediction also brings more computation and consumption of resources to the cellular networks. For example, requesting/responding to a new movement takes a long time. Although some solutions are introduced to enhance the mobility prediction, there has been little in the way of computation analysis.

1.2 Significance of the Study

LBSs are an important matter in cellular systems because they rely on radio waves to carry communications and limited bandwidth is defined. Radio waves go through walls and physical borders and they are targeted to cover as large an area as possible to serve everyone who is inside range. Improper mobility prediction for LBSs technique can waste the bandwidth and constitutes an overhead of the network especially in radio waves. Denial of services may occur.

Accurate and fast transmission of digital information and service over the wireless channel has become increasingly important. Therefore, many services are accessible in cellular environment. Mobile phone systems have added other applications such as E-commerce, E-learning, E-business, social networks and mobile TV. The radio signal transmitted by the Base Station (BS) is shareable to everybody as it uses either the same network or a public medium (i.e. airwave).

During delivery of the service to the MU, the service uses the downlink channel, if the network provides inaccurate and huge amounts of information need to be filtered. Thus, an overhead to the downlink channel, numbers of MUs served will dramatically decrease and the bandwidth will be wasted.

Mobility prediction techniques at cell level are fundamental to LBSs. However, the use of MCM consumes a significant part of the overall system resource. The computation complexity of MCM when it is run over a large number of MUs, results in the target service becoming complicated and is always addressed to consume the bandwidth. Therefore, enhancing these kinds of mobility prediction techniques is a significant matter in cellular systems because the network has a limited bandwidth.

The mobility prediction process in cellular networks, particularly in wireless sections, balances sensible LBSs level against bandwidth consumption and denial of services. Mobility prediction either on a cell or an RA level technique incurs overheads on the transmission process. The overhead has an outcome on the cellular network performance in terms of the communication traffic, time delay on getting a request and the bandwidth. The traffic and LBSs delay are of particular importance and have become the subject of extensive research interest. Furthermore, the RA prediction also causes an extra overhead transmission and computation cost leading to increased cost of transmission. Meanwhile, it assists in handling the regular movement of MU.

A simulation model is used in this research to examine the performance of the introduced mobility prediction techniques. An implementation of a real network would be difficult so proper simulations are chosen. Therefore, real network validations are still needed. The results of experiments will corroborate the competency and the robustness of the introduced techniques. Java language is chosen to support the simulations. It is open source software and is commonly used for evaluating and developing network related research.

LBSs are already available commercially on mobile operating systems such as Android, IOS (iPhone) and Windows Mobile. Therefore, this research require software for the introduced mobility prediction techniques in mobile devices and network to allow better comparisons.

1.3 Research objectives

The aim of this thesis is to design a foundation for utilisation of a competent mobility prediction scheme in a cellular network with low computation, storage usage, bandwidth consumption and resource depletion that does not use the MU resources.

The mobility prediction techniques are utilised to anticipate the next movement of an MU. This helps the network to know which area (either cell or RA) will be visited by an MU, how many MUs will be handled in the new area and will give the new area enough time to prepare the required resources for an MU. From knowing the next movement of an MU, the network can deliver the target information that may be requested in on time fashion, avoid manual filters on mobile device side, avoid consuming bandwidth and do not go beyond the limits of the mobile user devices in terms of power limitations and screen size.

To alleviate the weak points of the existing mobility prediction techniques in LBSs, this thesis proposes an improvement of mobility prediction scheme of LBSs for 3G/Universal Mobile Telecommunications System (UMTS). The purposes of the improvement scheme are listed as follows:

1. To achieve mobility prediction on cell level, decreasing the service area.
2. To achieve mobility prediction on RA level.
3. To achieve use between network elements and integrate between them to produce a LBSs scheme that satisfies network specifications.
4. To increase the prediction success rate for MU next displacement.
5. To reduce the complexity requirements for execution time and usage space on the network.
6. Prediction of an MU next displacement by the network can be achieved without the use of the MU's resources. Therefore, there is no extra communication cost added and the dynamic restriction environment of the MU is not violated. The restriction in such environment is due to the limitations of the MU in terms of processing power, memory, storage, capacity and battery performance.

7. To avoid manual filtering for a huge number of results that may be delivered to the MU.

8. To prevent bandwidth wastage and denial of services.

The overall objectives of this study are to

1. Propose a novel cell splitting algorithm. The cell splitting is universal where it can be applied to all types of cell, it will be used by the mobility prediction technique at cell level to enhance mobility prediction success rates through reducing service area to sector instead of cell.

2. Enhance mobility prediction at cell level by using Markov Chain Model (MCM) to improve mobility prediction.

3. Propose a new mobility prediction technique at RA level using the developed Ant Colony Optimization (ACO) and analyze the performance of the proposed technique.

4. Propose a new LBSs scheme to overcome the prediction problems in the current technique and improve the performance of cellular networks by integration of cell and RA prediction techniques.

In order for this research to achieve the previous objectives, the following steps should be accomplished

1. Present a background research study on the concepts of LBSs.

2. Present a background research study on the concepts of 3G. This will allow a general understanding of the general framework of cellular systems such as 3G/UMTS technology and the basis of next generation 4G.

3. Present the weaknesses and drawbacks in mobility prediction over cellular networks.

1.4 Research contribution

In this thesis, a new cell mobility prediction technique is introduced based on the introduced cell splitting algorithm (NCPA). The new technique employs an adaptive model similar to the PLM and NMMP techniques in which their prediction is based on the MCM. In addition, the technique employs NCPA in order to reduce the service area and keep the prediction success rate higher to the extent possible. The new technique is competitive and more efficient in comparison to PLM and NMMP regarding measurements such as accuracy success rate of location prediction, memory usage and execution time. Finally, the Micro cell is considered.

Another contribution of this research is to design and develop a mobility prediction technique based on the developed ACO. It works on RA level for cellular network systems, satisfies the network requirement of 3G cellular network systems, is applicable for next generation cellular network systems and employs the features of 3G to improve the prediction success rate.

In this thesis, a new mobility prediction scheme for Location Based-Services is introduced based on the integration between cell and RA level prediction. Toward that end the LBSs have been analysed and the prediction success rate has been improved. The impact of prediction on LBSs in cellular networks has been shown and builds a strong background for future enhancement of the LBS techniques and architectures.

This research has also improved the prediction of a new MU displacement by sorting between the prediction processes. The mobility prediction works at the RA level and location prediction will specify the next RA that an MU will visit. Meanwhile, the cell level prediction evaluates all movement probabilities for the next RA before it is entered by the MU. The integration and enhancement mobility prediction on different levels improves the LBSs of the 3G cellular communications system in network access services by utilising the bandwidth, delivering target services, minimising the computation cost, consumption of resources and the overall cost of the location management process. These help achieve more accurate LBSs by avoiding services manual filter and denial of services.

The contribution of this research can be summarised as follows:

1. Generating a novel cell splitting to reduce service area by splitting a cell to sectors.
2. Enhancing the mobility at cell level which is based on MCM.
3. Generating a new routing area displacement prediction for location services which is based on developed Ant Colony Optimization (ACO).
4. Adopting the above proposed techniques to create a new efficient scheme and accurate LBSs for next generation cellular networks, with lower bandwidth usage and better computation time. Moreover, the introduced scheme is able to reduce the communication cost between network entities, as well as improving location based-services efficiency in terms of delay time.

In this research the work done to assist the contribution correctness is summarised as follows:

1. Validate the simulation of the introduced LBSs mobility prediction with the current LBSs mobility prediction techniques.
2. Another process forward simulation will be used, which simulates developed techniques using JAVA language and the cellular networks' simulation environment. These are used to measure the validation modelling of the introduced techniques, run experiments with comprehensive results analysis and compare the result of the introduced techniques with well-known techniques, in terms of prediction accuracy rate, resource consumption and complexity.
3. Examine the LBSs mobility prediction techniques by using JAVA language to investigate the performance of the current and introduced techniques.
4. During the course of this PhD research, the research outcomes and achievements were presented to external audiences through a number of publications.

1.5 Outline of the thesis

In addition to the introduction, there are six other chapters. Chapter 2 shows the cellular communications network development architecture, as well as 3G and 4G, UMTS architecture is discussed. In addition, the LBSs of cellular networks and key terminologies significant to the content of the contributions are illustrated. The LBSs classification, characteristics of the next generation of LBSs, components and technology are described and explained. Chapter 3 presents MCM, ACO, work related to LBS mobility prediction techniques over cellular communications network prediction are investigated in order to assist the conduct of this research.

Chapter 4 demonstrates a new mobility prediction technique based on MCM and the NCPA, which contains the performance modelling analysis of the introduced technique. Moreover, a new RA mobility prediction for cellular network systems based on the enhanced ACO is presented. The integration between cell and RA prediction levels are also introduced to present a novel LBSs prediction scheme.

Chapter 5 shows research methods and approaches that are followed to achieve this work. It involves explanation of the simulation model and the cellular network scenarios used in the thesis. The resulting discussions for enhanced ACO are shown and the optimal parameters are determined.

In chapter 6, the novel cell splitting is analysed. The chapter also describes the efficiency analysis of the introduced mobility prediction techniques and the performance comparison of the introduced techniques with the techniques that are already developed. By simulating the software using Java language, it was used to examine the prediction success rate, computation time and resource consumption. Finally, chapter 7 depicts and integrates conclusions and suggests future work in this research area.

Chapter 2

Location Based-Services over Cellular Networks

This chapter provides a brief background about cellular communications network types in the sense of brief background discussions about 2G, 3G and 4G, giving an exposition of 3G as UMTS architecture. Then the benefits and classifications of LBSs is presented. The chapter asks after the classification and the target market of such services and application types. What are the technical capabilities? What are the components and the technologies? What are the solutions for these services through GPS, cellular communications networks and WiFi? All these are illustrated in this chapter.

2.1 Cellular Communications Network Generations

The cellular communications network made a huge step in the way people communicate by making communication easier. This growth in cellular communications has been remarkable in the last few years in terms of the mobile technologies development and the number of the users itself.

The evolution of this technology is reaching the 4G. The previous generations were developed through aggressive research with the 1G, 2G and 2.5G developing simultaneously along with the 3G. The 1G was developed to provide the basic voice communication with mobile ability, while the 2G and 2.5G introduced the concepts of capacity and coverage. The 3G made the mobile broadband concept a reality for users by providing higher speeds for data transmission. This evolutionary timeline continues in developing to reach a new 4G which expands the MU services and higher data rates to support both low and high speed mobile applications [23].

2.1.1 Second Generation Network

At the end of the 1980s, the MUs were increased in number leading to a serious need for increasing the capacity of the network. This was achieved by introducing a digital system that could support services such as low bit rate data and traditional speech. These systems are considered the 2G cellular systems. The services supported by the 2G cellular system were added through using digital multiple access technology, such as Time Division Multiple Access (TDMA) and CDMA. This provided higher spectrum efficiency, better data services, and more advanced roaming. Standards for the 2G were deployed and put into use in ETSI called the Global System for GSM which enabled reliable services throughout Europe to support international roaming. The support of multiple users was introduced through TDMA technology. In the years since that time, GSM technology has been continuously improved in the sense of offering better services to satisfy the needs of the network subscribers. Based on the GSM system more technologies and new services have been developed, leading to create new systems known as 2.5 Generation (2.5G) systems [24].

Meanwhile, the United States of America started their own line of development for their 2G digital cellular systems. In 1991 the first digital system was introduced called the IS-54 Standard (North America TDMA Digital Cellular). Years later a new version supporting additional services (the IS-136 standard) was introduced. In 1993, IS-95 (CDMA One Standard) was deployed. The US Federal Communications Commission (FCC) allowed the 1900 MHz band spectrum to become operational, namely Personal Communications Service (PCS), allowing GSM1900 to enter the USA cellular communications network market. In 1990, a smaller scale of the 2G was defined by the Japanese Personal Digital Cellular (PDC) system, which was known as Japanese Digital Cellular (JDC) [24].

The main elements of the GSM Architecture reside in the Base Station Subsystem (BSS). This built up using Base Transceiver Stations (BTS), Base Station Controllers (BSC), and the Network Switching Subsystem (NSS) which hold Mobile Switching Centres (MSC). The Visitor Location Register (VLR) developed during that time as did the Home Location Register (HLR), the Authentication Centre (AC), and the Equipment Identity Register (EIR) [23].

2.1.2 Third Generation Network

The evolution in technologies created a need to develop more enhanced cellular communications networks than the one in the 2G or 2.5G in order to have faster data rate, higher data capacity and better quality of services. IMT-2000 as specified by the ITU emerged, involving the newly developed standards and specifications of the communications system which later came to be referred to as 3G cellular communications networks. The 3G system solved the differences in the standards such as in GSM and CDMA by introducing new solutions such as in roaming services. These standards were grouped into families to solve several issues and expand the set of services such as voice-video calls, and broadband wireless data transfer within the cellular environment [23].

The Third Generation Partnership Project (3GPP) worked on a wideband system based on the Wide CDMA (W-CDMA), referred to as UMTS, using the core of GSM. This solution improved the data rate in transmission from the mobile device over the network through different frequencies than 2G with a downlink rate up to 14.4 Mbps and uplink rate up to 5.8Mbps as in High Speed Packet Data Access (HSPDA) [23]. The 3G quality of services standards also assure subscribers of having available highest data rate that the operator provides [25]. The architecture of the 3G will be described in UMTS architecture section.

2.1.3 Fourth Generation Network

The rapid increase in the users' demands encourages the wheel of development and research towards new technology to keep turning and deliver new user experiences. The 4G introduced a new platform that combined all the kinds of known mobile technologies such as GSM, CDMA, UMTS, Wi-Fi, and even Bluetooth to deliver what is called the IMT-Advanced multiservice. Multiservice means integrating all the cellular services that the user has or would expect to have with highest service quality as it should [26, 27]. The IMT-Advance services provide fast interactive cellular services with enhanced data rate access, roaming capability as well as broadband multimedia. Long Term Evolution (LET-Advance) is one of the IMT-Advanced items already provided by 3GPP [28, 29]. Another item is WiMAX Multiple-input Multiple-output communications (WiMAX MIMO) through IEEE 802.16.

2.1.4 UMTS Architecture

UMTS is the 3G system promoted by ETSI and provides a vital link between today's multiple GSM systems and the ultimate single worldwide system for all cellular communications network. It is also referred to as W-CDMA and is one of the most significant advances to the evolution of communications network into 3G networks. It addresses the growing demands of mobile and Internet applications in the overcrowded cellular telecommunications sky. It will increases the network speeds and establishes a global roaming standard.

In order to express the mobility prediction techniques that have been made for the UMTS network, the author shall introduce its network elements. A simplified architecture of a UMTS system is shown in figure 2.1. UMTS is divided into three main components: the air interface, Universal Terrestrial Radio Access Network (UTRAN) and Core Network (CN), with the corresponding interfaces among them [30]. The CN, which is responsible for connecting UMTS to external networks, provides functionalities of switching calls for voice communications and Packet Switched (PS) services for data connections.

The Node B which is also called BSs and the Radio Network Controllers (RNCs) are collectively known as the UTRAN [31]. From the UTRAN to the CN, the RNC is responsible for handling of radio resources of UTRAN, Node B is the lowest element of UTRAN, which connects to an MU directly. RNC will make a decision where the traffic will be transmitted. Packet traffic is sent to a new component, serving GPRS (SGSN) and then to the Gateway GPRS Support Node (GGSN). The functions of

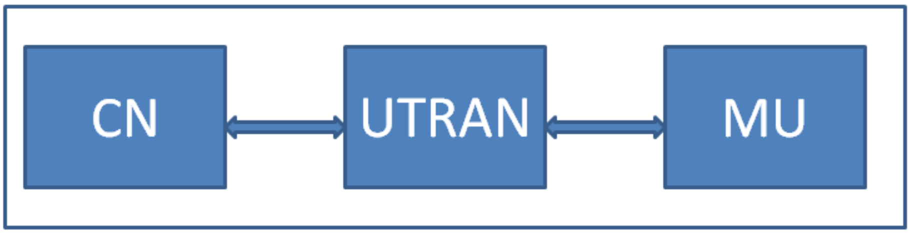

Figure 2.1: A Simplified Architecture of a UMTS System.

the GGSN are very similar to the normal IP gateway, which transfer the receiving packets to the appropriate Internet [32]. On the other hand, if there is a voice call from a subscriber, the RNC will transmit the traffic to the MSC. If the subscriber is authenticated before, the MSC switches the phone call to other MSC. The call will be switched to the Gateway MSC (GMSC) if the called end is in the public fixed phone network. The MU is the terminal of UMTS. It interfaces with the

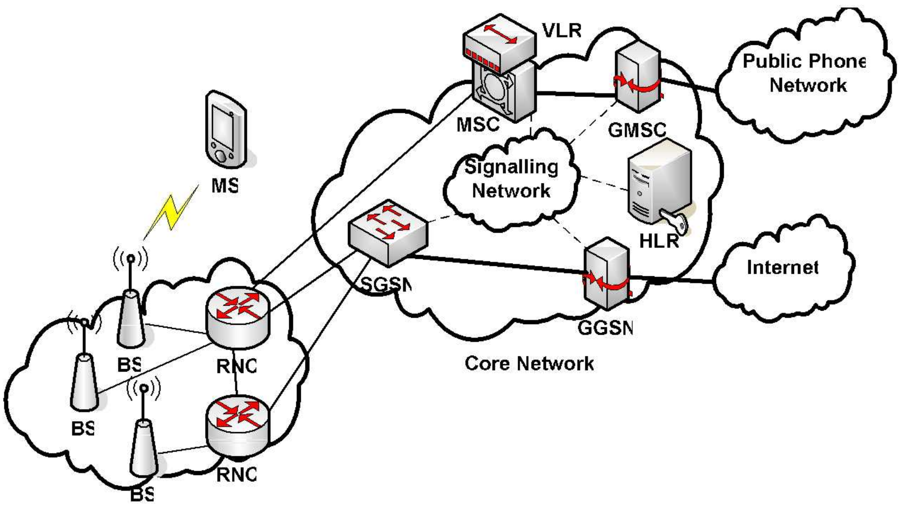

Figure 2.2: The Architecture and Connections between UMTS Components, [32].

radio interface of UTRAN and user applications. A diagrammatic illustration of the UMTS's architecture is shown in figure 2.2.

Figure 2.3 shows the infrastructure of UTRAN. The components that compose UTRAN are the Radio Network Subsystems (RNS). A UTRAN contains one or more RNS, each of which is connected to the CN respectively. A RNS can be divided further into two entities: RNC and BS called Node B in standards. One RNS contains only one RNC and one or more Node B [33].

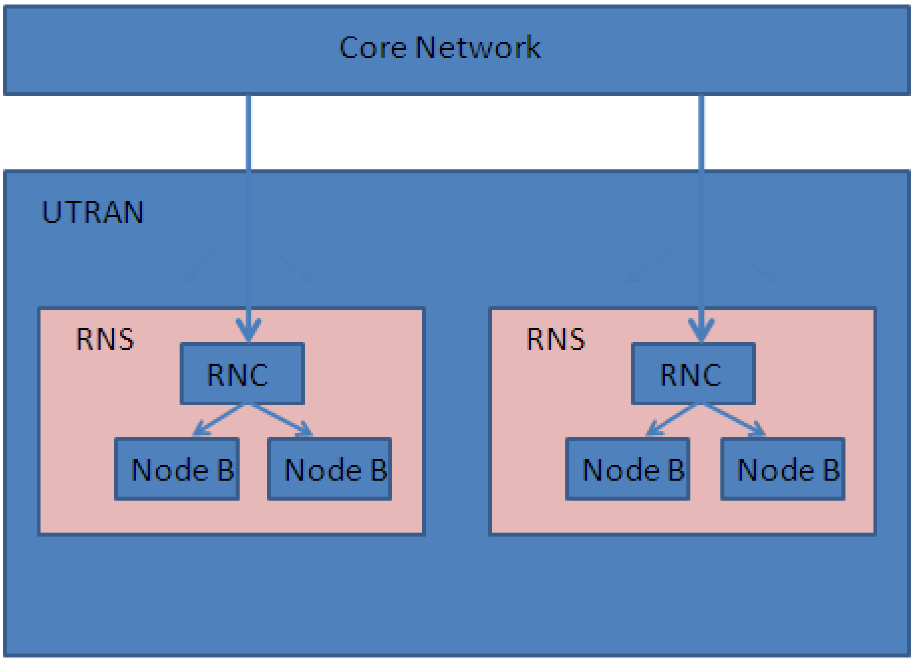

Figure 2.3: UTRAN Architecture, [33].

An RNC is responsible for the resources and transmission/reception in a group of cells. For each connection between an MU and the UTRAN, there exists an RNC, namely Serving RNC (SRNC) to control the establishment and the release of specific radio resources to this connection. If the connection state changes because of the move of MU, the connection may be handed over to a different RNC, namely Drifting RNC (DRNC) [33]. The serving RNC decides based on the parameters given by the MU and UTRAN, whether a handover is necessary and performs the initial handover. The serving RNC is responsible for the Macro-diversity, the Macro-diversity determines the threshold for the MU to connect more than one cell and which cell will be the serving cell.

2.2 Location-Based Services

LBS is the term that is applied to applications which use knowledge of the geographical location of an MU in order to provide a set of services based on that knowledge. Many services can be considered LBS such as navigation assistance, emergency location detection applications, disaster aid, finding friends in social networking, locating point of interest using map applications, etc. In order to use LBS the correct positioning technology is required, or using a geographical information system that shows the areas and through mapping the environment the mobile operator serves. LBS faced a lot of challenges in the past such as insufficient positioning technologies, limited standards that support it amongst operators and networks, inappropriate infrastructure such as lack of GPS enabled handsets etc. No business models were able to support LBS provision etc. Recently, there has been a modification on the business model by considering location as subject of operators.

LBSs is now supported by most mobile applications. LBS applications design features are started by collecting positioning data through GIS, and these data are mapped with sufficient information about the road network and points of interest. The accuracy and the extensiveness of the mapping have resulted in updating LBS. Finally, there is the cooperation chain between the whole parties, operators with their support, handset manufacturers, application developers and content providers to get the advantage of LBS technology and to be serviceable to the final users [34].

2.2.1 Benefits of Location-Based Services

LBSs are expected to provide a set of advantages and benefits for MUs, these benefits can be reached through the services served by the cooperation chain mentioned in section 2.2, enable the MUs to get every relevant material on the internet that aids him/her in taking decisions by filtering the important information to fit the position that he /she is located at, as in choosing the best hotel or restaurant in the area.

Another benefit is to provide MUs with instant information that is not usually known by MU to speed up their activities and decisions. This information can be served when reaching certain areas - road closures for example.

LBS applications also need less data from the MUs to access services, since LBS application will have this information by obtaining the position data automatically.

Furthermore, local information will be available for all the MUs who are within certain areas by sharing and tagging locations. This makes the set of MU movements with any associated tagged information a very helpful source of information for service providers and operators to build models that would enhance services.

2.2.2 Classifications of Location-Based Services

LBS can be classified according to different measures where each one holds many examples that have different technical specifications. These measures are: target market (consumer services), purpose of application, and technical features and capabilities [34].

1. **Target Market**

   LBS applications focus on three types of target markets [35, 36] which are "publically accessible for the mass market," "publically accessible for niche markets", and for "internal enterprise applications".

   (a) **Publically accessible (Mass market):** In these applications the consumers are the general public, and served with applications that do not require previous registration, for example applications that look for closest gas stations or restaurants. These kinds of LBSs must process:

   - **Scalability:** Ability to handle a huge number of requests.
   - **Performance:** Reasonable performance for the locations to be covered to avoid any network latency.
   - **Availability:** LBSs must maintain highl availability for the MUs since there is no specific way to know if the is system down, public MUs will only see no service available which will disappoint MU user experience.

   (b) **Publically accessible (Niche market):** In these applications the MUs on target are still the public but with specific interests. For example, shops can inform previous MUs about any special offers or sales just when they pass it by. These applications have mainly privacy issues rather than issues of performance, scalability or availability.

   (c) **Internal enterprise applications :** Usually these applications are applied inside an organisation or facility. For example, inventory tracking, personnel tracking and information retrieval. Most of these applications use certain hardware such as special mobile devices or take advantage of the latest smart phones models that use the latest mobile technologies. In this case the privacy of the employee should be taken into consideration, as well as protecting private internal data in a public mobile phone network by technical effort which is considered a challenge in such environments.

2. **Purpose of Application**

   Another measure that used to classify the LBS is the main purpose of the designed applications. The reason for use would differ from one LBS application to another driving more constraints and technical issues. The navigation applications which are very common for routing are used widely to direct the MUs from a point of origin to a destination. Entertainment applications also use LBS as in many social games and social networks, these applications are designed to locate and tag MUs in different locations. Furthermore, many of the information service applications which are used to help tourist users to locate, for example, the closest hotel, bus or train station or best restaurant in the area would be other uses of LBS. Emergency services are used to inform potentially affected users of any medical or police emergencies within an area. Business development aid information services employ the technology as in management chain and tracking shipment delivery or purchase.

3. **Technical Features and Capabilities**

   Technical features of LBS applications would consider other main classifiers. A number of examples are described as follow [37]:

   (a) **Point of retrieving location feature:** Cellular communications networks used to provide the position of the cellular based on transmission signals between the MU and the BS. This is considered as cellular network dependent, and this was before the appearance of GPS-enabled smart phones. Cellular network providers were responsible for supplying exposed location information to LBS developers. In new smart phones, the ability to determine their location is valid via GPS and digital compasses.

Using GPS consumes significant MU power so developers therefore avoid using it.

(b) **Point of requests feature:** In most of the LBS the services are reactive which means that provided after a request from the MU; i.e. the MU send queries and the application answers it. The other approach is proactive LBS in which the information is sent to MUs when they are approaching or entering certain locations.

(c) **Point of data and processes recording feature:** Usual LBS applications work on storing or processing MU current or previously recorded location. As that is the case, the data is considered as a single data point. But in current LBSs, there are set of records that hold more than a single data point. For example, the route or location trace information, combined with speed and direction, all would be stored [38]. The goal of the extra information is to aid systems in predicting the future location of MUs, as well as supplying the service providers with all the historical information that may be needed to enhance services.

(d) **Point of MU interaction feature :** An LBS application would support two kinds of MUs' interaction in the sense of requests of a single MU application or multiple MU request applications. The first one considered as "single - target application" where the second one may called "multiple-target application" which is the current motivation in Web 2.0 and social networking applications.

(e) **Point of collecting location feature :** LBS applications depend on different technologies to collect location data which are different in accuracy. For example GPS would not be useful sometimes indoors since it depends on view of satellites. To overcome such problems other technologies can be used such as cellular communications network or Wi-Fi. These technologies are discussed in section 2.2.4.

2.2.3 Location-Based Services Components

LBS architecture is built up upon several layers, each of which contains number of components. The first layer is User Interface (UI) which includes; LBS application, application server data and smart phone devices. The second layer is LBS middleware. The third layer holds core LBS features which are: Location Tracking, Geographic Information System (GIS) provider with data and Location Collection Services (LCS), see figure 2.4.

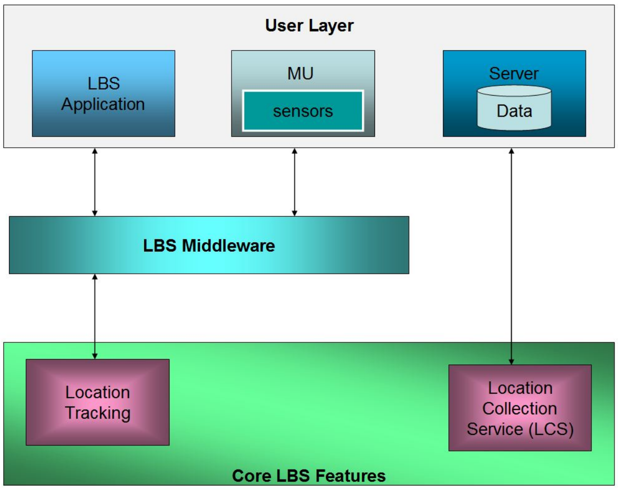

Figure 2.4: Diagram Showing Components of an LBS.

The following points explain LBS components and their functionality:

1. **User Side (UI) :** LBS Application is installed on Smartphone component and consists of number of sensors connected to a server component that stores the application's data.

2. **LBS Middleware :** Provides medium between LBS application and Core LBS Features layer. One example of such middleware is the OpenLS specifications.

3. **Core LBS Features :** Location Tracking used to store traces of the MU locations. It works on keeping records of MUs' locations, current and previous. It also detects the MUs located within a defined location in addition to generating MUs' movement model. The GIS provider is mostly responsible of

providing geospatial functionality that includes information such as maps, and visualisation of maps in addition to directory services. This can be found in "Google Maps". LCS is used to detect latitude and longitude of specific users by collecting their location.

2.2.4 Location Collection Techniques

The common idea that is shared by the most, is considering GPS technology as the only technology for location collection. In fact, there are several other technologies such as cellular communications network and Wi-Fi which also provide such services, each of which has different characteristics and techniques. GPS and Assisted GPS (A-GPS) are mostly used in outdoor environments in order to get the best accuracy at the expense of power consumption. However, cellular communications network-based solutions also provide accurate positions of MUs with less power consumption. Wi-Fi based technologies are mostly considered in the middle of the other technologies and usually depend on availability of Wi-Fi access points [39].

1. **GPS-based Solutions**

   Two main approaches are used for GPS based technology. In the first one, the device's position is triangulated based on signals from a number of satellites (about four GPS Satellites) based on the known position of the satellites, the time that messages from the satellites were sent and the time that they were received. The accuracy of this system involves outputs within about 5 to 10 meters of the true location. They depend only on the satellites with no aid from any other communications network. Although this is technology dependent, it sill consumes relatively more power from the receiver side (MU). This technology also an outdoor location to obtain a clear signal in addition to taking a relatively long time to lock onto GPS satellite signals.

   The second technology depends on the cooperation between GPS satellites and the cellular communications network which is why it is called the A-GPS. The servers on the cellular communications network provide information as in the accurate GPS satellites orbit information. This technology is considered more accurate and works well in highly populated areas where the GPS signal can not always be locked. But the dependency on the cellular communications network to assist in locating the receiver force him or her to be in the areas covered by these networks.

2. **Cellular Communications Network-Based Solutions**

   A number of solutions were given for LBS depending on the cellular communications network. These were based on number of features such as the cell of origin, time of arrival, the angle of arrival and enhanced observed time reference. Each feature is used to give one solution which is described as follows:

   - **Cell of origin (Cell-ID type) :** The location of the receiver (MU) is predicted according to the serving cell. This technology was used to locate the MU when making emergency calls.
   - **Time of Arrival (TOA) :** The position is calculated by measuring the distance from serving BS using the propagation time between the receiver and the station. All this is calculated by the cellular communications network system and here Absolute Time-stamps are considered.
   - **Angle of Arrival (AOA) :** This technology is used by the BS to estimate the location of the MU by estimation the angle of the signals transmitted by the MU. That could be achieved through the number of the installed antennas on the BS in each direction, in which the propagation phase difference between the received signals at each antenna on BS that is mapped to the MU's location. The location would be the overlapped area covered by each antenna in its direction. Finally, the mobile device hardware is enough to complete this technique.
   - **Time Difference of Arrival (TDOA):** In this technology the position of the MU is calculated using the algorithm that measures the time difference of the received signal by the MU which was transmitted by more than one base station.

The cellular communication network based solutions described above are worthy of use in this research because they do not totally rely on MU resources to determine the MU location.

3. **Wi-Fi Based Solutions**

   This solution basically depends on the recorded identity and signal strength of the recorded public Wi-Fi access points used by the device. This allows locating the device using triangulation on relevance to the connected access points which are stored in a database with their actual location. So this information is used to calculate the user device location.

2.3 Summary

This chapter has reviewed the cellular communications network generations form 2G, 3G to 4G. In addition, a descriptive example of 3G architecture in UMTS was included. Definition of the LBS has been described. The benefits of the LBS in different applications have been discussed. The classifications of LBS as in Target market, purpose of applications, and technical features and capabilities have been reviewed. A description of the components that build up LBS architecture has been discussed as in user layer which contains LBS application and data with Smartphone; and also the LBS middleware layer and the core LBS features layer. Last but not least, the location collection techniques have been described in the cases of GPS, cellular communications network and Wi-Fi.

Chapter 3

LBS Intelligent Mobility Prediction Techniques

Research related to LBSs mobility prediction for cellular communications networks is reviewed in this chapter. Well-known mobility prediction techniques designed for cellular networks are also reviewed. These techniques are either based on stochastic, probabilistic or hybrid techniques. The MCM and Swarm Intelligence (SI) such as ACO are presented.

3.1 Introduction

With the development of communication and computer technologies, wireless network devices now provide people with a level of mobility that enables them to communicate with others anytime and anywhere. The combination of mobility and networking has led not only to the development of a whole new class of very interesting applications, but has also created a new set of technical problems such as fragile wireless link, consumption of resources, and denial of services. One of the most challenging problems introduced by cellular networking is mobility prediction.

The cellular communications network is divided into cells; each cell covers a specific area within the network. The cell contains BS that response to do communications with MUs residing in the cell. Several cells that are grouped together belong to an RA. Consequently, the network consists of a set of RAs. When the

MU is at the boundary of either cell or RA and is going to a different one, the hand-off occurs and the connection in some cases will be lost because there will be no resources to handle the MU at the new serving area. In contrast, if the resources at the new serving area are enough, the connection is rarely lost. This is because when the MU sends a request message for a re-located RA in the new area, the time will not be enough to finish the hand-off procedure. Finally, if the connection is not lost during the Hand-off, a service may not deliver on-time to MUs.

If the network has enough information about MU and neighboured, appropriate artificial intelligent systems are employed. These help the network to predict the next displacement for MU with high accuracy. Then, resources will be saved and delay time for delivering the services will decrease which improves the network functionality such as paging, location update and Hand-off.

3.2 Swarm Intelligence

The Swarm Intelligence (SI) is addressed from natural behaviours of living being crowds. Crowd living supports beings in coping with difficulties that cause big problems or are not possible for a single being to resolve [40–43]. Thus, SI can be shown as a collaborative system in which an individual's knowledge can be utilised to overcome some of their own lack of awareness. SI has the ability to solve complex problems by individuals interacting with his neighbours with minimum communication media costs to characterise a global behaviour. SI does not depend on centralised control for problem solving.

SI systems in nature are responsive are observed managing phenomena such as flocking and schooling of bird and fish, respectively [44, 45]. Moreover, it is responsible for ant's movement from their colonies towards food and collecting dead ants. When one of a flock fails to achieve a task, the rest of flock can achieve the task. Some of the other advantages are summarised as follows:

- **Computational effectiveness**: The swarm works in a distributed dynamic for solving problem. Thus, the availability of multiple machine or processors can work in a swarm for reducing the execution time overhead.

- **Reliability**: The remaining flock tasks despite individual failure or a modifying environment can be assigned to the decentralised control, shared information, with simplicity for each one of flock. Also, there is no single leader failure for the SI system.

- **Scalability**: Flexibility and ability for adding or dropping one of the flock from the swarm without changing the programmes.

- **Self-organising**: There is no central leader for a swarm.

- **Longevity**: Multiple members of a flock resist more than a single agent.

- **Low-cost**: Simple communications and design require less hardware for solving complex problems.

These special advantages in SI give humans the ability to utilise same principles in many applications. Great achievements for SI have actually been shown in a number of applications including optimisation problem solving (Particle Swarm Optimisers (PSOs) [46–48] and ACO algorithms [19, 22]; ACOs will be discussed in this below), mobility prediction [16], RA in communication networks [49], game programming [50] and multi-robot systems [51].

Based on the previous advantages that have been discussed above, the ACO will be utilised and enhanced to be more efficient for LBSs mobility prediction over cellular communications networks.

On the opposite side, genetic algorithms were avoided in the present research because it is not the ideal algorithm for such problem. Such must have optimal solutions affecting real time with its limitation that its random solutions, convergence and computational costs for obtaining the solution are very high [52].

Moreover, neural networks algorithms were avoided in this thesis because of the difficulty in understanding the produced models. Also the "black box" characteristic of these algorithms, hence, there are no easy rules can be used to show how prediction was reached [53,54]. In addition, a full discussion for neural network in section 3.5.1.

The following sections discuss the history and modifications of the ACO that have been made.

3.3 Ant Colony

Dorigo et al., in [19] proposed ACO which was named as AS [19–22] and was inspired from ants' behaviour [55–57]. ACO is used to solve the TSP. The ACO model is useful when it is used in greedy heuristics to find acceptable results in early processing and complex systems.

The characteristics of ACO will make the model more sensible as it supports parallel processing while avoiding the dependence process and gives feedback on ants' behaviours in the search. It applied a minimal change to other combinative stochastic optimisation and it can also apply the same versions to the same problem without extra modifications to the problem.

The ant is not blind when it searches for food as it finds the shortest path to get the food to their nest. While moving, it leaves a chemical material of pheromone along its trail. This pheromone is a medium for communication between the ants. It presents the shortest path to collect the food rather than depending on the path itself. While an isolated ant moves randomly, an ant encountering a previous path can follow it. Hence, the path is reinforced by adding its own pheromone; the next ants follow the path with the highest pheromone amount. This process is analysed as a positive feedback loop where the probability of the path being used is increased by the number of ants which have previously chosen the similar path.

Figure 3.1 explains the ants' behaviour while seeking for food. The most shortest path that was crossed is the one for getting food from the source to their nest. As shown in figure 3.1.a. the ants walk from nest a to the source food directly. Suddenly, an obstacle crosses the path. Consequently, the crossing makes C side longer than D side, as shown in figure 3.1.b.

The ants will decide on which direction it will walk through to get the food source. This direction may be through C or the opposite side D. The beginning of ants' walks is arbitrary and drops pheromone on their way. The time needed towards and backward to the nest from D side is less than C side, therefore, the quantity pheromone that dropped at D side is more than C side. Thus, the number of ants walking through D side is more than the opposite side, which makes D side more attractive for the next ants.

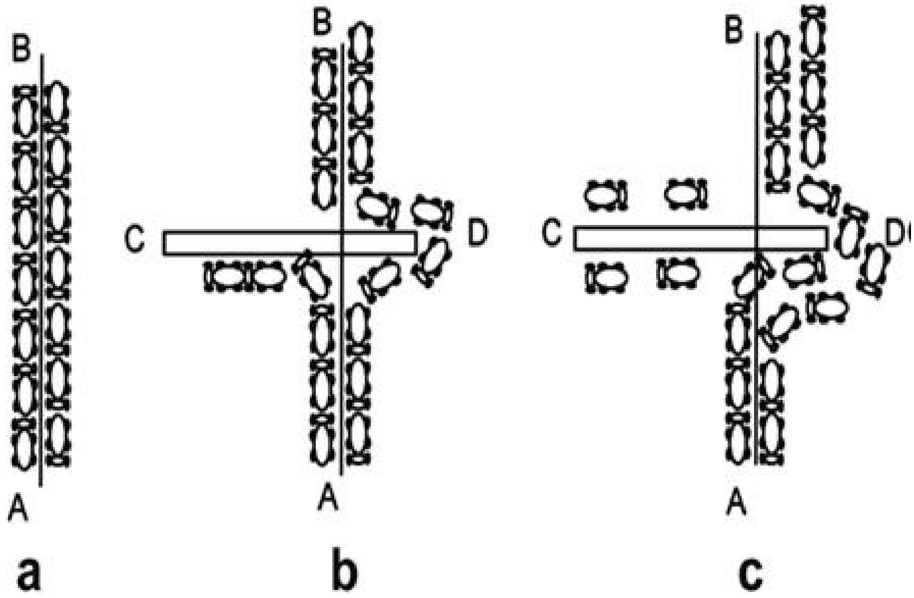

Figure 3.1: Ants Behaviour through Searching Food, [16].

The ant colonies are considered as artificial systems and the model as a simple agent with discrete time and ants are not completely blind.

3.3.1 Ant Colony Optimisation Algorithm

AS is described as the first ACO algorithm that was proposed by Dorigo [19] to deal with NP hard problem optimisation, such as TPS and vehicle routing. The ACO deals with these problems to find the shortest path in all visited cities once.

The ACO model has been motivated by the natural behaviour of the real ant colonies through searching for food. The pheromone trails are a type of distributed numeric information.

Regarding the TPS problem, salesman travelling is described as ants searching for food away from their nest to find the minimal path to visit each city once during the trip. This problem could be expressed as a fully connected graph G< N,E >, where N is the cities and E is the edges between these cities. All edges have the initial pheromone at the start of the algorithm, each ant starts the trip with random starting city and must visit all cities only once. After all ants finish the trips, pheromone must be updated on all edges. The length of the path or the distance between city i and j is calculated by Euclidean distance that is expressed in equation 3.1 [19]:

$$d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{3.1}$$

Let $b_i(t)(i = 1, ..., n)$ the number of ants in city i at time t and the total number of ants expressed in equation 3.2 [19]:

$$m = \sum_{i=1}^{n} b_i(t) \tag{3.2}$$

The path probability for the *k*-th ant from city *i* to city *j* expressed in equation 3.3 [19]:

$$P_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha * [\eta_{ij}(t)]^\beta}{\sum\limits_{u \in S_k(i)} [\tau_{iu}(t)]^\alpha * [\eta_{iu}(t)]^\beta} & \text{if } j \in S_k(i); \\ 0 & otherwise. \end{cases} \tag{3.3}$$

$\tau_{ij}(t)$ is the pheromone intensity of the edge between cities *i* and *j* at time *t*. The *k*-th ant at this time chooses the next city in which the time will be *t+1*. $\eta_{ij}(t)$ is the visibility between *i* and *j* at time *t*, and is calculated by the quantity of $1/d_{ij}$. $S_k(i)$ unvisited cities for the *k*-th ant during its trip. There are parameters that control the relative weight between density and visibility on the trail.

Each ant through its trip lays some pheromones on the ground. The next ant will follow the path with high probability, and thus support the track with its own pheromone. The overall pheromone is updated after the ant's cycle is completed. The intensity of pheromone is affected by the new laid and evaporation rate. Therefore, this is calculated by equation 3.4 [19]:

$$\tau_{ij}(t + n) = (1 - \rho) * \tau_{ij}(t) + \Delta\tau_{ij} \tag{3.4}$$

Whereas ρ is a coefficient, (1-ρ) is the evaporation rate of the pheromone on the trail between *t* and *t+n*. Thus, the value of ρ must be less than one and greater than or equal to zero, to avoid unlimited pheromone on the trail. The initial pheromone can be set as a random value that is preferred with a small positive number, and $\Delta\tau_{ij}$ can be expressed as in equation 3.5 [19]:

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{3.5}$$

m is the number of ants, $\Delta\tau_{ij}$ is the amount of the pheromone per unit on the path between cities i and j by k-th ant that is calculated by equation 3.6, whereas Q is a defined constant, L_k is the length of the path between cities i and j made by k-th ant [19]:

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{Q}{L_k} & if(i,j) \in \text{path is generated by ant } k\text{–}th; \\ 0 & otherwise. \end{cases} \tag{3.6}$$

3.3.2 Ant Colony Optimisation Modifications

Recent ACO research focuses on premature convergence of the pheromone on which the search concentrates at early stages. This negatively affects the performance of ACO and will lead to premature stagnation of the search. Search stagnation is proposed in [19] as the situation where all ants follow the same path which is generated by other ants and construct the same path over and over again. In other words, there are no new paths to be found anymore.

In order to improve the performance and reduce the computation cost, the relation between solution feature and the distance from good quality or optimal solution are required [58,59]. The Pheromone Trail Centralisation (PTC) [60,61] MAX-MIN Ant System (MMAS) helps to avoid premature convergence and improve the overall performance [62,63]. Moreover, long-term [19,64,65], mid-term [66] and short term pheromone enhancements are addressed to improve the ACO performance. The following sub-sections summarise the important enhancements that have been made on ACO which can be utilised in this research.

3.3.2.1 MAX-MIN Ant System

MMAS is introduced by T. Sttzle [67]. It obtains a better search process for the ACO algorithm by increasing the exploitation of the best solution and avoiding early search stagnation that occurs during the search [67]. MMAS meets this requirement by addressing the following keys:

1. The pheromone is affected by only best ant during a run or iteration of the processes that is executed after each iteration. This ant is the one which found the best path in the current iteration or the best path from the beginning of the processing. On the other hand, the best solution is depicted from the beginning of the trail.

2. To avoid early stagnation that may occur, they proposed the lower and upper limit of the pheromone during search, according to an interval $[\tau_{min}, \tau_{max}]$.

3. The initialisation value of the pheromone trail is set to τ_{max}, that is given a higher exploration of the best solution at the start of the algorithm.

3.3.2.2 Pheromone Trail Updating

In the MMAS technique, only the best ant is allowed to add pheromone on the trail after each iteration. Therefore, the pheromone trail update is represented in equation 3.7 [67]:

$$\tau_{ij}(t+n) = (1-\rho) * \tau_{ij}(t) + \Delta\tau_{ij}^{best} \tag{3.7}$$

$\Delta\tau_{ij}^{best} = 1/\ f(s^{best})$, $f(s^{best})$ represents the best solution cost of either iteration or the global solution. Sttzle and Hoos in [60] allowed only one ant to lay down the trail for MMAS that is based on either best-iteration(s^{ib}) or the global best solution(s^{gb}). Based on these choices, elements which a have high frequency in a good solution get larger reinforcement of the pheromone. Nevertheless, a judicious choice between the iteration-best and global-best ant for updating the pheromone trails depends on which one of them will give the better solution during the search.

When using only s^{gb}, the search gives a solution at the early stage of the search and may concentrate too quickly around this solution. The ability to explore a better solution is limited. Consequently, the quality of the solution is decreased dramatically. This bad feedback is avoided when s^{ib} is chosen for the pheromone trail update since the iteration best-solution may change from one iteration to another. The large and different number of solutions affects the reinforcement of the pheromone on the trail. Furthermore, the recommendation techniques are used as a mixed technique, s^{ib} as default and s^{gb} as fixed numbers of iterations for updating the pheromones.

3.3.2.3 Pheromone Trail Limits and Initialisation

According to the iteration-best and global-best ant for the pheromone trail update, search stagnation may occur. This takes place at each decision point when the pheromone trail for one path is considerably higher than all others.

In order to avoid search stagnation occurring, the next solution depends on the pheromone trails and the heuristic information. In general, heuristic information is addressed as problem-dependent and with a static result during the algorithm execution.

Hence, controlling the probabilities for choosing the next solution is the recommended key to achieve the pheromone trails balance during the execution of the algorithm. Furthermore, MMAS deals with this problem in a way that determines τ_{min} and τ_{max} on the minimum and maximum pheromone trails' for all paths $\tau_{ij}(t)$, $\tau_{min} \leq \tau_{ij}(t) \leq \tau_{max}$. In order to avoid the pheromone trail exceeding these limits; each ant will be checked after one complete iteration when the value of $\tau_{ij}(t)$ is higher than τ_{max} or lower than τ_{min}, $\tau_{ij}(t)$ sets τ_{max}, τ_{min} respectively. In addition, when imposing the value of $\tau_{min} > 0$ and $\eta_{ij} < \infty$ for all paths, the probability of choosing the next path is never 0.

The appropriate values for the pheromone trail limits are needed to avoid premature convergence for MMAS. MMAS should converge with each decision point, when only one of the pheromone trails has τ_{max}, while all other trails have a pheromone trail τ_{min}. The new solutions are always choosing the solution with maximum pheromone trail ensuring that it is based on the best-solution (path) which is found by the execution of the algorithm.

The notion of convergence of the MMAS differs in one slight way. However, it is an important feature from the concept of stagnation [19]. Hence, stagnation is addressed as the situation where all ants follow the same path. Also, the convergence situations of MMAS are avoided because of the pheromone trail limits.

The maximum pheromone trail is expressed in equation 3.8 [67]:

$$\tau_{max} = \frac{1}{1-\rho} \cdot \frac{1}{f(s^{best})} \tag{3.8}$$

The maximum possible amount added on the trail after each iteration is $1/f(s^{best})$. $f(s^{best})$ representing the best solution cost of either iteration or the global solution. After each new solution is found, τ_{max} is updated. Thus, the value of τ_{max} dynamically changes according to the new value of $\tau_{max}(t)$.

Based on the best-solution, avoiding heuristic information that affects the solution construction and depends on the relative difference between upper and lower pheromone trail limits is useful to extract sensible values for τ_{max} [60, 68]. The minimum pheromone trail limit can be expressed in equation 3.9 [60,67,68].

$$\tau_{min} = \tau_{max}/n \tag{3.9}$$

Where n is a number of instance cities.

Initial pheromone trail is one of the critical issues in MMAS. The better solution quality which can be found requires high exploration of the search space, thus the $\tau(0)$ is set to high random number. After the first iteration of MMAS, the lower and upper limit of the pheromone is calculated. In addition, the trail $\tau(1)$, is set to $\tau_{max}(1)$ to increase the possibility of finding out the best solution.

3.3.2.4 Pheromone Trail Smoothing

To improve the performance of the MMAS and reduce the ability of premature convergence that could occur, Sttzle and Hoos, in [60] proposed a mechanism, named Pheromone Trail Smoothing (PTS). This mechanism made better evaporation control of the pheromone on the trails and looked after the pheromone trails amount according to the maximum pheromone trail limit, PTS represent in equation 3.10 [60].

$$\tau_{ij}(t+n) = \tau_{ij}(t) + \rho * (\tau_{max}(t) - \tau_{ij}(t)) \tag{3.10}$$

$\tau_{ij}(t+n)$ and $\tau_{ij}(t)$ are the pheromone trails before and after the smoothing technique. The PTS mechanism is remarkable when the problem needs long run time. PTS increases the space of search and includes solutions with low pheromone trial.

The advantage of the PTS mechanism is concluded through the control that offers the evaporation rate. The value of ρ are $\rho < 1$ and $\rho > 0$, 1 (the mechanism will re-initialise the pheromone trail) or 0 (PTS is switched off), this indicates that the information gathering is not completely ignored, but merely weakened.

3.3.2.5 Pheromone Trail Centralisation

PTC is the mechanism which explained more enhancement for ACO and is considered as the best solution to control the pheromone trail. In other words, it is the solution that cannot be further improved [68].

PTC is depicted based on the PTS. PTC is a mechanism that improves and finds a very high quality solution, avoids a premature convergence, avoids partiality into the local search and increases the search space through increasing the probability of selecting a solution with low pheromone limit [61].

The technique is represented in equation 3.11 and 3.12 [61, 68]

$$\tau_{ij}(t+n) = \tau_{ij}(t) + \rho * (\tau_{cen}(t) - \tau_{ij}(t)) \tag{3.11}$$

$$\tau_{cen} = 0.7 * \tau_{max} \tag{3.12}$$

Whereas $\tau_{ij}(t+n)$ and $\tau_{ij}(t)$ are the pheromone trails before and after the PTC, τ_{cen} is the central pheromone trail value, which it is empirical tested.

3.3.2.6 A New Minimum Pheromone Threshold Strategy

Wong and See, in [69] proposed a new technique named A New Minimum Pheromone Threshold Strategy (MPTS). Then, they observed the performance of MMAS on quadratic assignment problems (QAPs). MMAS solved some QAP successfully. However, it has a difficulty and a weakness when it deals with a large instance of the QAP. They presented a new technique to avoid the weakness of MMAS, increase search diversification and memorise better solutions that were found.

In MPTS, a new pheromone threshold (τ_{mt}) is proposed. It is higher than the minimum pheromone trail limit and lower than the maximum pheromone trail limit that is used to monitor the performance of ants in the search process and how to avoid stagnation of the search process.

The value of τ_{mt} is set at the beginning of the algorithm throughout the execution. It is changed to prevent the search performance from dropping dramatically. The change is done by dividing the current value of τ_{mt} with a factor K after number of steps which are determined at the beginning of the algorithm.

During the search running, each value of pheromone trail (τ_{ij}) is compared to the τ_{mt}. When τ_{ij} is lower than τ_{mt}, it is set to τ_{max}. This guarantees the performance of exploration and includes the trial pheromones which have lower value. It is considered in the next component solution through changing the value of the pheromone.

In MMAS technique, the setting value is performed only when all ants cannot discover a better new solution. In other words, this occurs when the stagnation of the search is addressed. On the contrary, MPTS allows instance re-setting for pheromone and waiting when all ants arrive to stagnation search state. Avoiding re-initialisation of all trails at the same time, this leads to memorising some useful solutions that ants have learnt previously. Meanwhile, it is allowing the algorithm to find a better new solution.

3.4 Markov Chain Model

In this section, an analytical review of the MCM is presented. The sequences of MCM's equations for prediction also are discussed.

MCMs are used for analysing complex systems and predicting behaviour under uncertain dynamic conditions [70, 71]. Furthermore, they can yield present and future states independently of the past states [18, 72].

In real systems, the state changes from the current state to next state or remains in the same state. Therefore, the prediction of MCMs is based on a certain probability distribution [73, 74]. The changes from current state to next state are called transitions. Each change has a probability which is called the transition probability. Moreover, there are other examples for MCMs such as a simple random walk and weather predictions [75].

The probabilities are essential in real systems that are given the probabilities of the preceding states that can be expressed by a transition matrix [75, 76].

$$P = \begin{bmatrix} x & \bar{x} \\ y & \bar{y} \end{bmatrix}$$

$(P)_{i,j}$ is the probability. If a given state is known to be i, it will be followed by a state of type j. When a state of the system is known to be S at time 0, the prediction path can be represented by a vector, whereas the probability of S is 100% and the complement is 0%.

$$S(0) = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

The next state or path of S can be predicted by:

$$S(1) = S(0) * P = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x & \bar{x} \\ y & \bar{y} \end{bmatrix} = \begin{bmatrix} z & \bar{z} \end{bmatrix} \tag{3.13}$$

Here, z indicates the probability of the next state, which could be crossed by the user. The general rule to predict N paths that will be crossed is:

$$S(N) = S(N-1) * P \tag{3.14}$$

$$S(N) = S(0) * P^N \tag{3.15}$$

3.5 Mobility Prediction over Cellular Communications Network

Locating users as they move from one place to another in a cellular computing environment is the key to providing continuous services with unrestricted mobility. Therefore, the data management in this environment involves challenges in the need to process information during the move, to cope with resource limitations and to deal with heterogeneity. One of the applications of cellular data management is LBSs which have been identified as one of the most promising areas of research and development [77].

Strategies of location management in cellular environments can be classified into static and dynamic. In the static strategy, the updating operation is reduced according to the network topology. This technique suffers some inefficiency especially for users who are located around the RA boundaries and who cross these boundaries repeatedly. Moreover, RA sizes are fixed for all MUs as specified by cellular infrastructure, without considering their individual mobility and service request pattern.

Dynamic location updates have been developed to address and enhance the efficiency of the static strategy [78]. The updating operation is initiated according to the user's movement pattern and the frequency of its requesting service. Location is among the most important contextual information for mobile applications. Much of the previous work on LBSs treated location as an additional attribute of the data tables [79, 80]. In this way, LBS queries can be processed like ordinary queries except with additional constraints on the location attribute. Predictive location was dynamically introduced to predict an MU's future location based on the current location information, the user's historical mobility pattern and auxiliary information. Therefore, the mobility realisation and location determination are two factors in location prediction to determine the location of an MU at a time t.

Francois and Leduc [81] introduced the accuracy of prediction to evaluate models. Numerous prediction models were introduced to increase the accuracy of the prediction techniques for users with varying speed that was reported in the literature. However, none of them can fulfil the optimal prediction success rate and effective cost requirements. The literature is divided into three sections; namely, the cell-based techniques, the map-based techniques and prediction techniques that are based on MCM.

3.5.1 Cell-Based Techniques

In the cell techniques [82–87] a service area is partitioned into several cells. The cell covering the MU will page his or her device to establish a radio link in order to track the changes in the location of MUs.

The cells broadcast their identities and the MU periodically listens to the broadcast cell identity and compares it with the cell identity stored in its buffer. If the comparison indicates that the location has been changed then the MU sends a location update message to the network [88].

Prediction techniques that are based on a cell technique can be enhanced by heuristic methods and neural networks [89, 90]. Liou and Lu [89] divided the cell into two areas, edge and non-edge. The edge areas have neighbouring cells, while the remaining areas are considered as non-edge areas. When the MU is in a cell's edge area, the information is passed to a neural network which predicts, from the neighbour's cells, the next cell that will be visited. Another technique captures some of the MU activity and paths. These paths are progressively recorded, giving a history record which is used as an input to a neural network to predict the next cell that will be visited [90].

The techniques proposed in [89,90] suffered from a long training phase on mobile movements data which are used to build a knowledge base before making predictions. Therefore, the MU may change his or her activity, such as movement pattern or visiting a location he/she has never visited before, thereby bringing new cases which the techniques have not encountered in training. Hence, the prediction percentages dramatically decrease.

The techniques that are introduced in [16, 91, 92] are still based on cell mobility prediction. The smallest service area will then be represented by the cell. Heterogeneous and homogenous network prediction mechanisms were discussed in [92]. The main drawback of this technique was an extra overhead added to the network and the anticipated security issues did not take place. In [16, 91], the techniques which are based on temporal attribute to enhance the prediction success rate used closed sample, small region and restricted environment such as university urban. A long training phase was required [91]. The neighbours' history was not utilised and the fast mobile reaction for unexceptional mobility habits was also been not handled.

MPAS in [16] used the version of ACO that has been introduced in [19]. The service area represented by Micro and Pico cell, cell dividing has not used.

The segments of a highway connect a student or employees' accommodation with a university campus which is covered by a cell in MPAS. The MPAS prediction process is based on the user's usual habits such as the students who leave the accommodation during working days to go to the university and at weekends when he or she goes to the stadium instead of the university. If a new user enters the network, the MPAS prediction handled the MU according to his/her neighbours' histories. The history of each MU during days was memorised in the BS for each cell through special architecture which is named the "history table." Updating and processing the history table is handled periodically.

MPAS modelled MU displacements by ant colony going from current cell forward to one of the neighbour's cells searching for food. When a MU enters a new cell, the MPAS predictor is started. It creates movement table with 50 entries. This table is fed by entries from the history table of the same source and destination cell and the data for the same mobile identification. The rest of the entries of the movement table are then fed by other MU's history. For more details on movement table and precise mechanism for feeding see [16]. Moreover, each displacement prediction process for each MU needs to create a movement table to complete the prediction process. When the prediction process is finished, the MPAS will destroy the movement table that is related to such prediction displacement.

The MPAS creates a colony of ants of which the members have the same number of entries in the movement table. Each ant has a number according to the movement table, i.e. ant1, ant2, ant3 or ant50. Each ant is associated with two variables, pheromone and visibility. The next cell displacement will result after the pheromone and visibility manipulations [16]. Finally, the MPAS strengths and weaknesses are concluded as follows:

MPAS strengths :

1. MPAS based on ACO which has no tedious computation and sequence of complex equations.

2. MPAS did not need long training before prediction process. As a result, the learning phase was not required. This differs from the case of Hidden Markov Models (HMMs) in which long training phase are compulsory.

3. MPAS reacts with MU mobility changing. When the MU changes his or her route under certain circumstances, the MPAS will handle this situation be-

cause the prediction process is based on pheromone quantity on each route, i.e. the old route will not be preferred because the evaporation will decrease the pheromone on that route, thus the route will be less favourite for future displacements.

MPAS Weaknesses:

1. The MPAS service area is a cell which has too large a size. Global Position System (GPS) or Galileo technology will be needed to enhance prediction success rate [16]. Thus, the MPAS will be costly and complicated.

2. MPAS deals with a small sample in the smallest region, i.e. students, employees and the university campus. The MPAS presupposes limited activity for them.

3. Each MU needed to create a movement table for each displacement prediction introduces an extra overhead computation for MPAS.

4. The movement table contained 50 entries for each MU and his neighbours' histories which is not enough to provide full knowledge for the MU or about the other MU behaviours in the cell where the MU is located.

5. MPAS is based on the ant colony's equations introduced in [19]. The modification of ACO was omitted in MPAS. Therefore, search stagnation and consuming computation cost were addressed because there was no limitation for pheromone.

Recommendations for a suitable mobility prediction over next generation cellular networks :

1. Construct a mobility prediction technique based on the ACO, where the ACO modifications can be utilised to avoid search stagnation and reduce computation cost.

2. Find a mechanism or algorithm to reduce the service area to a portion instead of a cell. This virtually means splitting cells into smaller regions to increase prediction success rates.

3. The important thing is how to discover an algorithm for finding the MU location when the service area has been reduced. Since the time for finding MUs will be handled during the mobility prediction technique, a bad finding algorithm will affect the delay time and increase time to complete the prediction process.

This author in [93], introduced a new Splitting-based Displacement Prediction Approach for Location-Based Services (SDPA). The model reduced the service area to be less than the cell, however, this model deals with static splitting which means that SDPA can split a cell into a number of static regions. Sub-section 3.5.2 shows more details and comparisons for SDPA.

3.5.2 Map-Based Techniques

The map matching algorithm has been used for mobility prediction. Ren and Karimi developed the map matching algorithm through using other techniques such as MCM and Hidden Markov fuzzy logic to improve the mobility prediction for wheelchairs. In [94], the map matching algorithm has been developed through its dependence on the MCM and GPS sensor. The distance and the direction between the points which are recorded by GPS are used. Prediction of the direction of wheelchair users in sidewalk is considered as the outcome from [94].

Ren and Karimi [95] presented a map matching algorithm that is based on the GPS and HMM to navigate wheelchair users on sidewalks. The algorithm uses the data that are recorded from GPS, using HMM to determine the correct segment in a sidewalk network.

In map matching, using the fuzzy logic and the data gathered from GPS is considered as one of the techniques that are proposed to navigate the wheelchair user in sidewalk areas [96]. GPS data and the map of the target area are stored in the server side and the analysis of the data is performed by the fuzzy logic. Therefore, the incorrect direction will be eliminated and thus it will advise the wheelchair user how best to reach a destination [96].

The map matching techniques area proposed in [94–96] suffered from many major drawbacks. All of them are tested and evaluated for wheelchair only on university campus sidewalks and it works only outdoors. These techniques are based on GPS navigators. Therefore, anyone who needs to use them must have GPS sensors. However, the GPS sensors lead to extra physical cost bearing in mind that they may not be applicable for all mobile devices. Moreover, GPS suffers from inaccurate data on narrow roads, in high buildings, higher-end GPS users is used to improve the signal, instead of low-end.

In urban areas, the navigation of wheelchairs is difficult because the satellite signal could be very poor in such areas. This causes a conflict and an odd drawback for those techniques from the viewpoint of how the wheelchair users can be navigated in urban areas when the GPS is not accurate in such areas.

Map-Based techniques [97, 98] determine a user location as a point on a road instead of a cell, using geo-positioning systems such as GPS. A service area is partitioned into road segments that assist in determining a specific requested service such as the nearest restaurant or a park. On the other hand, the destination must be determined before starting to explain the shortest path to reach the target. If the target point is not previously determined, the conservative routing algorithm cannot be used to reach that point. GPS has another drawback as it only works outdoors because it cannot detect satellite transmissions indoors, especially in steel-framed buildings [99]. Furthermore, it is not accurate for home or office applications [87].

PLM is a technique obtained from the Map-Based model without some of its limitations, such as the need to know the endpoint of travel before starting. A service area is modelled as a graph; the edge indicates a road segment and the intersection of edges is represented as a vertex [14]. During a user trip travelling on a road, the network generates a trajectory. The trajectory defines a sequence of connected road segments or a sequence of connected vertices between two locations, namely the start point and the end point. The user trajectory is stored in a database to assist in predicting its future trajectory when it begins a new journey. The historical trajectory information that is stored can be used to infer the number of times the user has travelled on each road segment and the trajectory choice at each intersection. The data are then used to predict the travel of a user.

PLM depends on creating a Dynamic Computational Window (DCW). A DCW is defined as a circular clipping window that centres around the user's current location to retrieve information from a database for location prediction [14]. The size of DCW dynamically changes relatively to the speed of the user. PLM does not allow a given user to visit each of the trajectories more than once for the whole trip which means that the user cannot turn around at an intersection. Extra calculation is needed because the end of travel has not previously been determined.

SDPA [93] has been developed to improve prediction success rate and minimises consumption of resources and the overall cost of the location management process comparing with PLM. Also, the SDPA reduces the service area and the number of predicted routes during the MU trip by dividing the cell into eight equivalent regions. Thus, the SDPA approach improved the location prediction probability over PLM. The average complexity that is required for usage space is smaller than the PLM approach. In addition, these techniques still work on cell level which is more expensive in terms of message passing and execution times because the SDPA and PLM are executed in tight time slots. Both of them work at the cell level. Moreover, SDPA is based on a static algorithm for reducing service area into small regions instead of cells. This was considered as another drawback.

3.5.3 Markov Chain Model for Prediction

There are many different techniques used to enhance the mobility prediction. MCM is one of the most commonly used in prediction [100–104].

In [104], the MCM is used to anticipate the next displacement which is based on the mobility history. The area that is predicted is too large because it contains many cells (Location Area LR). The new mobile entrance to the network may decrease the prediction percentage that is already made by the model.

The models which are introduced in [101, 102] enhance the mobility prediction by using the second order MCM. The enhancements have been applied on the computation process or prediction percentage.

The model which is proposed in [102] introduces an efficient mobility prediction by using both incoming and outgoing handoff prediction; other parameters are used such as road topology, handoff area points inside the cell, cell shape structure and the average time lasting in each service area segment. The model offers acceptable results. However, the implementation cost and response time are significant and the service area is a cell that would be predicted is too large, therefore, the manual filter may be employed.

Sun et al. in [101], assert that the user's knowledge is the important key for the prediction process. The user's future knowledge is collected from the mobile side such as a user's diary, e-mail or instant messaging. The model provides good prediction percentages when it collects the knowledge, but when no knowledge is available the prediction dramatically decreases. The obstacle is how the knowledge can be collected, thus this model poses a conflict for MU privacy.

In [105], the authors introduced a new mobility prediction technique based on the notion of MU profile. Each MU has many behaviours. Therefore, each one of them has more than one profile. Thus, the storage overhead was addressed and profile-based for each MU was handled by the MU equipment. This was considered as the crucial drawback of this technique because the mobile equipment has limited resources and power.

The mobility history is considered as the main parameter in the HMM for the models that are proposed in [100,103,106,107]. These models will be applicable when the BSs are not managed by the network entity whereas all previous movements of MU are saved and manipulated. Nonetheless, the main drawback is the computation cost which the models need. These models suffered from a very long training phase, time required and slow reaction to a new behaviour of MU.

Other prediction techniques such as Ashbrook and Starner [108] tried to predict the user's future movement using a modified k-means clustering algorithm and MCM. This technique used the modified k-means for discovering a new location by clustering GPS data and used a single MCM to predict future movement. The Ashbrook and Starner technique does not consider how the user moves or the paths taken during a trip, but considers where the user is. For example, when the user leaves home, the predicted destination is school if this is his/her most frequently destination from home. But if the user leaves home en-route to a shopping centre or to another place, this becomes a problem. The wireless signal has been used for indoor sensing, such as a home, office and building environment, e.g., RADAR where it is based on IEEE801.11 wireless Local Area Network (LAN) technology. It has been developed by a Microsoft research group to use for location sensing in a small area [109]. The current location services determine through calculation the location of a user by the radio-frequency signal strength between a base station and a receiver. There are commercial products which use the same technique. Moreover, the Naive Bayes technique, the grid technique, the graph technique and the Dakkak technique are addressed as the important techniques in indoor prediction [110–114], where the signal is weak or noisy. These techniques are based on one of the filtering models such as the Kalman filter [115–117] the particle filter [118–121] and upon fractional differentiation [122]. These indoor prediction techniques only work indoors and each building needed a special recognition hardware to be suitable for the prediction process.

S. Bellahsene et al. in [15,123] introduced a new mobility prediction architecture which is based on two nodes of the network: global prediction and local prediction. The global prediction works on the enhance gateway while the local prediction works on the base station level. The drawbacks which are addressed in [123] are the delay of response and the model which does not have a good prediction percentage due to the movements of MU. This is described by Random-Way point mobility model.

In [15], NMMP is introduced. The model appeared as an enhancement to the random movement method more than those in [123]. The NMMP model is based on two prediction levels, namely, the Global Prediction Algorithm (GPA) and the Local Prediction Algorithm (LPA). The GPA is run by an Enhanced Gateway (EGW) which is considered as the root of cellular network. The GPA is responsible for handling the regular user's movements. The LPA is run by an Enhanced Base Stations (EBSs) in order to predict the MU's random movements within a cell.

The NMMP handles different types of MU movements and it has many drawbacks. The first drawback is the communication cost which is more expensive. NMMP does, however, solve the PING PONG handover problem (although that problem had already been solved in [124, 125]). The communication cost consists of EGW cost, EBSs cost, cell cost and the cost of routers which are used to connect between all of them. Moreover, the communication cost affects the delay of response and updating history. A group of cells that are elected to be in the next displacement belongs to a different EGW router which doubles the communication cost for all processes needed. This is used to achieve the operations related to the prediction process such as updating history.

Secondly, the time managements of NMMP are weak. GPA and LPA worked on different time slots which mean that there is no overlap between the times needed to achieve both of them. In a sense, the total time for NMMP is the GPA and LPA times. In other words, the total time is the time performed by both the GPA and LPA.

3.6 Summary

In this chapter, the research related to ACO has been reviewed. The literature for the mobility prediction techniques has also been reviewed. Some techniques are based on stochastic algorithms; others are based on probabilistic algorithms while others are based on, e.g. ACO, MCM, HMMs and data mining algorithms. The techniques are based on one assumption, either on HMMs or data mining algorithms. These techniques would be unnecessary for the cellular communications network if there was an efficient algorithm to solve that problem in a reasonable amount of time.

Some researchers tried to design an LBSs mobility prediction technique based on HMMs, temporal attributes or data mining algorithms in order to provide better prediction success rates. However, most of the techniques for mobility predictions are based on previous assumptions which have prediction success rate flaws in terms of no balance between prediction success rates that has been achieved and their resource overhead. None of these researchers studied the relationship between prediction and performance (memory usage). Many updates have been developed to speed up these techniques, but this improvement consumes a significant portion of the overall system resource. Therefore, the research herein will endeavour to design a new scheme to provide the mechanism for a better balance between mobility prediction success rate, memory usage and complexity time appropriate to the cellular communications environment.

Chapter 4

Cell-Routing Area Multi-Levels Mobility Prediction

This chapter utilises the knowledge presented in previous chapters to introduce a Cell-Routing Area mobility prediction scheme, which is based on the combination between cell and Routing Area. A Novel Cell Splitting Algorithm (NCPA), Location Prediction based on a Sector Snapshot (LPSS) and New Routing Area Displacement Prediction for Location-Based Services (NRADP) will be introduced to accomplish a mobility scheme for cellular communications network such as UMTS to improve LBSs. The features and processes of those techniques as well as the characteristics, which are not maintained, are described. The developed techniques are competitive and more efficient in prediction success rate, time complexity, delaying time and memory usage compared to the Prediction Location Model (PLM), New Markov-Based Mobility Prediction (NMMP) and Mobility Prediction based on an Ant System (MPAS) technique.

4.1 Introduction

The most widely used mobility prediction techniques for LBSs over cellular communications network are based on the problem of either the stochastic or probabilistic models. For instance, the Markov Chain Model (MCM) is also used for mobility prediction that is based on stochastic calculation whereas its performance relied on the difficulty of the stochastic model. The difficulty of the stochastic model affected MCM whereas the memorisation lossless and the long training phase are addressed as the challenges. Rather, Hidden Markov Models (HMMs) is more commonly employed more than MCM [126]. HMMs offer flexible structure that can model complex problems. On the other hand, because of their flexibility, the accurate solution requires a very long time and training samples [127]. The PLM [14] and NMMP [15] used MCM to improve their prediction success rates.

The Ant Colony Optimisation (ACO) algorithm is a kind of probabilistic technique for solving complex computation problems. Many improvements have been made to the original ACO algorithm to produce an acceptable version for path prediction. The MPAS [16] is based on the basic version of the ACO to improve mobility prediction over cellular network. Thus, many challenges were addressed such as search stagnation, complex computation and memory usage wasting.

In this thesis, a new prediction scheme is introduced which explains how both developed prediction techniques communicate together. It is a combination of prediction techniques at different levels which means that the first prediction technique, named as NRADP, works at RA level and LPSS is the second technique which is turned on through cell level. The striking characteristics of the developed techniques work on prediction at different levels of a cellular network with different network components to be used. Consequently, the execution time overlapping is utilised because both of those techniques are independently executed. In other words, the LPSS works behind the NRADP. Because these techniques work at different levels, it can be termed as fair techniques.

The NRADP works at the Routing Area (RA) level to determine which RA the Mobile User (MU) will visit next. NRADP uses a new developed ACO algorithm with some enhancements. When the next RA is determined, the LPSS works to prepare all the movement possibilities that may be done by the MU in that RA.

The LPSS employs MCM similar to the PLM and NMMP techniques in which their prediction success rate is based on the previous MU movements. In addition, LPSS adopts NCPA for balancing between prediction success rate and size of service area.

NCPA is valid to split any cell types to reduce the serving area in a cellular communications network, a sector is the portion of cell that is produced from the splitting technique. Basic arithmetic operations such as summation and multiplication are used to achieve the technique. Thus the novel technique is dynamistic.

4.2 Problem Definition

In 3G cellular networks, regions are divided into RA, each of which contains a set of cells; the radius of a cell in a populated area is 250 meters [31], whereas the non-populated areas are covered by larger size cells. This fact leads to delivery of a massive amount of information. As a result, this information may degrade the accuracy of services provided to the user. In such a case, there is a need for manual filtering. Manual filtering often lets the MUs use their devices whilst moving through, and interacting with dynamic environments. This is intended to increase the relevance of the information retrieved by users of mobile information systems and remove results that are deemed irrelevant to an MU's location. This process conflicts with the restrictions of an MU, such as the power consumption, storage space, screen resolution and battery performance and low computing power and resources.

Furthermore, the manual filtering would take extra time to improve the precision of the retrieved information. This time is usually long and sometimes leads to delivery of incorrect information due to the movement of the user to a new location which has different information from the previous location. This appears especially when a large number of results are returned to the MU.

These filters have been implemented in LBS. These problems cannot fulfil the requirements of LBS in terms of accuracy prediction success rate and cost effectiveness. However, these problems can be avoided and the requirements of LBS can be enhanced by four processes. Firstly, the time by which the service is requested by the user and the time within which the user gets the service are relatively short. This fits with the period of staying in that location for a specific period, whereas the proportionality between the two periods reasonably allows the user to benefit from the information associated with current location before moving on to a new location, especially if the MU is in constant motion. Secondly, the volume of results returned to users of mobile information systems is small. Thirdly, enhancing the accuracy prediction leads to retrieval of information that is relevant to an MU's potential future location. Fourthly, satisfying the previous processes by finding a technique for reducing the size of service area, therefore, dividing cells into smaller regions is needed.

4.3 A Novel Cell Splitting Algorithm (NCPA)

This section introduces and describes a novel, efficient algorithm for splitting cellular cells and locating the MU. Also, the algorithm which is built to handle a certain cell type will be used in other, different cell types (i.e. pico, micro, macro and rural) based on the symmetry features.

4.3.1 Splitting Algorithm

In a cellular communications network, the cell is considered as a circle graph. In this research, the symmetric characteristic of the circle is exploited; where if one portion of the graph is known, the remaining portion of graph can be predicted. The proposed algorithm utilises the symmetry by splitting the cell into four quadrants $q = Q_i \mid_{i \in [1,4]}$. The quadrant division depends on the angle path. The angle path (P) is calculated by $P = \sum_{\theta=0}^{360} Q_i$. Where Q_i is determined as shown in (equation 4.1)

$$Q_i = \begin{cases} i = 1, & \text{when } \theta \ \ in\,[0, 90]; \\ i = 2, & \text{when } \theta \ \ in\,(90, 180); \\ i = 3, & \text{when } \theta \ \ in\,[180, 270]; \\ i = 4, & \text{when } \theta \ \ in\,(270, 360); \end{cases} \tag{4.1}$$

To split a cell area into n equivalent sectors, apply the following rule: Let *(x,y)* be a point in the *xy*-plane that is selected randomly from a circular region with radius r and centred at the origin, if the circular region is divided to 2^n sector, where n=3,4,5,....., named $S_1, S_2, S_3, ..., S_{2^n}$. Also assume that the centred angle of each sector is:

$$\alpha = \frac{360°}{2^n} \tag{4.2}$$

Let λ be the number of sectors in each quadrant. Each quadrant is divided into uniform sectors as follows:

$$\lambda = \frac{2^n}{4} = 2^{n-2} \tag{4.3}$$

Then, this rule arranges the sectors in the plane in a way that ensures an easy relation in determining the location of the MU that has a point *(x,y)*.

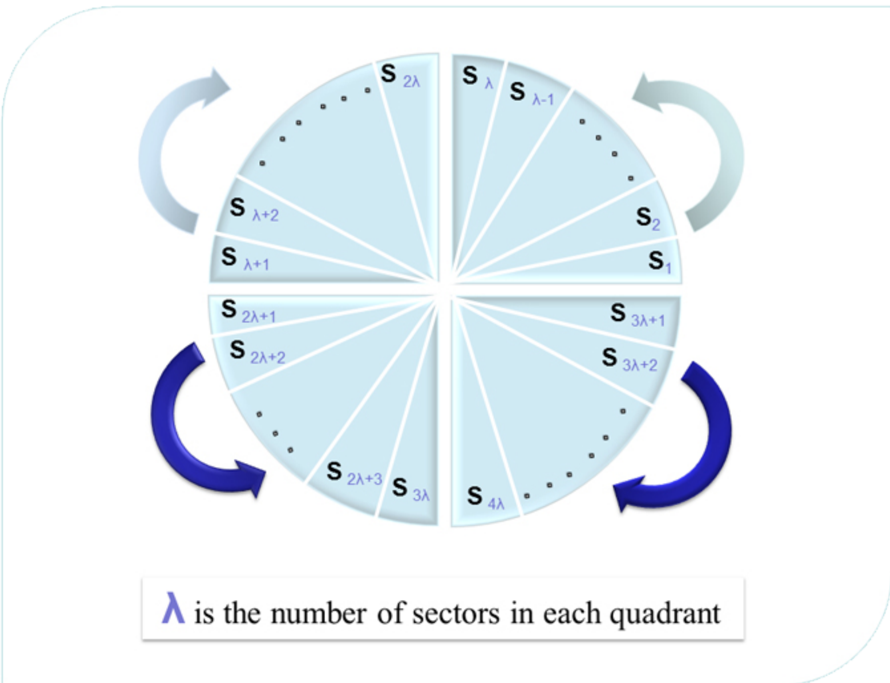

Figure 4.1: The Technique for NCPA.

Figure 4.1 shows the NCPA, where number of sectors in each quadrant is equivalent to other quadrants in the same cell. The numbering of sectors is drawn in a way that assists in generating a general algorithm for an unspecific number of sectors regardless of any cell types. The numbering direction is depicted, where the arrows direction indicates how the numbering will be in each quadrant. Precisely, numbering in the first and third quadrants proceeds clockwise, while the numbering in the second and fourth quadrants proceeds counter-clockwise.

Every cell in cellular communications network is virtually divided. Also, the service area will be presented by a sector, as follows:

NCPA Algorithm for splitting a cell into sectors

Each cell C should undergo the following processes:

1. Determine the radius of cell is r.
2. Compute the quadrant $q = Q_i \mid_{i \in [1,4]}$.
3. Determine number of sectors s in cell C, where s=*3,4,5,......*
4. Compute central angle for each sector $\alpha = \frac{360°}{2^n}$.
5. Find number of sectors in each quadrant $\lambda = \frac{2^n}{4} = 2^{n-2}$.
6. Sectors Numbering.
   - Numbering the sectors in odd quadrants proceeding clockwise.
   - Numbering the sectors in even quadrants proceeding counter-clockwise.

4.3.2 Locating MU

To determine the sector within which an MU is located, apply the following steps:

Step1: identify the quadrant in which an MU is located:

To determine the quadrant within which an MU is located, the point *(x,y)* of that MU is compared with every interval as in the following equation (4.4):

$$j = \begin{cases} 1 & \text{when } x > 0, y \geq 0 \text{ or } x \geq 0, y > 0; \\ 2 & \text{when } x < 0, y > 0; \\ 3 & \text{when } x < 0, y \leq 0 \text{ or } x \leq 0, y < 0; \\ 4 & \text{when } x > 0, y < 0; \end{cases} \tag{4.4}$$

Where $j \in [1,4]$ denotes the location of the MU that occupies a point *(x,y)* with respect to the intended quadrant.

Step 2: identify the sector in which an MU is located: Firstly compute the R as follows: $R = \left|\frac{y}{x}\right|, 0 \leq R \leq \infty$, then the values of R will be compared within the intervals according to equation 4.5 to determine which sector it belongs.

$$S = \begin{cases} S_{\lambda j-(\lambda-1)} & \text{if } 0 \leq R < \tan\alpha; \\ S_{\lambda j-(\lambda-2)} & \text{if } \tan\alpha \leq R < \tan 2\alpha; \\ S_{\lambda j-(\lambda-3)} & \text{if } \tan 2\alpha \leq R < \tan 3\alpha; \\ . & . \\ . & . \\ . & . \\ S_{\lambda j-1} & \text{if } \tan(\lambda-2)\alpha \leq R < \tan(\lambda-1)\alpha; \\ S_{\lambda j-0} & \text{if } \tan(\lambda-1)\alpha \leq R \leq \infty; \end{cases} \tag{4.5}$$

Where S represents the sector id.

Using cell splitting in mobility prediction is inspired by [93]. Splitting a cell into smaller regions reduces the size of service areas in comparison with the original cell size and the amounts of data that are delivered to MUs and that will be reduced. These factors assist in improving mobility prediction for LBSs.

In this research, NCPA is used to split a Micro cell into eight equivalent sectors, whereas a quadrant contains two sectors. LPSS technique, see section 4.4, utilises NCPA for splitting cells and finding an MU location.

Each MU has *(x, y)* coordinates, according to these coordinates the sector where the MU is located will find out, as follows:

NCPA Algorithm for location of MU:

Each MU should undergo the following processes:

1. Determine the point of the MU *(x,y)*.
2. Calculate quadrant number in which the MU is located j, where *j=1,2,3,4*.
3. Compute $R = \left|\frac{y}{x}\right|, 0 \leq R \leq \infty$.
4. Compare R with the intervals that are determined in equation 4.5.
5. Find sector identification s, where the MU is located.

4.4 Location Prediction based on a Sector Snapshot (LPSS)

This section presents LPSS. This technique is based on a third generation cellular network, such as the UMTS.

After introducing High-Speed Downlink Packet Access (HSDPA) technology to UMTS network, the transmission rates expected from such wireless communications are up to 10 Mbps [128]. For the implementation of LPSS, no GPS receivers are required since the control is done by the BS.

The LPSS is a mobility prediction technique which improves the prediction of locations in LBSs for micro cell based-on NCPA, see section 4.3. The LPSS divides the Micro cell into eight equivalent regions (sectors). In this technique, an update message is sent to the network with the current user location whenever a change in the moving direction of the user is detected. The main contribution of LPSS targets the LBS's cost by deploying a MCM that allows intelligent LBSs to minimise the computation cost, consumption of resources and the overall cost of the location management process. The LPSS technique utilises geometrical and topological techniques allowing users to receive desired services in a timely fashion.

4.4.1 LPSS Sectors Determination

Based on the NCPA which is discussed earlier in section 4.3, each quadrant is divided into uniform sectors (λ). Knowing that the number of sectors in a cell (2^n), where n can be 3,4,5,.....,. In this research, the number of sectors has been chosen to be 8; whereas n=3; which is the empirical test for splitting the cell into a small region to be covered. Table 4.1 illustrates this technique. It is notable from the table that the obtained area from Micro type by using 8 sectors (98214.28571) is smaller than the extreme area in Pico type (125714.2857).

The LPSS address these problems by dividing each cell into eight equivalent sectors (small region). This technique reduces the number of relevant services within the small coverage area of each cell.

Table 4.1, depicts that 8 splitting sectors are chosen to be intermediate between

Table 4.1: Optimal Area of Sector for LPSS.

Cell	Radius			Area(m^2)		
Types	(m)	No Splitting	2 sectors	4 sectors	8 sectors	16 sectors
Pico	100	31428.57143	-	-	-	-
	200	**125714.2857**	-	-	-	-
Micro	200	125714.2857	62857.14286	31428.57143	15714.28571	7857.142857
	500	785714.2857	392857.1429	196428.5714	**98214.28571**	49107.14286

4 and 16 sectors splitting. Based on 4 sectors, the service area is still large which leads to sending a huge amount of information/data to the MU. This fact violates the LBS's constraints. Meanwhile, even if using 16 sectors will result in a small service area, a crucial drawback is addressed that the number of decisions being made will be increased, and this badly affects the prediction success rate.

The geometry used in the NCPA helps to reduce the volume of results returned to users of mobile information systems, thereby avoiding the need for manual filtering and improving the precision of information retrieved, increasing the accuracy of predictions and meeting the characteristics of the mobile device such as the power consumption, storage space and low computing power and resources.

4.4.2 LPSS Principles

Discussions are now presented in the phases used in the LPSS technique and the steps that follow. Figure 4.2 shows the flow of LPSS. Pre-launching the LPSS, environment's parameters are initialised, such as number of cells, number of sectors and splitting the cells. In addition, a number of relevant parameters are described in chapter 5.

To ensure that the accuracy of the results is not affected by previous turns, the procedure of splitting cells is a predefined step. In this process, a virtual splitting for each cell in a network is performed in order to produce eight sectors. The splitting process is done once without the need to recalculate because it is not affected by natural changes such as closed roads, maintenance and congestion. Consequently,

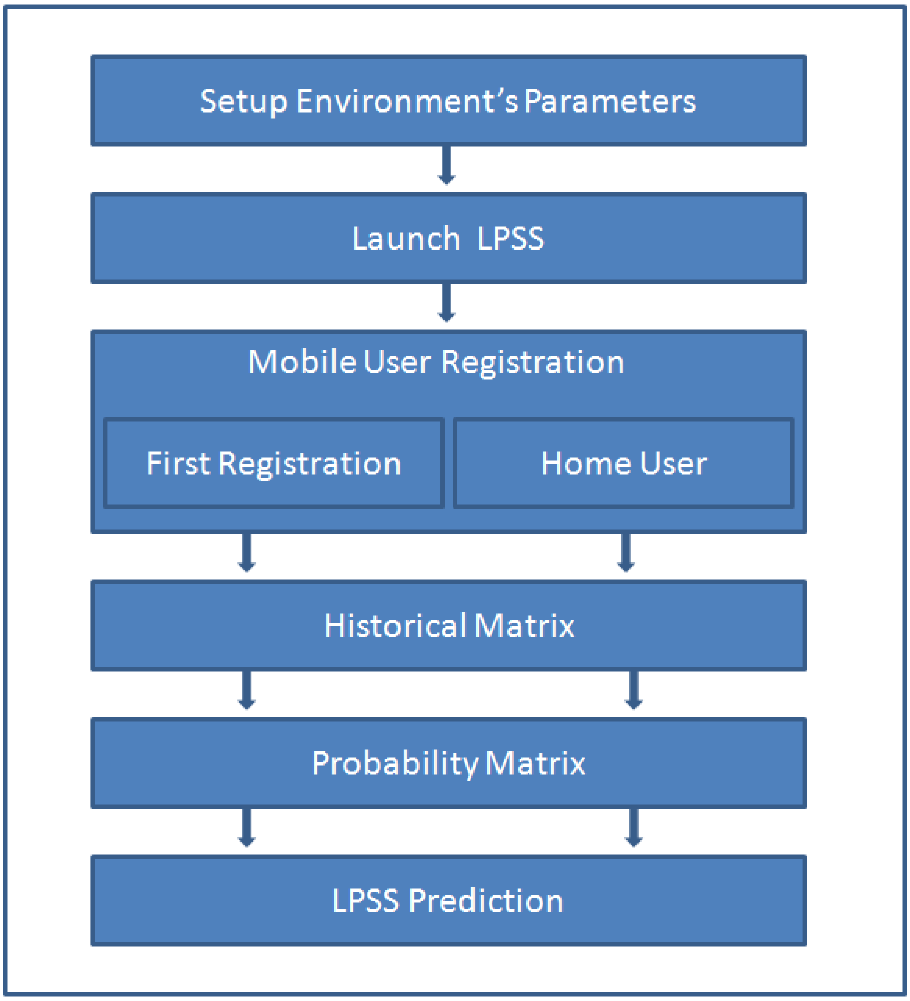

Figure 4.2: LPSS Execution Phases.

the splitting is excluded from the computation cost as it has been processed before running the technique. When the execution is started, the information about the sectors is stored in the database.

When an MU registers to a network, the current x,y are provided to LPSS through the History of MU. The specific sector in which the MU is located will be calculated by using step 1 and step 2 which are described in section 4.3.2. The output for this step is the sector identification where the MU is located. The MU in LPSS can be in one of two states, FIRST REGISTRATION and HOME USER. In the FIRST REGISTRATION state, the historical movement matrix is built by the neighbours. This information is stored in a database. In the HOME USER state, although there is a historical movement matrix, there is still a need to update it to ensure the matrix is consistent and up-to-date. Transition and probability matrices are built based on the historical movement matrix. Therefore, the historical movement matrix must be up-to-date for the MU movements. The probabilities of each sector around the MU are derived based on the transition matrix. In the meantime, the current state vector for the MU is initialised and then multiplied by the transition matrix. The result is the probability that the user will be moving to each sector around the user, i.e. the potential sectors. Finally, the LPSS behaviour when an MU enters a new RA is illustrated in section 4.6.

4.4.3 LPSS Mechanism

In order to demonstrate the LPSS technique, a set of parameters is defined. Table 4.2 summarises the parameters needed to perform the LPSS technique.

Table 4.2: LPSS Parameters

Parameters	Description
j	ID of the cell
i	The Sector ID where the MU is located,
	the current location L_k at current time T_k.
k	The sequence time for MU movements,
	the next location L_{k+1} will be predicted at T_{k+1} which is the later time.

To split a cell area into eight equivalent sectors, the NCPA in section 4.3 is used where n=3, α=45° and λ=2 by using equation 4.2 and 4.3 respectively. The eight sectors in cell C_j will be illustrated as in equation (4.6)

$$C_j = \sum_{i=1}^{8} Sec_{c_j,i} \tag{4.6}$$

Where i =1,2,...,8 is the ID of the sector.

To determine the sector within which a MU an MU is located, longitude (x) and latitude (y) of the MU are processed by step 1 and step 2 which are described in section 4.3. As a result, the sector where the MU is located will be determined.

The dynamic movement of an MU through a period of time to T_{k+1} will result in changing the current location to a new neighbouring sector. After a set of time interval, the MU will have to be moved through a number of sectors. These sectors are stored in a database to assist in predicting a new sector to be entered.

When a new MU self-registers, he or she does not yet have a record in the database. The historical movement of the MU is derived from all MUs, or more precisely from neighbouring users. Historical data that are stored in the server can be expressed as in equation (4.7):

$$H_(Sec_{c_j,i}, t_k) = \begin{bmatrix} N_{m,i}/N_m & N_{m+1,i}/N_m & N_{m+2,i}/N_m & \ldots\ldots & N_{m+n,i}/N_m \\ N_{m,i+1}/N_{m+1} & N_{m+1,i+1}/N_{m+1} & N_{m+2,i+1}/N_{m+1} & \ldots\ldots & N_{m+n,i+1}/N_{m+1} \\ . & . & . & \ldots\ldots & \ldots\ldots \\ . & . & . & \ldots\ldots & \ldots\ldots \\ N_{1,n}/N_n & N_{2,n}/N_n & N_{3,n}/N_n & \ldots\ldots & N_{n,n}/N_n \end{bmatrix} \tag{4.7}$$

Where N_m is the number of the traversal over sector m, and $N_{m,i}$ is the number of times the user has entered sector i when the user had been in sector m. When the user locates at $Sec_{c_j,i}$ at T_k then the available sectors at T_{k+1} are $Sec_{c_j,i+1}$, $Sec_{c_j,i-1}$ and the facing sector in the neighbouring cell $Sec_{c_p,q}$, where p is the neighbouring cell *ID* and q is the facing sector *ID*. Based on figure 4.3, when the user is located at $Sec_{c_1,1}$, then N_1=1,$N_{2,1}$=$N_{8,1}$=$N_{Sec_{c_2,5},1}$=1/3.

The historical matrix is periodically updated to achieve consistency. It is also updated when N_j is incremented by one and $N_(j, i)$ is incremented by one. To reach the probabilistic information for the predicted next state, a transition matrix is needed as in equation (4.8):

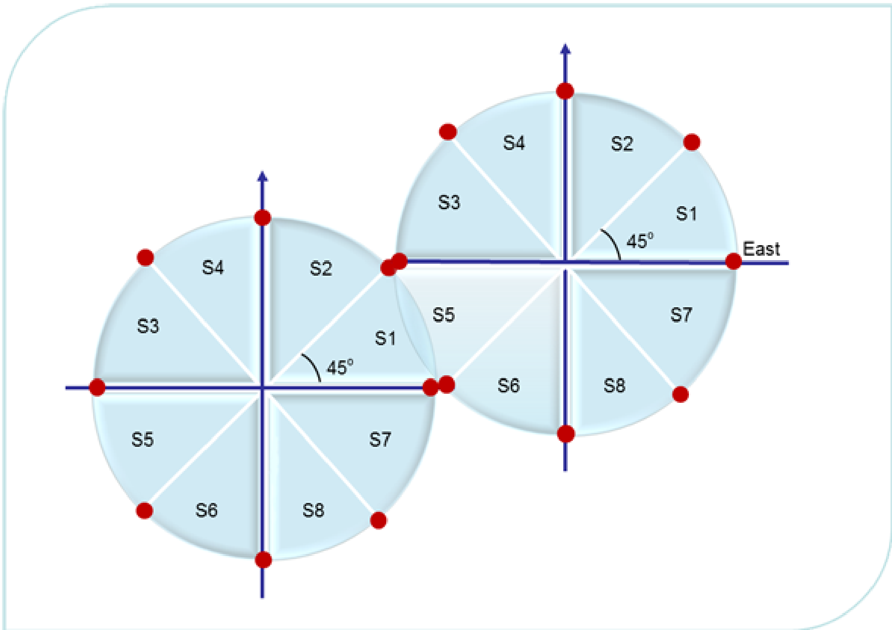

Figure 4.3: Movement of MU between Sectors in Two Cells.

$$TP(Sec_{c_j,i}, t_k) = \begin{bmatrix} P(Sec_{c_j,1}, Sec_{c_j,1}) & P(Sec_{c_j,2}, Sec_{c_j,1}) & \dots\dots\dots & P(Sec_{c_j,n}, Sec_{c_j,1}) \\ P(Sec_{c_j,1}, Sec_{c_j,2}) & P(Sec_{c_j,2}, Sec_{c_j,2}) & \dots\dots\dots & P(Sec_{c_j,n}, Sec_{c_j,2}) \\ P(Sec_{c_j,1}, Sec_{c_j,3}) & P(Sec_{c_j,2}, Sec_{c_j,3}) & \dots\dots\dots & P(Sec_{c_j,n}, Sec_{c_j,3}) \\ . & . & \dots\dots\dots & \dots\dots\dots \\ . & . & \dots\dots\dots & \dots\dots\dots \\ P(Sec_{c_j,1}, Sec_{c_j,n}) & P(Sec_{c_j,2}, Sec_{c_j,n}) & \dots\dots\dots & P(Sec_{c_j,n}, Sec_{c_j,n}) \end{bmatrix} \tag{4.8}$$

The current state of an MU after registration in a network can be represented as in equation (4.9):

$$Currentstate = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix} \tag{4.9}$$

So the next state will be predicted after multiplying equation 4.9 by equation 4.8. The resultant vector is expressed in equation (4.10):

$$Pr = \begin{bmatrix} Pr_0 & Pr_1 & Pr_2 & Pr_3 \end{bmatrix} \tag{4.10}$$

Where Pr is the probability that the MU will travel to surrounding sectors, and

$Pr_0 + Pr_1 + Pr_2 + Pr_3 = 1$.

Logically, the values of *Pr* will give the indication of the next sector to be visited in the next state since the highest *Pr* will give the highest probability of the sector. Generally, to generate more predictable sectors for further states, equation 4.10 will be multiplied by transition matrix 4.8. In other words, the operation that resulted in equation 4.10 will be repeated.

4.5 A New Routing Area Displacement Prediction

If the cellular communications network has enough information about the MU and its neighbours, appropriate artificial intelligent systems are employed. These help the network to predict the next displacement for an MU with high accuracy, sensible resources will be saved, delay time for delivering the services will decrease and improved network functionality such as paging, location update and Hand-off occurs.

This section discusses NRADP, the MU's behaviour and prediction processes are modelled by an ant colony. The developed approach works on the RA which means that every RA is classified as an independent colony and control itself. Variables pass through them because each one of them needs to know the visibility of his neighbours. Also, the developed model deals with mobility state for MUs. Hence, the idle state of the mobility model is handled.

4.5.1 NRADP Principles

The NRADP is based on the responsibility of the RA component instead of using the MU or cell. This helps avoid the computation power required by MUs. This could be a significant improvement since power and resource limitations are obstacles for mobile manufacturing.

The mobility prediction technique at RA should help to avoid the cell side problems. These problems are identified in the complexity cost and prediction algorithm to perform in two closer time slots. By including wide areas and extra computational resources that may be required for the process in RA, this would occur without any limitations due to the fact that the process is based on the equipments' efficiency at the service provider's side instead of cell side.

The SGSN manages the RA, and each RA contains one or more cells based on the radio specifications and geographical features, as shown in figure 4.4.

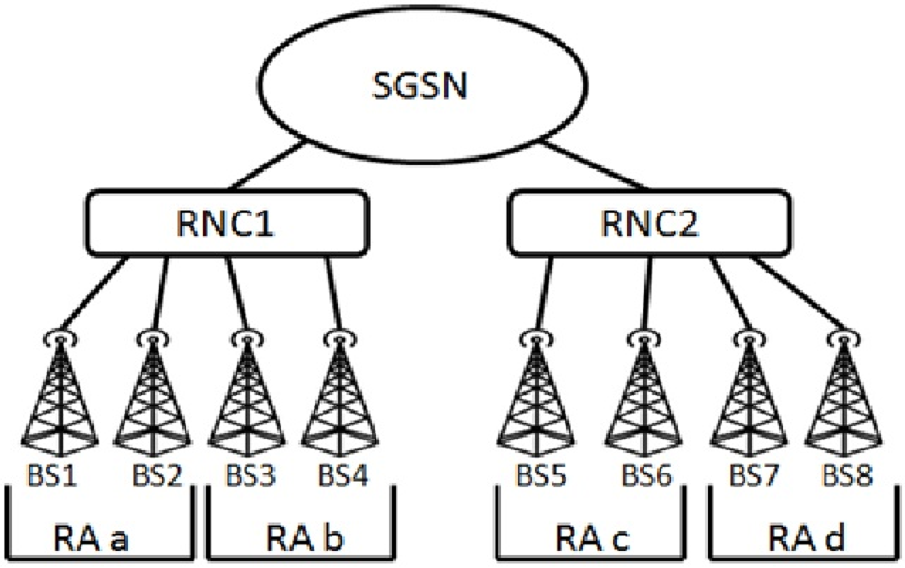

Figure 4.4: Routing Area Coverage.

The SGSN is responsible for managing and updating the history displacements for all MUs which are residing in it. Moreover, it handles the NRADP technique to predict the next displacement for the MU according to the current location, history displacements and visibility to surround neighbours.

When an MU enters the network, the SGSN uses his and neighbours' histories to make a relation between them. Thus, the prediction percentage and handling any unusual movement is enhanced. In contrast, if SGSN does not contain the history displacements for the MU, it should use the history of its neighbours.

Each RA is modelled by a colony and each MU is modelled by an ant. An ant goes from current RA to neighbouring RA looking for food. In the food search the ant prefers to go through the usual paths or according to the displacement of his neighbours. The NRADP contains a set of phases, each phase gets and passes information from the previous and the next phase, respectively. As shown in figure 4.5.

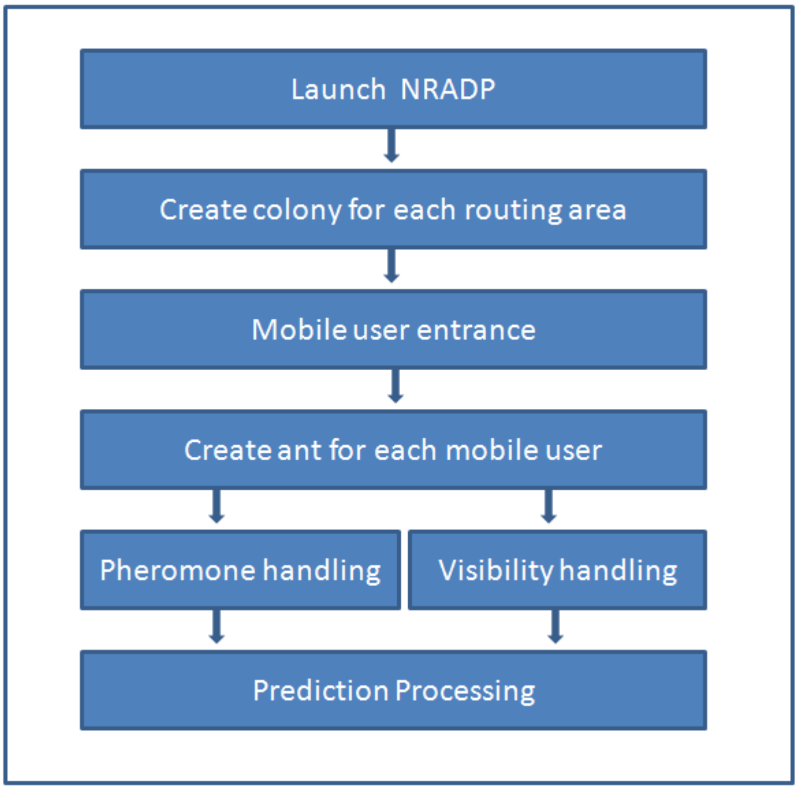

Figure 4.5: NRADP Execution Phases.

4.5.2 NRADP Visibility and Memorisation

Each RA is handled by one SGSN. The SGSN memorises old movement for all MUs, making the behaviour of all MUs known to obtain a good prediction percentage.

There are two types of memorisation (visibility), local and global memorisations where each MU has both of them. Local memorisation memorises how many times the MU goes from where he resides in an RA to each one of his neighbours' RAs. On the other hand, global memorisation describes how many MUs crossed a specific RA to each one of their neighbours' RAs, as shown in figure 4.6.

For example, as shown in figure 4.4, suppose that the MU resides in RA A and moves towards RA B. When the MU enters the RA B, local and global memorisation would be updated.

For global memorisation, if no MU has previously visited this RA, the global memorisation will be fed by a new row that represents the MU. But if the RA has been visited by at least an MU, the counter will be increased by one. Meanwhile, the counter of local memorisation will be increased by one, if the MU was in the RA

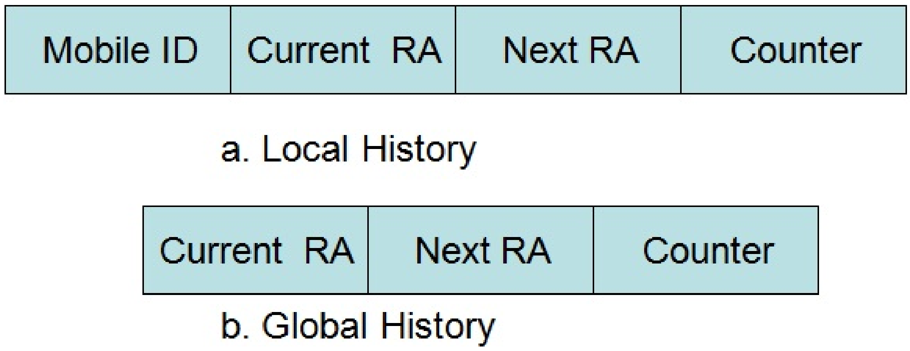

Figure 4.6: Structure of the Memorisation Entity.

before, a new memorisation row will be added, if this visit is considered as the first one.

In local and global memorisation, data type of counter field in figure 4.6 is represented by NUMBER, after a long time of running the algorithm on a huge number of MUs, the range of the NUMBER increases constantly, after t time a BIG NUMBER will occur which leads to complex manipulation and increases the processing time [129, 130].

To avoid the BIG NUMBER and keep the counter field for local and global up-to-date, the counter will be multiplied by weight W, where W between 0 and 1.

Table 4.3 describes the local memorisation data in each RA for each MU and applying the same way to deal with global memorisation. Also, multiply each neighbour RA by W to keep the same ratio between all neighbours.

Table 4.3: Neighbouring History for Local Visibility.

Mobile ID	Current RA	Next RA	Counter
1	1	2	2000
1	1	3	1000
1	1	4	5000
1	1	5	4500
2	.	.	.
3	.	.	.

4.5.3 NRADP Visibility Manipulation

RA and MU are modelled by colony and ant, respectively. When the MU enters and the registration is made to a cellular communications network, the network creates an ant for each MU. Subsequently, the RA where the MU resides starts to manage the memorisation process, as mentioned in the section 4.5.2.

Memorisation entity is used to calculate the visibility variable *(V)*, it is represented by a vector *(n)* and its length based on the number of adjacent RAs A_{RA}. An element of this vector either local or global represents the ant visibility of an adjacent RA. In a sense, the local memorisation reflects the MU's behaviour. On the other hand, global memorisation reveals all MUs' behaviours at such RAs. The local visibility is managed by equation (4.11).

$$V_L = \begin{cases} X+1 & \text{if the MU exists in } Nr; \\ X=1 & \text{if MU does not exist in } Nr \text{ before;} \end{cases} \tag{4.11}$$

The V_L is a local visibility, L between 1 and A_{RA}, X is a value that starts from 1 and Nr is a local memorisation table which stores the adjacent RAs. Meanwhile, the global visibility is represented by equation (4.12)

$$V_G = \begin{cases} Y+1 & \text{if the MU exists in } Mr\text{ ;} \\ Y=1 & \text{if MU does not exist in } Mr \text{ before;} \end{cases} \tag{4.12}$$

V_G is a global visibility, G between 1 and A_{RA} for each MU, Y start from 1, Mr is a global memorisation table which stores the adjacent RA, where each mobile affects on this equation.

In order to make a relation between local and global memorisation, V_{all} is calculated by equation (4.13)

$$V_{all} = P * V_L + (1-P) * V_G \tag{4.13}$$

Where P between 0 and 1.

The combining of local and global memorisations is proposed to achieve the prediction process based on the MU's behaviours itself and surrounding neighbours.

Based on equation 4.13, the change in P value should balance the participation for both local and global memorisation. In this work the optimal value of P is empirically tested for achieving optimal prediction success rate, see section 5.6.2.

When an MU visits a new RA; if he depends only on local memorisation, the failure prediction possibility of new RA will be increased, because the prediction will depend on the most visited local RAs. Also, pheromone does not have enough information for prediction. Thus, the neighbours' behaviours must be considered to improve the prediction and to avoid the bias of the MU's usual behaviour. In such a situation, the P value in the equation 4.13 should be decreased in order to decrease the participation of the local memorisation.

Meanwhile, if the MU's behaviour was built only according to the global memorisation, i.e. the behaviour of the neighbours considered as the main source for predicting the new RAs, the MU will drift from the usual activity and usual displacement. Thus, the P value should be maximised to make a balance between the local and global memorisation.

Every MU in the cellular communication network affects the local visibility through his movements, where the local visibility is processed in a way to memorise their behaviour and use it for future displacements. the steps of handling local visibility are presents as follows:

NRADP algorithm for handling local visibility handling

---

1. Get MU identification.
2. Get routing area identification where MU resides.
3. Discover neighbours' routing area in step 2.
4. Determine if the MU has been in the routing area in step 2.
   - when the MU has never been in the routing area.
     (a) Feed memorisation table by the MU ID.
     (b) Set local visibility to the initial value, where $V_L = 1$.
   - when the MU previously visited the routing area.

(a) Increase local visibility by one, where V_L=V_L+*1*.

5. After δ *t*. This is a multiple of time-steps.

   (a) Local visibility will be multiplied by weight *W*, where V_L=V_L*W.

   (b) Repeat step **5a** for routing areas that are obtained from step 3.

The algorithm of NRADP global visibility is slightly different in comparison to the algorithm of NRADP local visibility. Handling of an MU in global visibility is not based on the MU identification.

4.5.4 NRADP Pheromones and Heuristic Management

The management of pheromone is addressed as one of the important factors to improve the NRADP prediction process. When each ant needs to move to a new location, i.e. new RA, this means that it needs to use the probability decision which is based on pheromone value. The pheromone signifies the knowledge about earlier experiences of the ant's own colony and the other colonies in the same network.

4.5.4.1 NRADP Representing Pheromone

To represent pheromone updating in NRADP, pheromone values which are found in RA must be constantly reduced as a function of time. Nevertheless, while the MUs are handled in a discrete-time process, discrete-time considers the convenient way to control the pheromone updating. Additionally, updating and controlling the pheromone incurs computation cost. Therefore, a new system is required such as NRADP to control the interval on which this process must be carried out to satisfy the constraints and the architecture of the cellular networks.

In NRADP, pheromone updating handles the mobility state and speed of the MU. If the MU has idle state or their speed exceeds speed limits in a cell, the pheromone is managed by RA to avoid frequent calculation and message passing. Also, the realisation of computation cost will be needed. Moreover, when an MU has idle state, the UMTS protocols and the control given to the RA level, the NRADP does not conflict with UMTS specifications and no need appears to restructure the network itself. In contrast, if the MU is in a connected state and his speed is within the range of cell speed, the pheromone updating control goes to the cell itself because the distance crossed in the region will not be long compared with when an MU moves at high speed.

The frequency of pheromone updating is dynamically chosen to classify the MU for which pheromone is allowed to update. Also, the density of pheromone is not affected by exceptional cases ensuring that the values are always close to their ideal values and avoidance of the outdated and unusual pheromone may occur.

4.5.4.2 NRADP Pheromone Limitation and Initialisation

Initialisation pheromone is considered as one of the factors that participate in improving the prediction success rate, through minimising the time needed to calculate the best quantity of pheromone that would be laid into the RA, which is used in the future displacement.

The first ACO algorithm [19] has a search stagnation problem; the search focuses on the early stage of the algorithm running. This means that no area would be discovered in the future, because all ants will follow the path that is previously generated with the highest density of pheromone.

In NRADP, the previous intensities of the pheromones for all adjacent neighbours are required. Suppose that Ph is a vector of pheromone from 1 to A, where A stands for the number of adjacent RAs. At the first time $t(0)$ of the algorithm running, each MU lays a random number that represents a pheromone, section 5.6.1 discusses the value of random number, at $t(1)$ the pheromone lower and upper are calculated, to avoid search stagnation. This is inspired by MMAS technique [67].

In NRADP any MUs who hold pheromone (τ) which exceeds the limitations, the upper and lower limits of pheromone are determined on $t(1)$. This MU, should die by ignoring it from the algorithm. This will lead to prevent the prediction and avoid any bias which may occur.

The new value of pheromone of an MU dies before being re-calculated. When the value of $\tau(t)$ is greater than τ_{max} set to τ_{max} and when $\tau(t)$ is smaller than τ_{min}

set to τ_{min}.

The value of τ_{max} is calculated in equation (4.14)

$$\tau_{max} = \frac{1}{1-\rho} \cdot \frac{1}{average(\tau_{RA})} \tag{4.14}$$

Whereas τ_{max} is the maximum quantity of pheromone that lays in RA by each of the residing MUs, this laying is performed when an MU goes from RA to another one of his neighbours. ρ is a coefficient, (1-ρ) is the evaporation rate of the pheromone in the RA between t and t+n. Thus, the value of ρ must be between 0 and 1 to avoid unlimited pheromone in the RA. The pheromone for each RA is τ_{RA}.

The minimum value is represented by equation (4.15)

$$\tau_{min} = \tau_{max}/m_c \tag{4.15}$$

Considering m_c, the number of MUs residing in such RA at the time when its value would be calculated.

4.5.4.3 NRADP Pheromone Updating

The pheromones in NRADP are considered as the communication media between all MUs. Pheromones have two roles: they allow indirect collaboration between MUs (agents), and they act to communicate individual awareness between MUs to improve the prediction for future displacements.

The pheromones are considered as "Stigmergy". The Stigmergy is defined as a kind of communication interaction between agents without direct connection between them. The interaction occurs when one agent changes the environment in which he resides by any action. Consequently, all other agents response to this change.

In NRADP, the MU moves to a new RA which is partially based on the amount of pheromones. The preferable RA is the one that has the higher density of pheromone. Thus, the amount of pheromone that is to be laid by an MU should be controlled because it affects the intensity of communications that makes the RA more preferable. Meanwhile, evaporation rate should also be controlled in order to reduce the intensity of communications. Over time, when no more MUs cross an RA, this means that no more pheromones would be laid down and the RA will start to lose its pheromone progressively.

When a hard hand-off occurs for an MU, the MU changes the RA to another one. At this time, the MU deposits his pheromone in the RA which has just been left. The amount of pheromones is deposited in each RA represented by equation (4.16).

$$\Delta\tau_{i,j} = \begin{cases} \lambda * Q * t_{staying\_in} & \text{if } \lambda * Q * t_{staying\_in} < Q \\ Q & \text{if } \lambda * Q * t_{staying\_in} >= Q \end{cases} \tag{4.16}$$

Whereas Δ $\tau_{i,j}$ is the pheromone quantity that would be laid down in the RA by the MU when he left RA i to RA j. Q is a constant which represents the maximum quantity of pheromone that would be laid in each RA. The value of Q is greater than zero > 0. Section 5.6.1 shows the optimal value of Q. $t_{staying\_in}$ is the time that has been spent by the MU in RA i. λ is a constant fraction whose value is $0 < \lambda < 1$. λ is used to prevent the pheromone amount that has been laid from exceeding the Q value since this amount proportionally increases over the time.

When the value of Δ $\tau_{i,j}$ is less than Q, the MU's pheromone affects the pheromones held by an RA proportional to the time spent in that RA. If Δ $\tau_{i,j}$ is greater than or equal to Q, the MU spends a very long time in the RA, which means that the MU is working or living there. This leads to having a pheromone quantity greater than Q, therefore the quantity that will be laid down is all Q, to avoid the bias of the quantity that may lay down and stagnate the search.

Each MU has the same process for laying pheromone. Therefore, the pheromone quantity that is laid in this RA plays the main role of motivating other MUs to go towards it.

MUs in cellular communications networks move constantly. This movement needs a mechanism to forget old predictions, which makes the prediction up-to-date for the new movements of MUs. In NRADP, the mechanism is the evaporation process; the pheromone level is decreased after each slot of time.

In NRADP, after δT the evaporation process will take a place to decrease the pheromone level at each RA in the network; this is represented by equation 94.17)

$$\tau_{acc\_RA_i}(t+1) = \tau_{acc\_RA_i}(t) * (1-\rho) \tag{4.17}$$

Whereas $\tau_{acc\_RA_i}(t)$ represents the cumulative pheromones in RA i, $(1-\rho)$ is the evaporation rate.

A small value of ρ carries out pheromone evaporation slowly and the pheromone will accumulate more in a RA. A large value of ρ leads to forgetting the behaviour of other MUs and the prediction turns more towards random. In a case when ρ equals 1, the prediction becomes completely random. The value of ρ affects the prediction success rate by permitting forgetting the behaviour of the elder MUs and to remove the biased MUs' behaviour. Section 5.6.1 illustrates the optimal value of ρ.

4.5.5 NRADP Prediction

When a registration to the network is made for an MU, the SGSN creates an ant to represent the MU. Whilst, moving the ant will deposit a pheromone on RA, this would be considered the communication channel between all ants in the cellular communications network.

At the first entrance of MUs to the network, no pheromone would be found from any neighbour, that is why the prediction success rate very low. Over the time, each RA has its pheromone which predicts the most likely RA for future displacement.

Finding the probability of each RA, the previous MU's visibilities and the intensities of the pheromones for all adjacent neighbours are required. Suppose that Ph is a vector of pheromone from 1 to A, where A stands for the number of adjacent RAs. The probability for the MU moving from current RA C_{RA}-th to j RA is expressed in equation (4.18).

$$P_{C_{RAi,j}}(t) = \frac{[\tau_{C_{RAij}}(t)]^{\alpha} * [V_{allC_{RA}ij}(t)]^{\beta}}{\sum\limits_{u \in Ph_A(i)} [\tau_{iu}(t)]^{\alpha} * [V_{all_{iu}}(t)]^{\beta}} \tag{4.18}$$

Whereas $P_{C_{RAi,j}}$ is the probability of the MU at RA i at time t to RA j , t is the time factor, τ is the pheromone level and V_{all} is the visibility (memorisation) of the MU. The visibility here, V_{all}, is obtained from the combination between local and global visibility. For more details see section 4.5.3.

Probabilities of all RAs that surround the RA where the MU resides in are calculated in equation 4.18. The highest probability should be taken into consideration as the next RA that the MU will visit. Hence, the next displacement is expressed in equation (4.19).

$$Next_{RA} = \max(P_{C_{RAi,j}}(t)) \tag{4.19}$$

$Next_{RA}$ is the next displacement.

In the NRADP prediction phase, the next displacement for each MU will be predicted according to a set of processes. These processes are arranged in a way to prevent the consistency of prediction environment in cellular communications networks and it is shown as follows:

NRADP prediction algorithm for next displacement of an MU

Each MU in NRADP should be processed according to the following steps:

1. Determine MU identification which would be processed.
2. Fetch global and local histories that are related to the MU.
3. Prepare neighboured routing areas' pheromones and visibilities for the MU where they reside. *Ph* would be created.
4. Calculate probabilities for the surrounding routing areas. This is performed by equation 4.18..
5. Get max probability from step 4 according to equation 4.18, which represents the next displacement.

4.6 LBSs Mobility Prediction Scheme (Message Managements between NRADP and LPSS)

In this section, a new mobility prediction technique is investigated. The proposed technique is based on two complementary prediction techniques at different levels: the NRADP and LPSS prediction techniques. The former has been implemented in the RA level while the latter technique detects the regular RA of the MU according to the cellular communications network standardisations. The latter has been implemented at cell level and works on the back of the RA prediction technique, NRADP, to prepare all possibilities that could happen by constant movements of MU in next RA. Figure 4.7 illustrates the message flow of the combined NRADP and LPSS techniques.

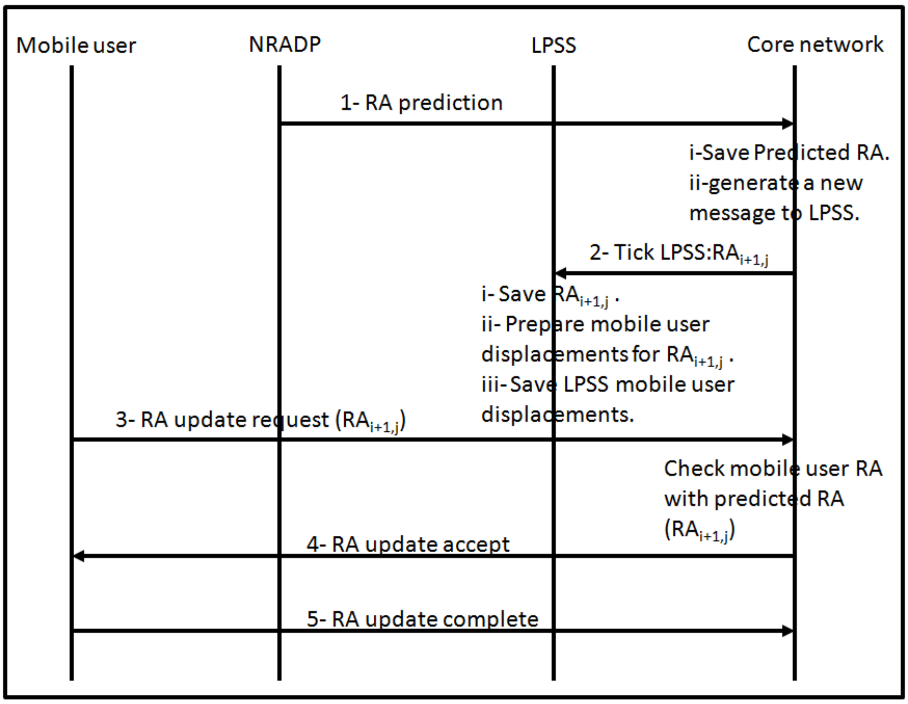

Figure 4.7: Message Flow for the Developed Mobility Prediction Scheme.

If the NRADP fails in providing a correct prediction for the next displacements of RA because of unexpected directions taken by the MU, the scheme will perform the location update procedure according to the UMTS standard. In the location management, the MU informs the network of its location through RA update procedures. In this case, the prediction is yielded by the LPSS technique. However, the time between starting and completing the RA update procedure is very small; the LPSS technique will work only on the nearest cell of the next RA in order to prepare all movements of the MU in that cell and guarantee that these movements will be prepared before the MU enters a new RA. Moreover, after the RA update procedure is finished, the LPSS continues to prepare all movements of the MU for the rest of cells in the new RA. Figure 4.8 shows the steps when NRADP fails to predict next RA.

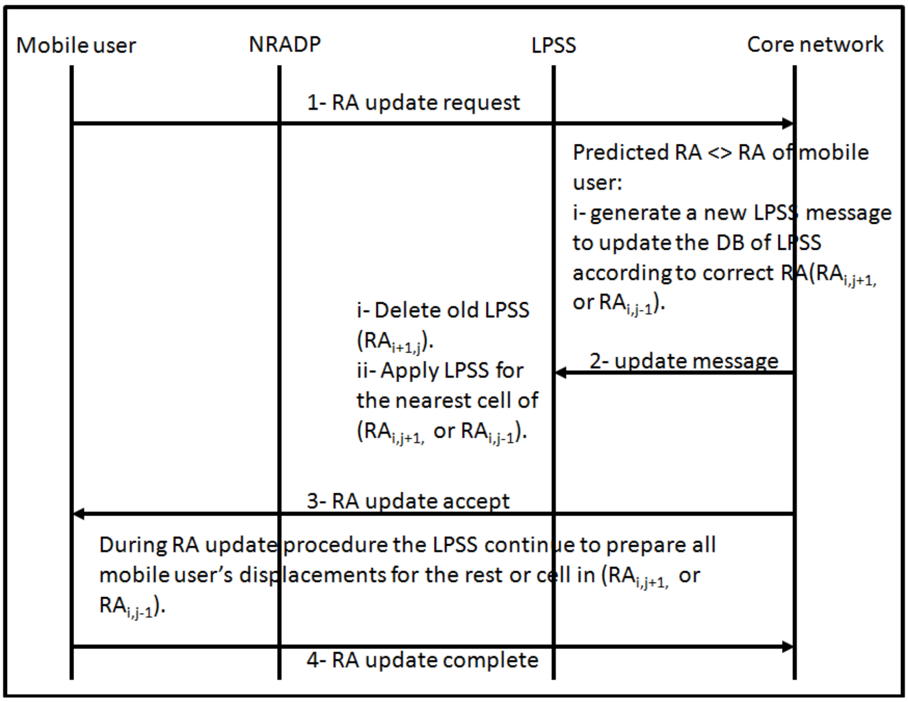

Figure 4.8: Message Flow for the Developed Mobility Prediction Scheme when NRADP Failed.

The following steps illustrate the message flows between NRADP and LPSS. These steps include the success and failure of NRADP.

Step 1: let RA_{ij} be the current RA of an MU and $RA_{i+1,j}$, $RA_{i-1,j}$, $RA_{i,j+1}$, $RA_{i,j-1}$ are the neighbours (adjacent RAs) of RA_{ij}. When the MU moves towards $RA_{i+1,j}$, the NRADP detects the regular RA and sends the message to the core network that is: *(RA prediction)*.

Step 2: core Network will save the predicted RA and send a message *(Tick LPSS)* to the LPSS algorithm and the ID of predicted RA ($RA_{i+1,j}$).

Step 3: the LPSS will prepare all MU displacements in the predicted RA that may occur by the MU in the $RA_{i+1,j}$.

Step 4: the update procedure is executed in two situations:

- Normal location update is performed when the MU detects that the location has been changed.

- Periodic location update is exercised even if the MU does not move. That is, the MU periodically reports its 'presence' to the network.

In both situations, the MU sends the RA Update Request message to the Network.

Step 5: the network will check if the RA that is received by an MU and the predicting RA are not equal (failed). *Steps 6-8* are executed. Otherwise *(Successes procedure)*, these steps are skipped.

Step 6: the core network generates a new LPSS message to update the database of LPSS according to a correct RA ($RA_{i,j+1}$ or $RA_{i,j-1}$) and sends a message to LPSS *(Update Request message)*.

Step 7: LPSS delete the old displacements that have been generated in $RA_{i,j+1}$. Meanwhile, LPSS apply for the nearest cell of ($RA_{i,j+1}$ or $RA_{i,j-1}$).

Step 8: During the RA update procedure, the LPSS continue to prepare all MUs' displacements for the rest of the cells in ($RA_{i,j+1}$ or $RA_{i,j-1}$).

Step 9: The core network sends RA update message to an MU to accept the routing area update *(Routing Area Update Accept)*.

Step 10: The MU sends the RA update complete message to the core network to confirm the relocation of other parameters such as Temporary Mobile Subscriber Identity (TMSI).

4.7 Summary

New mobility prediction techniques have been proposed based on a well-known ACO and MCM. These techniques are independently combined to introduce the LBSs mobility prediction scheme. Message passing between proposed techniques was also discussed. The standard ACO has been developed to satisfy the compatibility with cellular communications network structure. Also, a dynamic cell splitting has been introduced in which the cellular cell splitting and finding the MU location were achieved. Moreover, the techniques offer the following features, which may prove advantageous.

- The RA mobility prediction technique (NRADP) is fair because it is running at the core network which has the powerful resources.

- The cell mobility prediction technique (LPSS) takes the advantage of using the novel cell splitting algorithm (NCPA) to improve the prediction success rate.

- LPSS execution time does not take place because it is running before an MU enters a new RA. This RA will prepare all possibilities of MU displacements between sectors before it is entered by the MU.

It is worth considering NCPA technique in which the new splitting may be used as primitives. There may also be useful analogies to be found in wireless sensor network or other groups.

Chapter 5

Implementation and Simulation

This chapter shows details of the simulation procedures and evaluation methods that were commonly used throughout this research. A justification of the implementation of the Developed Mobility Prediction Techniques for LBSs and network simulation environments are also provided. The chapter also provides the significant metrics that are used for measuring, evaluating, characterising and comparing the performance of mobility prediction techniques over cellular networks. Finally, the optimal values for the newly developed Ant Colony Optimisation (ACO) parameters are obtained, which it uses in New Routing Area Displacement Prediction for Location-Based Services (NRADP).

5.1 Simulation Overview

There are three methods for performance estimation: simulation, analytical modelling and measurement. It would not be practical if we used the analytical modelling technique in this study. This is because of the environment of wireless medium that varies in terms of time and space. Therefore, simulation was chosen as the most appropriate approach. Measurements from real systems are excluded because the implementation of the developed techniques in a real cellular communications network would have consumed too much time and would have been so costly that simulation would have first been required in any event.

Figure 5.1 provides the structure of the methods for studying the performance of systems [131].

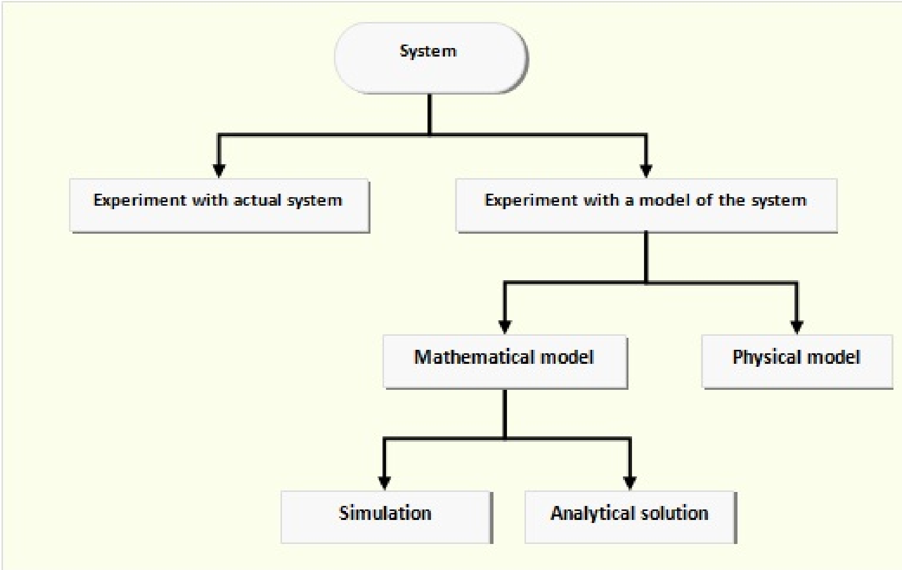

Figure 5.1: The Methods for Studying the Performance of a System, [133].

The analytical model is used after building the mathematical model. The mathematical model must be examined to see how it can be used to study the system being represented. The analytical solution is a good method for studying the system when an analytical solution to a mathematical model is available and when it is computationally efficient. In addition, the simulation method is used when both the real systems and their mathematical models are complex.

This research is a technical topic. The performance evolution includes several methods, i.e. simulation, analytical modelling, and measurements [132]. With all the above being equally considered, the most suitable way to conduct research for this study is to adopt a simulation.

As it is usual for primary investigations, the simulation enables change of network topologies, protocols and parameters in order to be carried out easily and in a realistic time frame. Simulation provides more flexibility than the real network implementation. It also involves fewer complications. More control over the network conditions could be achieved by using simulations.

The research method of this study was simply based on known network simulation tools, data collection from universal datasets, and simulation runs by using a simulation program developed in the Java computer language.

The methodology used in this research follows the standard practice for conducting a performance modelling analysis: construct the mobility prediction model, validate the model, vary modelling parameters, and analyse the results. This is achieved by: (i) introducing a Novel Cell Splitting Algorithm (NCPA); (ii) generating new mobility prediction schemes by using different components of cellular networks such as cell and Routing Area (RA) levels; (iii) investigating the previous mobility prediction techniques that are used in LBSs for the UMTS; and (iv) constructing the Developed Mobility Prediction Techniques and validating the predictions.

5.2 Network Simulation Tools

The performance can be evaluated, investigated and analysed using simulation tools or practical real networks [132]. This research is based on the network simulations. Practical real times are excluded due to the lack of resources to implement the approach. Therefore, a simulation approach is used instead. In general terms, simulation allows changes to the network topology, protocols and parameters in order to be carried out easily and in a realistic amount of time. The research method is based on simulation models, dataset and collecting data from simulation runs using Java simulations.

Within the simulation process, data were collected from simulation runs, and then quantitatively analysed. The analysis and critical evaluation of data were based on two criteria: (i) the results collected from the developed techniques, and (ii) the findings from recent literature within the field of the study.

It was difficult to select a suitable simulation environment to simulate such networks since there were several points to keep in mind. These involve aspects of simulation such as the need for software modification and expandability, as well as the availability of such a simulator. There are several simulation tools that can be used to simulate cellular and wireless networks. The most well-known tools are mentioned here.

5.2.1 GloMoSim

The Global Mobile Information Systems Simulation Library (GloMoSim) [133] is a scalable simulation environment for wireless and wired network systems. Given that it is not an open resource, it was not used in this research. Therefore, modifications in the source code cannot be made. For this reason it was not used as a simulation tool in this research.

5.2.2 OPNET

The Optimal Network Simulator (OPNET) was based on discrete analytic and hybrid simulation modes. OPNET is an object-oriented simulation tool with a hierarchical model structure. OPNET's UMTS model suite enables one to model UMTS networks to evaluate end-to-end service quality, throughput, drop rate, end-to-end delay, and delay jitter through the radio access network and core packet network [134]. However, as with GloMoSin, it is not open source and it is not easy to make modifications and expandability when required.

5.2.3 NS-2

The Network Simulator (NS-2) is an open source simulation tool developed by the University of California at Berkeley [135]. It is a free simulation tool and runs on different platforms such as Linux and Windows. NS-2 that was built on discrete simulation modes has supported some wireless modules [136–138]. Therefore, the present research uses NS-2.

5.2.4 Java Language

In the present research, Java language was chosen to model the proposed techniques. It is a programming language introduced by Sun Microsystems. It is known as a multiplatform, a platform-independent, and an object-oriented programming language [139, 140].

Multithreading was introduced in Java as a useful technique since it allows the programmer to structure different parts of the program into different threads. Implementing the user interface of software as a separate thread is a common example of such structuring, where multiple threads can communicate via reads/writes of shared objects [141]. Further discussion on software design using multithreaded Java is seen in [142]. Java threads can also be run on multiple hardware processors [143, 144] or on a single processor using the thread library [145].

Demand has increased for using Java for high-performance parallel applications [146]. Java's clean and type-safe object-oriented programming model and its support for concurrency [147,148] make it an interesting environment for writing consistent parallel programs [149–152]. For shared memory machines, Java has offered a common multithreading paradigm [153]. Also, for distributed memory machines, Java has provided Remote Method Invocation (RMI), which is an object-oriented translation of Remote Procedure Call (RPC) [153]. There are many advantages in the RMI model for distributed programming, including the seamless integration with Java's object model, heterogeneity and flexibility [154].

5.3 Mobility Models

Mobility model is used to express the behaviours of Mobile Users (MUs) in a network. These behaviours could be velocity, location, direction, and how those are changing over time. There are a group of mobility models that use the movement histories of similar users [155, 156]. Meanwhile, the model has the functionality to control and monitor the network itself, such as maximum number of users per one cell and determining which MU needs a registration, re-registration, hand-off, location update paging and when this will be made.

There are different cellular mobility models to mimic the MU movements in the real life. The most common mobility models are:

5.3.1 Fluid Flow Model

In this model the MU movement is represented at a macroscopic level [157–160]. This model is used to represent the traffic on highways. The result obtained bear testimony that [161, 162] the behaviour of traffic generation is similar to a fluid in a pipe. But the model is unable to represent individual user movement, including situations that may occur during movement such as stopping and starting [163, 164]. As a result, this model is not appropriate to represent the MU movements. Therefore, fluid flows model was not considered applicable for use in the research conducted for the investigation reported herein.

5.3.2 Trace Based Models

The modelling of MU in Trace Based models are based on the real world activities that are carried out by the users in the course of their normal or exceptional activities, recording such information into digital memory. tracing and using that data to predice future movement. Such traces were gathered, e.g. from a 2003 surveillance of city coaches [165], GPS or by real life simulation. Hence, the trace-based model contains Real-world Mobility Traces, Artificial Mobility Traces [166–168], and Activity-based models [169]. Therefore, in the present study, the trace-based models have been avoided because real MU movements are not described by those models.

Moreover, during MU movement, he/she is reading the post-processed trace, filing and replying to them, and synchronising the MU movement and the timestamp stored in the file.

The Real-world Mobility Traces and Activity-based Model are carried out as more realistic models and are reusable. Still, they have drawbacks such as communication cost, time consumption and no free parameterisation. Free parameterisation is another advantage introduced by artificial mobility trace and no feedback on driver behaviours such as accident details, risk warnings, or road jam information are addressed which is a drawback [170].

5.3.3 Random Waypoint Model

The Random Walk Model is the simplest mobility model. It is the most widely used model because it has the ability to describe individual movement for each MU according to cell locations [171–173]. Furthermore, this model does not depend on the previous state which it named as memory-less, nor does it need extra time for pre-processing.

The MU stays in a cell or moves to a neighbouring cell according to random possibility. In a sense, it is a movement from a current location to a new one by speed and direction that are totally random travel.

Nain et al in [174] studies the variation of random walk modelling. Two drawbacks are addressed when an MU reaches the boundary of network. The first one is Random Walk with wrapping, and the second one is Random Walk with reflection. These drawbacks have been overcome [156]. For further details about the Cellular Mobility Model, see [158].

The Random Waypoint model [175] has been obtained from the random walk model, the whole movement of the mobile user is divided into a sequence of pause and motion period. The mobile user stays at a specific area for a certain time period before leaving to the next, the levels of randomness are based on his speed, direction and pause time.

The Random Waypoint is a fine mobility model for simulating different types of mobile user's behaviours in urban areas, such as walking, running, biking or driving, since these behaviours are considered randomised with enabling change of speed and direction [15, 176].

In [176] the cell residence time, speed and the size of serving area for Random Waypoint were analysed through using different types of distribution, i.e. exponential, uniform, etc. This study was based on real movements of mobile users in small resolution to validate the characteristics of the Random Waypoint model. As a result, Random Waypoint has less randomness and is valid in the real world movements that have been collected [176].

Common sense led to the choice of the mobility model as it respects and satisfies tracking movement of MUs in real life. To evaluate prediction algorithms, a realistic model is required. This model does not contain any enhancements such as memorisation, which illustrates the real result and evaluates the prediction algorithm.

Some researcher users have relied on their own models or enhanced models. The accuracy of predictions obtained has been between 74% and 95% [16]. But the comparison between these works is difficult because they do not reflect real user movement. The results obtained give higher prediction accuracy than the real results since part of mobility models give a prediction percentage.

In this research the Random Waypoint is chosen to obtain the approximate prediction that will be achieved without using mobility models that are already enclosed in a prediction. Furthermore, the Random Waypoint model is implemented in NS-2 which is freely distributed. For more details about NS-2 see section 5.2.3.

5.4 LBSs Implementation Tools

This study suggests NCPA relies on the structure of the cellular cell and the size of the cell. It is applicable for rural, micro, macro and pico cells. Furthermore, this research presents new mobility prediction techniques based on the developed ACO and Markov Chain Model (MCM). The developed ACO algorithm is used to predict the next RA where the MU will go and stay. Here, the prediction will be based on the difficulty of the NP hard problem. MCM is used to predict the next sector displacement for an MU which is based on the random movement of the MU.

The Java software tested the developed technique in action. As compared with the theoretical, the simulation results prove that the LBS mobility prediction scheme is appropriate for the cellular environment. Therefore, developed ACO and MCM are important for this research. They are used to design a new LBS mobility prediction scheme for UMTS. This research compares the performance characteristics of those models (MCM, ACO, developed ACO) used in prediction techniques by implementing each algorithm.

5.4.1 Implementation of A Novel Cell Splitting Algorithm

The NCPA contains two functions: (i) splitting any cell type into small regions named by sector; and (ii) locating the sector where the MU is located at the time.

To implement splitting and locating functions in the cell splitting algorithm, the standard Java function and math packages are used. Figure 5.2 illustrates the flow processes for the cell splitting algorithm.

The program creates finding sectors by inputting the cell type to quadrant calcu-

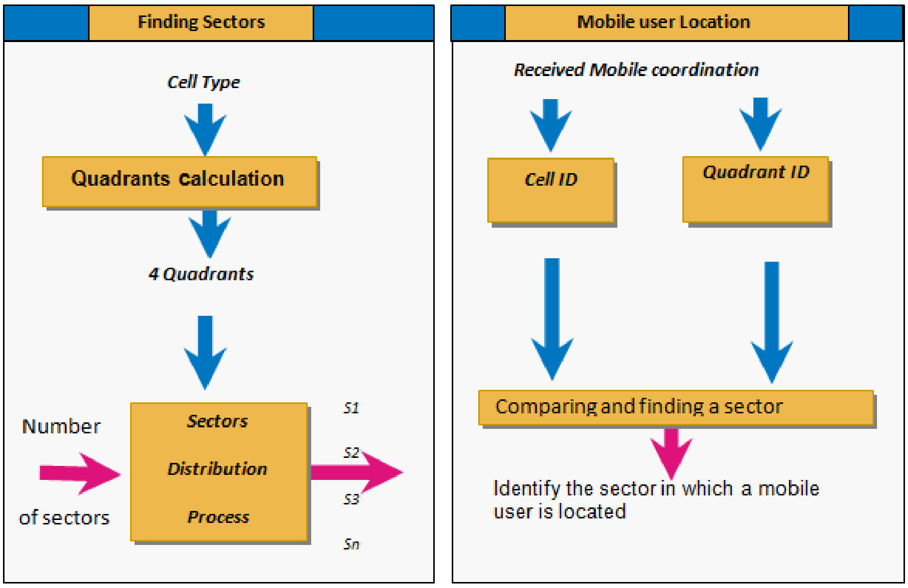

Figure 5.2: Flow Processes for Cell Splitting Algorithm.

lation, where the quadrant division depends on the angle path. The four quadrants will be processed in the same way, where each quadrant is divided into uniform sectors. The output is a set of sectors representing the cell network in a different way. Based on MU coordination, the cell and quadrant identification within which an MU is located will be found. Whereas, to identify the sector where the MU is located depends on comparing operations between all the sectors that are generated to a certain cell. Section 4.3.2 discusses the steps to find a sector. For convenience and timing, the NCPA splitting algorithm was divided into two programs, as listed below.

1. **CellSplitting.java** (see Appendix C.1 for source code)
   CellSplitting is responsible for splitting a cell based on the cell type and the size of each sector.

2. **FindingMobileUser.java** (see Appendix C.2 for source code)
   FindingMobileUser is based on the MU's coordination and the sector where the MU is located will be determined.

5.4.2 Implementation of Markov Model

MCM is used to provide mobility prediction for an MU at the cell level for a cellular communications network and, more precisely, for the UMTS network. The Developed Mobility Prediction Technique is a Location Prediction based on a Sector Snapshot (LPSS), which relies on the cell splitting algorithm. Figure 5.3 illustrates the MCM prediction processes.

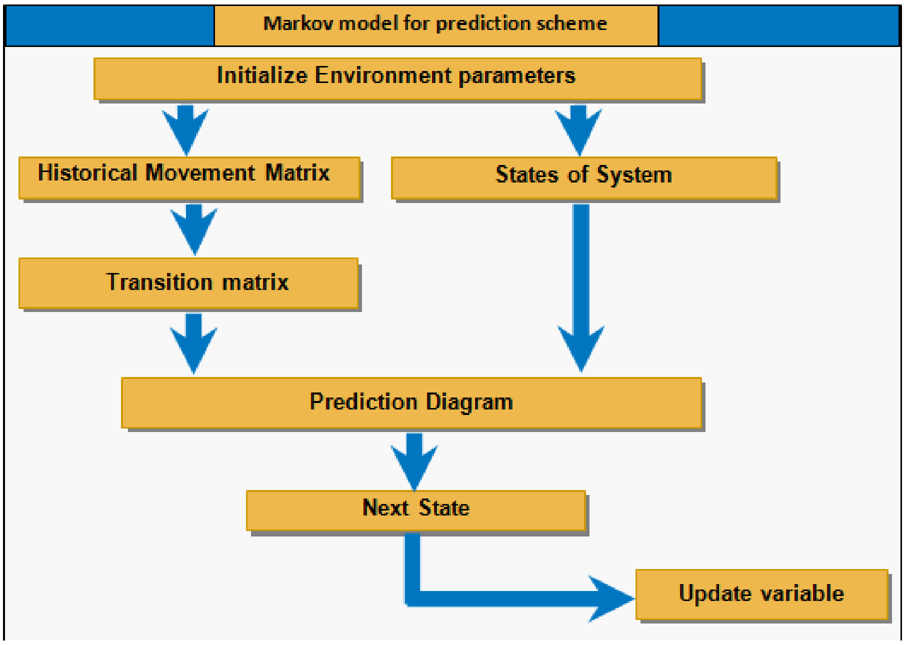

Figure 5.3: Functions Processes for MCM Prediction Technique.

To initialise the environmental parameters is an important phase in simulation, such as splitting cells, length of matrixes and system states. However, all parameters had been initialised before the simulation began. When the execution starts, the information about the sectors are stored in the database by the historical movement matrix built from neighbours, which is handled to generate transition matrix. Meanwhile, all the probabilities that may face the MU are processed by system states. This information is stored in a database. The potential, and most desirable, sector where the MU will go is offered by a prediction diagram. Finally, this allows keeping the variables up-to-date.

For convenience and timing, the MCM prediction process was divided into three programs as listed below.

1. **FillMobileTracking.java** (see Appendix D.1 for source code)

   FillMobileTracking is responsible for filling the historical matrix. It is generated from MU movements.

2. **ReducingProbabilty.java** (see D.2 for source code)

   ReducingProbabilty is responsible for generating transition matrices.

3. **Prediction.java** (see Appendix D.3 for source code)

   Prediction contains the methods that are responsible for predicting a next displacement for the MU at the cell level, for updating environment parameters and for system state.

5.4.3 Implementation of the Developed ACO Optimisation

The introduced routing area mobility prediction NRADP is based on developed ACO. To implement the developed ACO for mobility prediction, the parameters management is the core issue that must be addressed to improve the prediction success rate and avoid the bias for exceptional cases. Pheromone parameter is important to avoid the search stagnation problem. The search focuses on the early stage of the algorithm running. Furthermore, visibility is responsible to describe the MU's behaviour to their neighbours. That mean keeping up-to-date with MU's behaviour. The visibility parameter is processed in a certain way to discard old memorisations. Figure 5.4 illustrates developed ACO prediction processes.

For convenience and timing, developed ACO process was divided into six programs, listed below.

1. **VariableManipulation.java** (see Appendix E.1 for source code)

   VariableManipulation shows a set of variables required to program developed ACO and basic initialisation of parameters.

2. **initialPheromone.java** (see Appendix E.2 for source code)

   initialPheromone is responsible for initialising the pheromone for each RA.

3. **ProcessingPheromone.java** (see Appendix E.3 for source code)

   ProcessingPheromone is responsible for managing pheromone updating

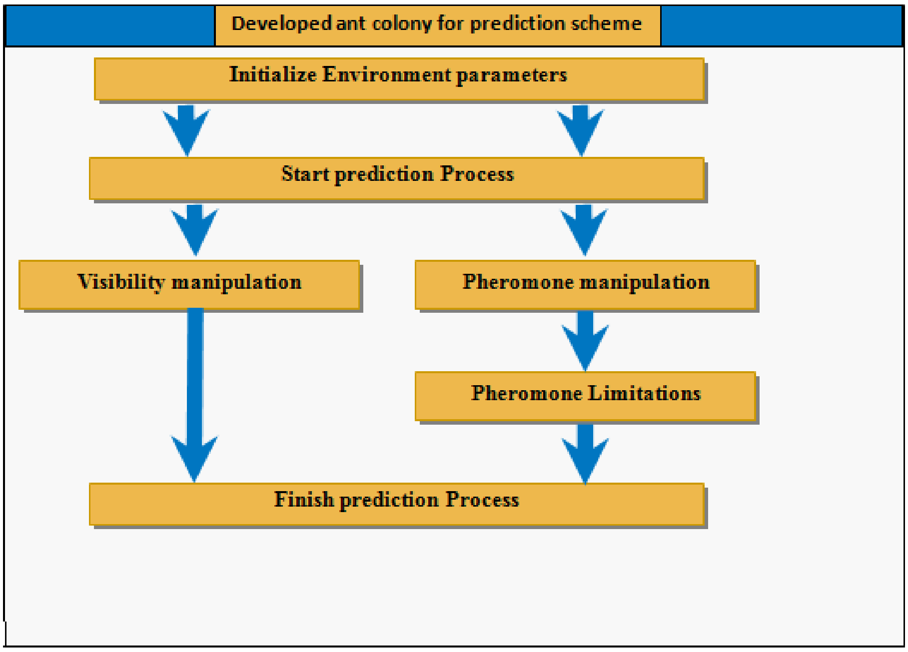

Figure 5.4: Functions Processes for Developed ACO Prediction Technique.

during the running of the algorithm.

4. **LInitialVisibility.java** (see Appendix E.4 for source code)
   LInitialVisibility is responsible for initialisation of the local visibility.

5. **GInitialVisibility.java** (see Appendix E.5 for source code)
   GInitialVisibility is responsible for initialisation of the local visibility.

6. **UpdateVisibility.java** (see Appendix E.6 for source code)
   UpdateVisibility presents the effectiveness of local and global visibility in prediction, and the processing to update the visibility.

5.5 Simulation Design

The simulation in this thesis was executed ten times. The results of the ten simulations were then averaged to obtain consistent results and reach a steady state not influenced by short term differences. The simulation included the input simulation parameters mentioned in table 5.1 and other parameters mentioned in chapter 6.

5.5.1 Component of Simulation Model

The UMTS model is based on a Third Generation Partnership Project (3GPP) release 1999 standard. Figure 5.5 shows the simulation model used in this research. The model is based on the UMTS system architecture, as shown in figure 5.6.

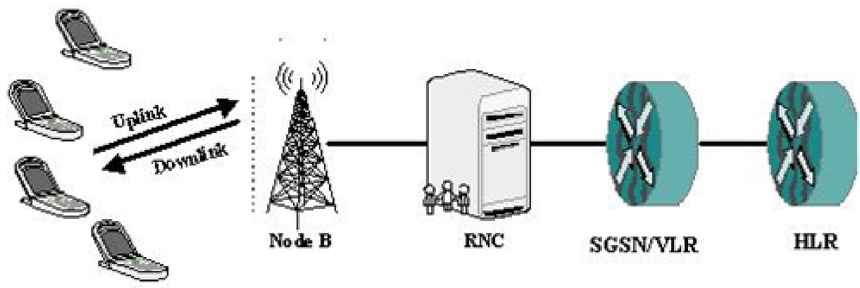

Figure 5.5: Simulation Model.

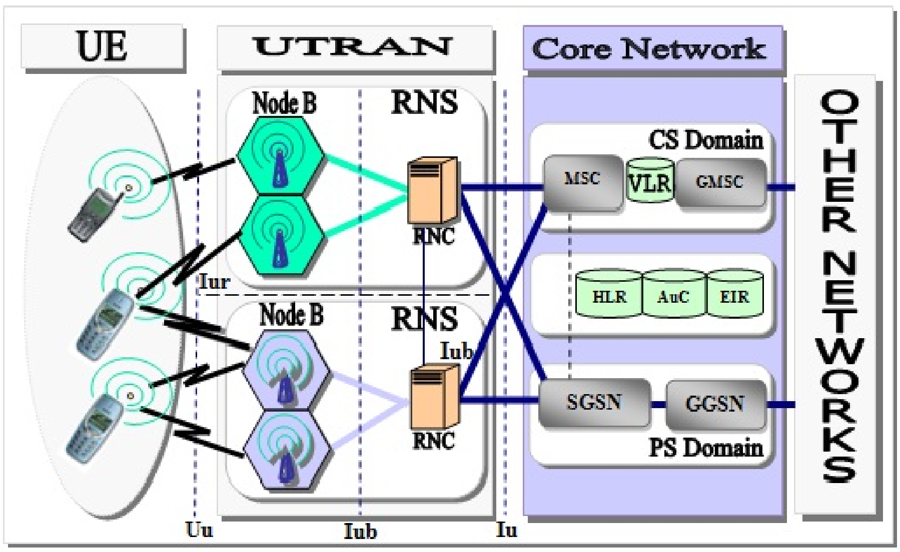

Figure 5.6: The UMTS Model Architecture.

The flow control and logical relationships between the components of the simulation model are shown in Figure 5.7:

The following subsections discuss the components of the simulation model that are used in the simulation scenarios.

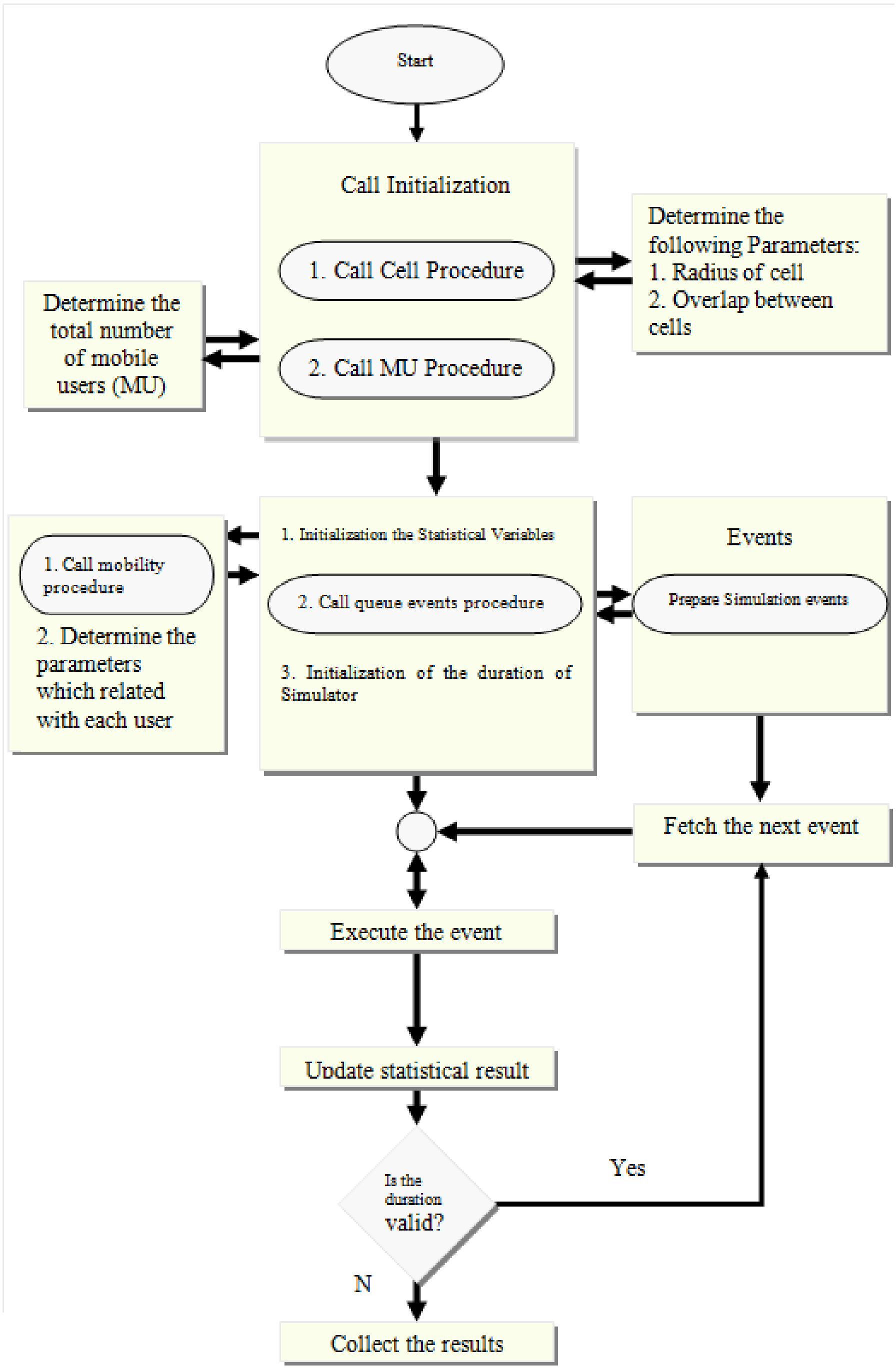

Figure 5.7: Logical Relationship between the Simulation Model Components.

5.5.2 Configuration and Creation of RNC Node

Radio Network Controller (RNC) is the first node created in the UMTS model. Taking mobility into consideration, each cell was linked to an RNC. Therefore, each RNC is responsible for one or more cells and controls their radio resources. Each RNC node has an address (ID) which must be set before creating a RNC node.

5.5.3 Configuration and Creation of Cell Node

The cell node is the second node created in the simulation. The parameters that are set in the beginning of creating the cell node are as follows:

1. Number of cells.
2. Determining the coordinators (x-axis and y-axis) for each cell.
3. Determining the radius (R) for signals to define the coverage area for each cell.
4. The ID of RNC to which RNC cell belongs.

By the consideration of mobility, the number of cells relies on the total area of the simulator. Therefore, another parameter will be the number of cells required. Furthermore, in this simulator the cell works as a BS. The BSs are portioned into RA. The RA of an MU is tracked by the Core Network (CN), i.e. by the GPRS Service Node (SGSN). See Appendix B.1 and B.2 for source code.

5.5.4 Configuration and Creation of MU Node

It is evident from figure 5.6 that there are two MUs. The first MU belongs to the first RNC, which has two cells. The second MU belongs to the second RNC, which also includes two cells. The cell and RNC must be determined when the MU is created (i.e. which cell and RNC the MU belongs to).

5.5.5 Configuration and Creation of VLR/SGSN Node

The fourth node created in simulation is Visitor Location Register (VLR) / SGSN. Each VLR/SGSN node has an address as the identity (ID), and the identity which the serving network belongs to. A set of VLR nodes was created and then portioned into two groups for the purpose of mobility. Each group belongs to a network called a home network for that node.

5.5.6 Configuration and Creation of GGSN/HLR Node

The fifth node created in simulation is GGSN. It contains Home Location Register (HLR). Each HLR node has an address (ID) which must be set before creating a VLR/SGSN node. Each network has one HLR node.

5.6 Simulation Parameters Setup and Environment

A simulator was created using Java programming language, see figure 5.8, a visual representation for the simulation. The movement is recorded to train the program to learn how the MU moves during different trips. Different samples of data are used to test the performance of the developed techniques.

In this research the parameters setting are classified into two categories:

1. Cellular communication network parameters, (see section 5.6.1 for more details).

2. The developed ACO parameters, (see section 5.6.2 for more details).

The cellular communications network parameters settings are determined before the simulation begins, whereas the developed prediction technique enhancements have not been affected.

5.6.1 Cellular Network Parameters

The input parameters of the simulation environment are shown in table 5.1. There are more relevant parameters which are described in chapter 6 for simulation analysis. To simulate a cellular network, the simulation needs to be done over a very

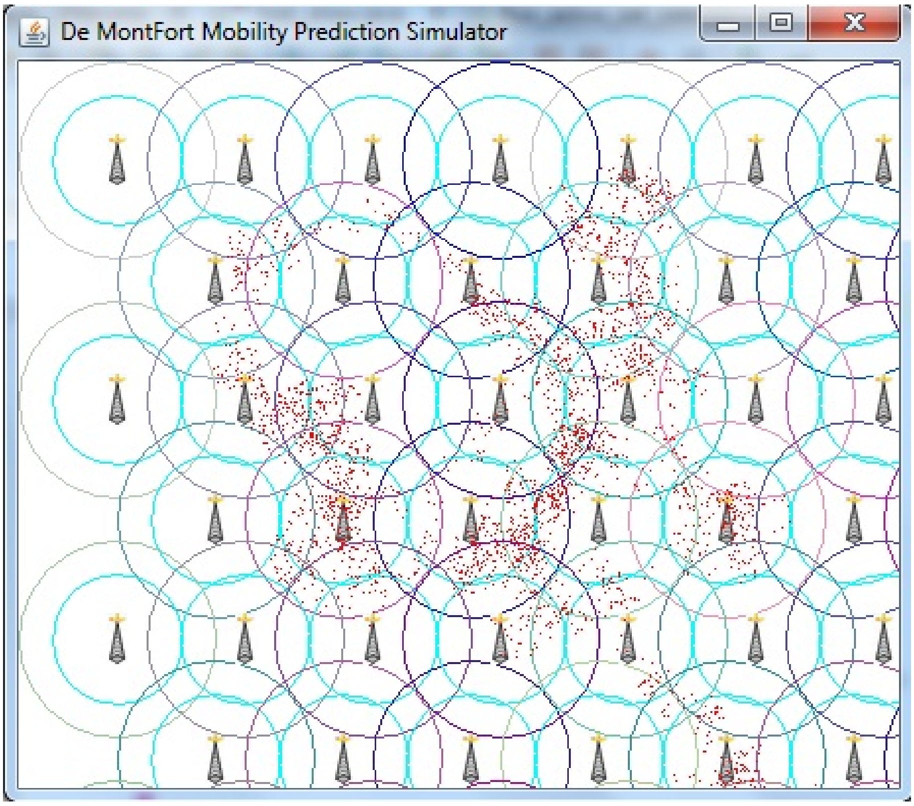

Figure 5.8: A Snapshot for the Simulator.

large coverage area. That is why the parameter setting is set using the parameter assumption, as described in previous researches and standardised over 3GPP specification- no extra hardware is required- [177–179], as shown in table 5.1. The various user environments will affect the quality of communication based on the user environment requirements [125, 180]. The parameters are configured as shown in table 5.1.

5.6.2 Developed ACO Parameters

This section discusses the parameters that influence the prediction success rate of the developed ACO, where the parameters need to be setup before the RA mobility prediction simulation began.

A range for each parameter is defined and this generates different parameter combinations. The developed ACO is executed according to these combinations. The process of obtaining the optimal parameters lasted for several weeks. The

Table 5.1: Input Simulation Parameters.

Parameter	**Value**
User Environment (Parameter setting)	
Velocity of MU	
Slow Pedestrian	5.6 k/h
Fast Pedestrian	11.2 k/h
Slow Vehicle	44.8 k/h
Fast Vehicle	89.6 k/h
Call origination rates	1.4, 2.8, 5.6 call/h/user
Cell-Base Station (BS)- or Node B Parameter	
Number of cells	100
Radius of a cell	250 m
Antenna type	Omnidirectional Antennas
Buffer size	3.75 MB
delay time between sent packets	10 ms
Transmission Rate of HSDPA	up to 10 Mbps
Downlink Bandwidth	32 kbps (Kilo bit/Sec)
Uplink Bandwidth	32 kbps
Interface (Link) Between RNC and Node B	
Downlink Bandwidth	622 Mbit/sec
Uplink Bandwidth	622 Mbit/sec
Downlink Delay	15 ms
Uplink Delay	15 ms
Queue Size	2000 byte
Link Between RNC and Core Network (SGSN, GGSN)	
Bandwidth	622 Mbit/sec
Delay	0.4 ms
Queue Size	1000 byte

optimisation used the CRAWDAD's dataset which is verified by the authors [181]. The same dataset is also used in evaluating the NRADP. The dataset is discussed in section 5.9.

The experiments in this section were made to obtain the optimal value for each parameter. The parameters were tested to evaluate the RA mobility prediction technique, which include: Parameter-1: the factor which affects the evaporation rate. Parameter-2: the quantity of the initial pheromone that would be laid on each RA. Parameter-3: the quantity of the pheromone that would be laid by each MU over time. Parameter-4: calculating the participation success rate of the local visibility compared with global visibility. Parameters-5: determining the effectiveness ratio between pheromone and visibility, represented by α and β.

For parameter 1, the prediction success rate is tested over varied evaporation rates. Figure 5.9 shows the prediction success rate percentage over the change on factor ρ. The experiments were carried out on a range of ρ between [0, 1], where its increment was moved up by 0.1. From the experiments the prediction success rate was varied from 46.11 to 71.67. The highest prediction success rate was achieved when the value of ρ was between 0.6 and 0.8, in this range the value of ρ was large enough to evaporate the pheromone highly. For high evaporation rate, the old history of MUs would be forgotten from the RA and new displacements for an MU and his/her neighbours were obtained. Therefore the RA's history was more likely to be valid. However, the prediction rates were 71.39 and 70.83 when the value of ρ was between 0.9 and 1, respectively. That means the prediction success rate went down when ρ was rear or equal to 1, since the large value of ρ stimulates RAs to delete newer and valid history and displacements.

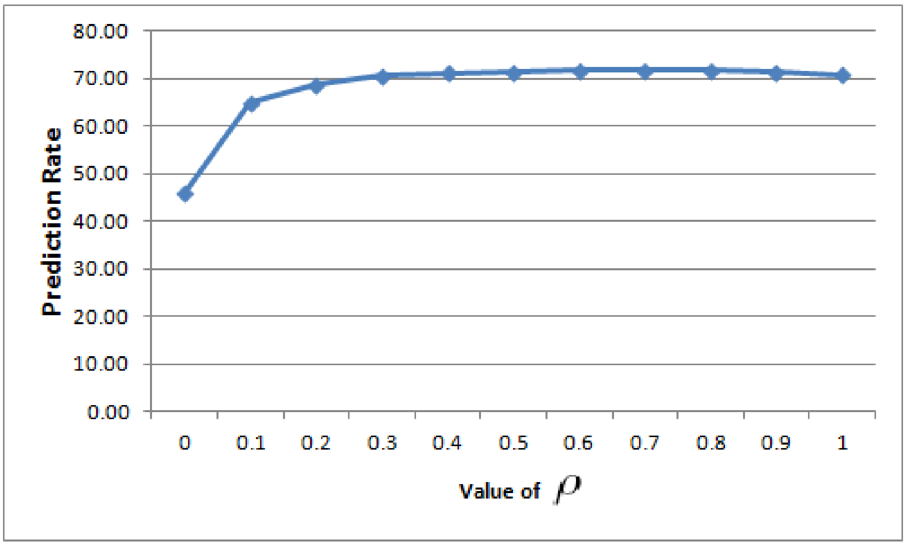

Figure 5.9: Prediction Success Rate According to the Different Values of ρ.

Using ρ between 0 and 0.5 decreased the prediction rates comparing to the use of ρ between 0.6 and 0.8, because using a small value of ρ would decrease the evaporation rate considerably. Therefore RAs would accumulate more histories and old displacements, making all the information in RAs out-of-date.

Figure 5.9 depicts the optimal values of ρ were between 0.6 and 0.8, where the highest prediction rates were achieved over the change to ρ. These values encouraged the RA Developed Mobility Prediction Technique to avoid search stagnation, finding new solutions and prevent the deletion of any new solution.

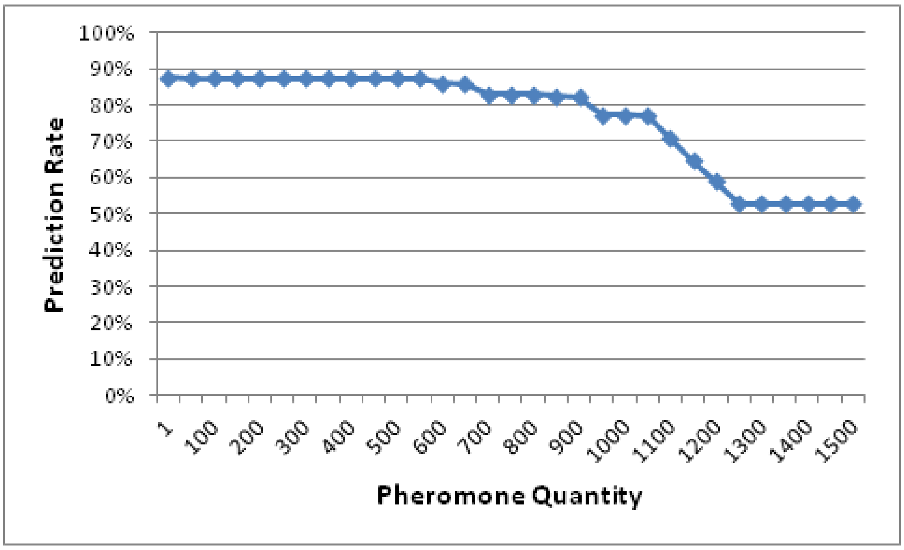

Figure 5.10: Prediction Success Rate Over Varied Initial Pheromone Quantities.

For parameter 2, the prediction success rate over varied initial pheromone quantities is examined. Figure 5.10 describes the initial pheromone quantity that would be laid down on each RA before starting the running of the technique. The prediction rates between 53% and %88 over varied amounts of pheromone quantity. The highest prediction success rate was 88 when the amounts of pheromone were setup to 1. As a result the best amount of pheromone to be laid down was 1 unit. The use of small amounts of initial pheromone would save computation costs. To show the effectiveness of pheromone quantity that will lay down during the running of the algorithm, the next parameter is addressed.

For parameter 3, explains the prediction success rate changing compared to the pheromone quantity that will be laid. Figure 5.11 and table 5.2 show the prediction

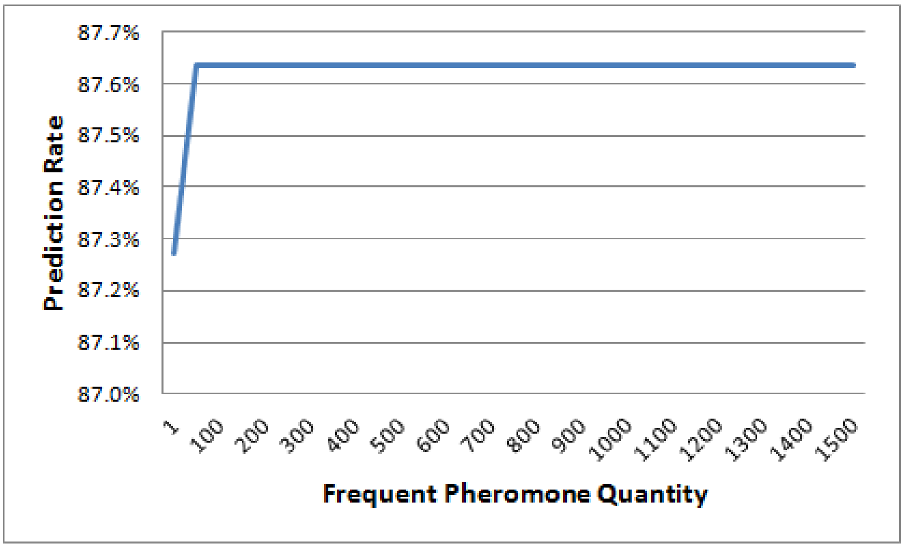

Figure 5.11: Prediction Success Rate Over Varied Frequent Pheromone Quantities.

Table 5.2: Prediction Success Rate for Frequent Pheromones.

Pheromones	Prediction success rate
1	87.3%
100	87.6%
200	87.6%
300	87.6%
.	87.6%
.	87.6%
.	87.6%
.	87.6%
1500	87.6%

rates over the change of pheromone amount that would be laid down by each MU, using 1 unit of pheromone resulted in a 87.3 prediction rate, the more pheromone units to be added, the caused prediction rates increases slightly in this manner. This increase continues until reaching 50 units. At this point the prediction success rate became flat at 87.65. So any further increment of the pheromone amount would have no effect on the prediction rate. Therefore, the optimal value for the pheromone amount would be 50 units addressing the best prediction success rate possible.

For parameter 4, the significant combination of local and global visibility for the MU is validated. Figure 5.12 shows the prediction success rate according to the changing between local and global visibility participations. Based on equation 4.13 two values should be avoided in order to utilise these two concepts, namely 0 and 1.

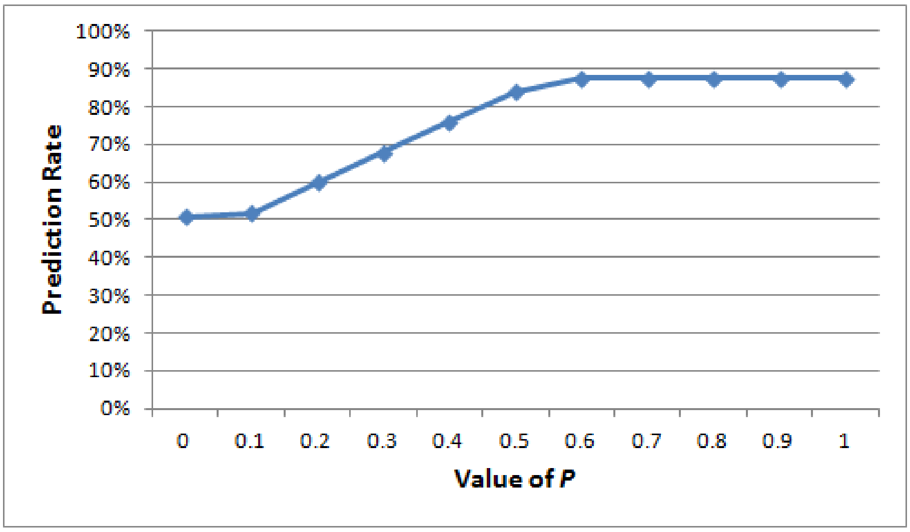

Figure 5.12: Prediction Success Rate According to the Changing Values of P.

When the value of P equals zero, the local visibility would be eliminated. This means the RA will use the neighbours' heuristic information to predict the next displacement for an MU. Thus, the MU cannot visit any of its favourite RA. In other words, the MU displacements would be predicted randomly.

On the other hand, the global visibility would be deleted from equation 4.13 when using one as value of P. For example, when an MU located in an RA which does not contain any local visibility related to this MU, the next displacement would be based on its local visibility. Discovering new RAs based on pheromone, it has a low possibility of discovering any new RA that has never been visited before. Hence, the balancing between local and global visibility should be addressed as a significant parameter for the mobility prediction technique.

To achieve balancing between local and global visibility, P was set to 0.6. This value guarantees full participation of both local and global visibility, as well as obtaining a better prediction rate. See figure 5.12 and table 5.3.

For parameter 5, the prediction success rate is tested over a varied distance

Table 5.3: Prediction Success Rate Over Varied Values of P

Value of P	Prediction success rate
0.1	52%
0.2	60%
0.3	68%
0.4	76%
0.5	84%
0.6	88%
0.7	88%
0.8	88%
0.9	88%

between alpha and beta. Figure 5.13 shows the effect that resulted from varying the values of alpha and beta in order to determine the best values to gain the highest prediction rate. As shown in figure 5.13, it was noticed that when both Alpha and Beta were equalled, the prediction success rate was highest. Therefore, both Alpha and Beta are going to be chosen according to the results. That is, the values of Alpha should be chosen to be equal to values of Beta to achieve better prediction rates.

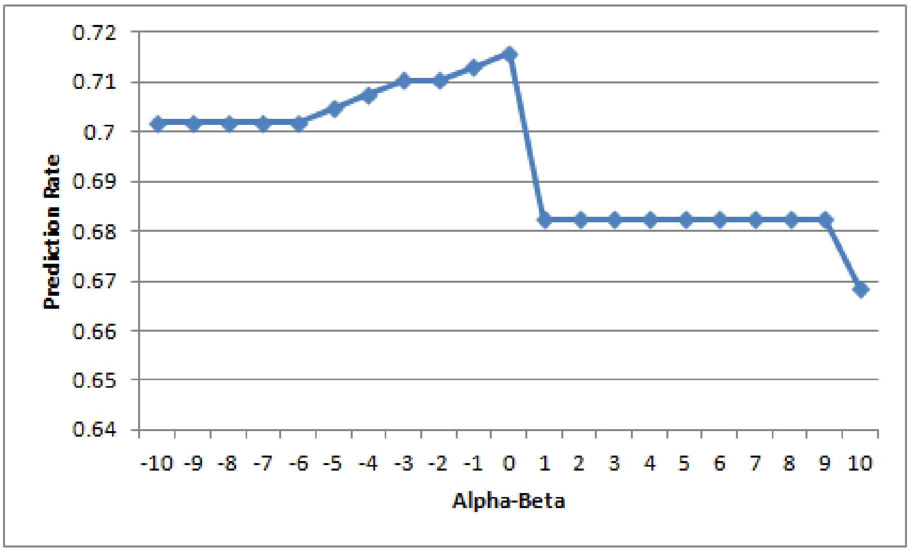

Figure 5.13: Prediction Success Rate According to the Varied Alpha-Beta.

After this discussion for determining which value has the greater effect on the prediction rate. It is noticed that the Alpha with equal value to Beta making the pheromone weight over the visibility weight shown the better prediction. Thus, the optimal prediction success rate was almost 72% when using Alpha values equal to the Beta values.

5.7 Simulation Model

The simulations were done over Pentium IV computers with 2 GB RAM and CPU speed of 3 GHz. The operating system used was Windows XP, where the LAN speed was 100 Mbps.

For chapter 6, there were two simulation scenarios. The first scenario was built to examine LPSS for LBSs, which is based on NCPA to handle different cell types. The LPSS model was simulated to calculate the prediction success rate and the cost per unit of time for MUs with different mobility for each requested ratio.

In this scenario, the cellular communications network consisted of 100 cells. The number of cells in the simulated experiments varies between one, two, three, five, fifty and one hundred cells with a fixed radius of 250m each (micro cell).

A sectoring antenna is used in cellular communications network cells that cover only part of BS's area. Three sectoring antennas are often used to cover and present one cell, each sector has a ray width of 120 degrees. The sectoring antenna is beyond the scope of this thesis. Although, the introduced NCPA algorithm is not affected, it is based on virtual splitting of its cell. In this research Omni antennas; namely, Omnidirectional antennas are used to cover all the area around a BS and GPS service is used to obtain the MU's location.

The movement with different speeds - slow pedestrian speed, fast pedestrian, slow vehicle and fast vehicle with measures of 5.6 km/h, 11.2km/h, 44.8km/h and 89.6km/h respectively - was recorded to train the program to learn how the MU moves during different trips. Different samples of data were used to test the performance of the LPSS. In addition, the pause time for each movement lasts for 20 seconds or so. The transmission rate is about 8 Mbps. Those parameters include the keys applied by the simulator for 1800 seconds. Each experiment consisted of 10 different iterations to improve accuracy. Each experiment took five hours. In this design, in addition to the input parameters which were shown in table 5.1, the following assumptions were used:

1. **Network modelling :** Cellular Communications Network-Based Solutions for finding location is used as that in [182]. Each cell has a unique identifier determined by its x and y coordinates. Numbering starts from the centre cell and expands radially across the entire network.

2. **Request service modelling :** Services arrive for MUs according to a Poisson distribution with mean m=1 per unit of time.

3. **Mobility modelling:** Mobility modelling: The Way-Point mobility is used, where the simulation model implements the MUs' cell residence time with a Poisson distribution with mean r , where r is a discrete exponential variable that can take on value *0, 1, 2, ...* . The MU's displacement in small resolution is described by a degree of randomness [15].

4. **Initial position :** The initial position for an MU is chosen randomly where they belong in a coverage area of the network.

5. **Time delaying :** The time delay to message exchange between databases is constant and assumed to be 1 ms.

6. **Cycling :** The cycle time for the MU is 10 *ms.*

The second scenario examined the prediction success rate, delay time, search stagnation and memory usage for NRADP which is based on developed ACO algorithm for LBSs. Chapter 6 analyses more performance metrics. In addition to the input parameters shown in table 5.1, this scenario used five more assumptions are summarised as follows:

1. There is one GGSN including 46 RAs.

2. The number of MUs in the mobile network under investigation varied from 1 to 10, according to the scenario.

3. The MU resides in a different RA during the simulation.

4. An RA is formed of two cells.

5. The real dataset is used which was prepared by CRAWDAD. See section 5.9 for more details.

5.8 Performance Metrics

Performance metrics measure the actual outcomes of the developed prediction techniques for a cellular communications network. The proper measurement of these metrics is a precondition for evaluation of a cellular communications network's performance or judgment of performance using different prediction techniques. The following metrics are considered in this thesis:

5.8.1 Prediction Success Rate

The prediction success rate is the ratio between the number of correct predictions and the total number of predictions [16].

5.8.2 Memory Usage

The memory usage is defined as the amount of memory allocated to execute a certain command. The deniability of services over the cellular communications network can be reduced by the reduction of memory usage that can be achieved.

5.8.3 Execution Time

The execution time is the length of time needed to execute a certain command. Reducing the execution time by the developed technique can lead to reducing the delay time between the request and delivery services.

5.8.4 Search Stagnation

The search focuses on the early stage of the algorithm running. That means no area would be discovered in the future, because all ants follow the path that is generated before with the highest density of pheromone.

5.8.5 Prediction Overhead

A cellular communications network's prediction overhead is a ratio of bits that are utilised in the components of the network by using the developed techniques. Bits represent control and management bits that have been used to serve techniques.

5.8.6 Delay Time

The delay time is the average time period required between requesting and delivering a service for an MU during the simulation running. The MUs that go out of coverage area or switched off are not included in this metric.

5.9 DataSet

A dataset is a collection of data (observations) presented in a tabular form. Each column represents a particular variable. Each row corresponds to a given member of the dataset in question. Each value is known as a datum. The dataset is used to test the developed techniques to certain problems and whether these proposed solutions can approximate the reality or overcome current unsolved issues.

In the case of this research, a dataset that contains a trace of MU movements, where the logs contain cell information such as cell identification, RA identification, time staying, and visible cells. It is worth mentioning that in this dataset the Location Area (LA) used is equivalent to RA in UMTS. The dataset is gathered from 10 MUs' phones. This dataset was prepared by CRAWDAD and verified by the authors [181]. CRAWDAD is the community resource for archiving wireless data at Dartmouth [183].

5.10 Summary

In this chapter, the implementation used to examine NCPA and Developed Mobility Prediction Techniques have been described. The implementation software used to examine and compare the performance characteristics of the current techniques and Developed Mobility Prediction Techniques. Furthermore, the simulation approach that was used to examine the mobility prediction techniques for LBSs has been illustrated. The simulation tool used to create the scenarios engaged to simulate the cellular network was defined. The result collected by the simulation is quantitatively analysed to validate the performance of the developed techniques and compare their performance with the current techniques. Finally, the initial parameters used to perform the simulation are validated and analysed.

Chapter 6

Results Analysis and Discussion

The previous chapters in this research introduced mobility prediction techniques over UMTS for LBSs, and a Novel Cell Splitting Algorithm (NCPA) as well. Chapter 5 discussed simulation environment, parameters set up, and metrics that are used to measure the performance of the techniques developed compared to current techniques.

This chapter aims to evaluate, investigate and analyse the performance of the techniques developed. The chapter is divided into three main sections: section 6.1 presents the results that were collected from the simulator, where the NCPA complexity time and stability over different cell types are discussed. The LPSS technique is analysed based on the results that were gained from the experimental measurements. LPSS is also compared with the current mobility prediction techniques such as PLM and NMMP as described in section 6.2. Finally, section 6.3 shows an extensive evaluation of the performed analysis for NRADP according to the metrics that were defined in chapter 5. Some enhancements were suggested and the influences of such enhancements were evaluated experimentally. In addition, comparison with MPAS is offered.

6.1 NCPA Computation Performance Analysis

This section demonstrates the computation cost of NCPA in terms of splitting the network cells and finding the sector ID where the MU is located.

6.1.1 NCPA Splitting Network Cells Complexity

The results shown in this sub-section present only the performance of splitting the network's cells, taking into consideration the different cell types (Pico, Micro, Macro, and Rural). This splitting was preformed once before the mobility prediction scheme had begun. NCPA is a virtual splitting where closing roads under certain circumstances, such that an accident which could be caused by a human or natural being, would not affect the splitting. Effectiveness appears only when a new component is added to the cellular network. Specifically, when a new cell is added, the NCPA splitting is executed to resort the network structure according to the changes.

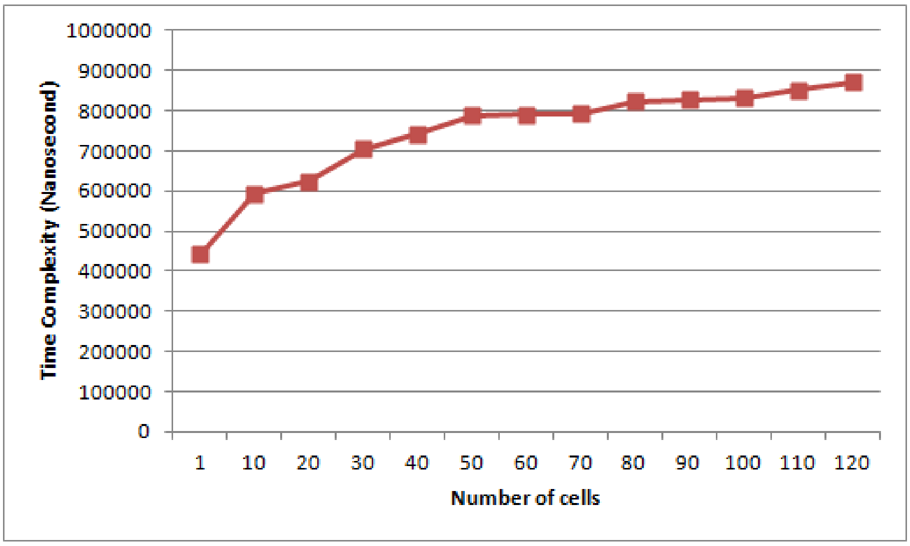

Figure 6.1: NCPA Time Complexity for Micro Cell Splitting.

Figure 6.1 shows the complexity time needed to split a cellular network, where the network includes up to 120 Micro cells. The y-axis represents the computation cost in nanosecond, and the x-axis shows varied numbers of cells from 1 to 120 cells. When the splitting was preformed to generate the sectors based on one cell, execution was 442041 ns. The execution time increased according to the increment in the number of cells. The highest execution time was obtained when 120 cells were used, where the execution time was 871290 ns.

The analysis was carried out to investigate the execution time for NCPA splitting over different cell types. Table 6.1 summarises the execution time that was needed to apply NCPA on Pico, Marco, and Rural cell. The execution times were 442041, 442041, 442041 ns for those cell types respectively. The execution time was 871290 ns when the type of cells was Pico and the number of cells was 120, the execution time needed for 120 Macro cells was 871290 ns, and it took 871290 ns of execution time for 120 Rural cells.

Table 6.1: NCPA Time Complexity Needed for Different Cell Types

Cells Number		Splitting Time (Nanosecond)		
	Pico	Micro	Macro	Rural
1	442041	442041	442041	442041
10	594126	594126	594126	594126
20	623974	623974	623974	623974
30	705939	705939	705939	705939
40	740999	740999	740999	740999
50	786957	786957	786957	786957
60	789799	789799	789799	789799
70	791694	791694	791694	791694
80	823438	823438	823438	823438
90	828176	828176	828176	828176
100	831018	831018	831018	831018
110	851391	851391	851391	851391
120	871290	871290	871290	871290

According to the previous discussion, figure 6.1 and table 6.1, NCPA would be considered more scalable. Low execution time is needed to split the all cells in a cellular network. In a sense, the complexity time is trivial as even the NCPA execution was applied before the mobility prediction scheme had begun the run. Thus, the NCPA splitting is worth using for all cell types. In the present research Micro cell was used and the next section investigates the complexity time for finding the MU in Micro cells.

6.1.2 NCPA Finding MU Location Complexity

This section discusses the results that were obtained from finding the location of the MU during their constant movements. Sub-section 4.3.2 introduced a new technique which uses the serving area as a sector instead of a cell, where a cell was considered the smallest service area in a cellular communications network. Based on NCPA splitting, the network is built up of sectors. Thus, the time for finding where the MU is located is an important factor to reduce the delay time in the constraint environment such as mobility prediction for LBSs.

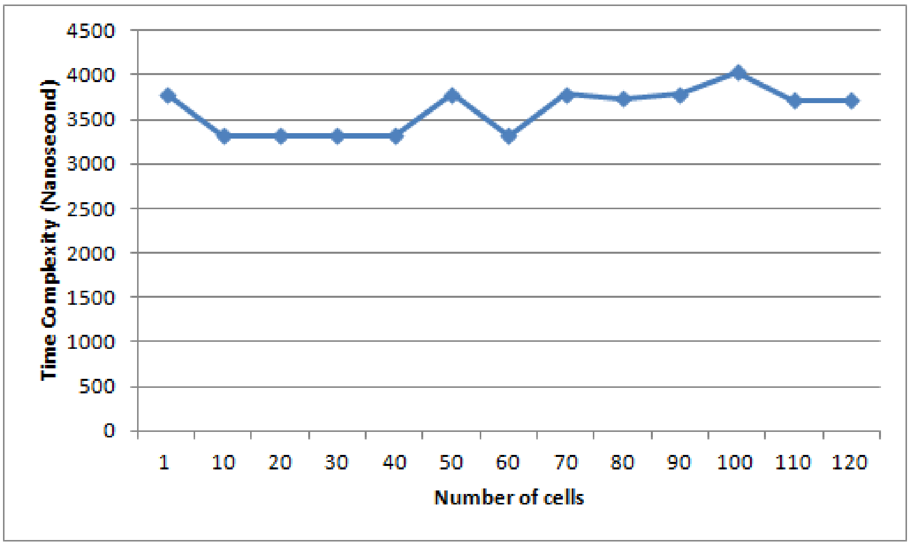

Figure 6.2: NCPA Time Complexity for Finding MU in Micro Cell Splitting.

Figure 6.2 shows the results of the experiments for the time needed to discover the location of MU. Again, the location here is a sector, the cellular network's size varied from one cell to 120 cells, and the execution time was measured in Nanosecond; the analysis showing changes in the execution time according to the varied networks' sizes.

Although a step more in the correct investigation direction, the above description is an important factor for mobility prediction to reduce computation cost because NCPA discovering MU algorithm was used during the prediction process. Thus, the time needed to process it was taken to be worthy of study.

The time that it took NCPA for discovery varied from 3316 ns to 4038 ns at its maximum. Figure 6.2 depicts a low irregularity in the execution time that refers

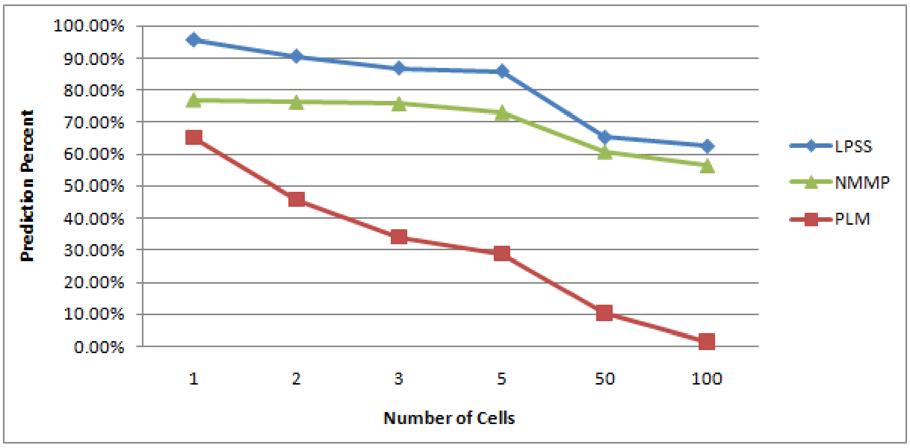

Figure 6.3: Prediction Performance for Sector Snapshot for Location-Based Services.

to the availability of resources on the machine during the experiments of NCPA execution. The execution time was measured in nanosecond which is a very precise unit and NCPA has used basic mathematic operations. The conclusion indicated that using NCPA will improve the performance of the common prediction techniques significantly.

6.2 LPSS Experiments and Result Analysis

Corresponding to the prediction performance analysis, phase of experiments were designed to evaluate the proposed technique which included: Phase-1: experiments to evaluate the prediction accuracy, which is the ratio between the number of correct predictions and the total number of predictions [81]. Phase-2: experiments to evaluate the memory usage reduction. Phase-3: experiments to evaluate the execution time. Phase-4: experiments to evaluate the prediction success rate over time.

In phase 1, the performance of the LPSS is compared with both NMMP and PLM techniques in terms of prediction accuracy rate. Figure 6.3 shows that LPSS improved the prediction success rate compared with both NMMP and PLM. This improvement is due to the nature of the mobility pattern in which the MU travels into a series of predicted cells and the changing number of cells visited within a trip. This conclusion is generally valid, though the improvement may differ with a different set of assumptions.

Figure 6.3 shows that the percentage of correct predictions in the LPSS is more than 95.61%, as the MU moves through one cell, compared with 76.98% and 65.13% in NMMP and PLM techniques respectively. An increase in the number of cells leads to a decrease in the correct prediction success rate in both techniques. The explanation for the achieved results caan be stated as follows: when the MU moves over more than one cell, the end trip can be reached from different routes, through different cells due to the size of the cells. So, such prediction will be low. On the other hand, in one cell, the movement of the MU in the LPSS is kept within bounds of the sectors within the same cell. So, when the MU leaves the sector and goes to a neighbouring sector, they are is still within a relatively small area. Thus, the prediction percentage logically increases. In the NMMP technique, the number of selection choices is larger than LPSS, which decreases the accuracy of the right next displacement for MU. On another hand, while using the PLM technique, the movement of the MU within one cell will involve many intersections in different routes.

Table 6.2: Prediction Success Rate for LPSS, NMMP, and PLM

Number of Cells	LPSS	NMMP	PLM
1	95.61%	76.98%	65.13%
2	90.54%	76.27%	45.90%
3	86.85%	75.80%	34.05%
5	85.87%	73.13%	28.84%
50	65.38%	60.89%	10.34%
100	62.58%	56.45%	1.50%
Prediction success rate average	81.1365%	69.92%	30.96%

Moreover, in two cells a natural decrease in the prediction rate is shown since the number of decision points increased due to the area covered, as mentioned in the previous paragraph. So this decrease ratio in the prediction rate will be almost the same up to five cells. Sine, each cell has a circular shape with a radius of approximately 250 m. Therefore, the area of each cell approximately equals 0.2 km^2

and the area of five cells equals 1 km^2. LPSS shows a high correct prediction success rate in areas whose size is approximately five cells. In practice, this area is sufficient for users' activities in urban areas as it is a typical size for a city centre, university campus or small town.

Furthermore, in order to show more behaviour of the techniques on higher resolution, the cells are increased from five up to fifty cells. This shows a dramatic decrease in the prediction rate since both area and the number of decision points are increased as shown in figure 6.3.

It is acknowledged that the knowledge of the next location of a given user's movement is considered as an important factor for mobility prediction. This fact is satisfied more by LPSS than either NMMP or PLM in high resolution behaviour. Table 6.2 summarizes this satisfaction by presenting the overall average correct prediction rate for LPSS, NMMP, and PLM.

In phase 2, the importance of the memory usage reduction is utilised. To test the effectiveness of the memory usage reduction, different numbers of cells for the coverage area were studied. The average of memory usage in each technique is used to test the memory reduction. The LPSS technique requires 14.65 kB for space storage while NMMP and PLM require 27.77 kB and 121.91 kB respectively.

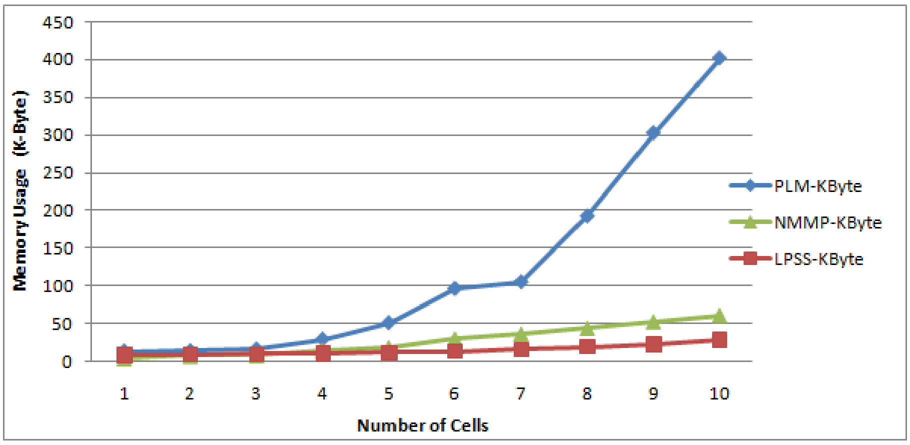

Figure 6.4: Memory Usage for LPSS, NMMP and PLM.

Figure 6.4 illustrates the differences in total memory usage among the LPSS, NMMP and the PLM techniques. In comparison with the different techniques, the proposed LPSS technique performs better in reducing the memory usage. This conclusion is generally valid, though the improvement may differ with a different set of assumptions. This improvement is due to the division of the cell into a set of sectors, where each sector acts as a serving region that retrieves the information related to that sector only.

The irregularity in PLM is caused by the concept of using the road segments which could be affected by closing roads under certain circumstances, such that an accident which could be caused by a human or animal and such factor as road jams. All the while, such problems can be seen neither from NMMP nor LPSS, since NMMP depends on the cell and the LPSS depends on sector of the cell.

Furthermore, the mobility pattern can be used. With it the MU travels into a series of predicted cells and changes the number of cells that were visited within a trip. It is noted that whenever the number of cells is increased, the memory usage will be increased. This is due to the fact that whenever more cells are used, more computation and memory will be used. This fact will be discussed in Phase 3. In conclusion, the mobility pattern factor considers the other factors that may reduce the memory usage.

In phase 3, the execution time is studied in all three different techniques: LPSS, NMMP, and PLM. Figure 6.5 shows the results of the three techniques in terms of execution time using the same method that was used in both phases 1 and 2, with a variation in the number of cells from 1 to 10.

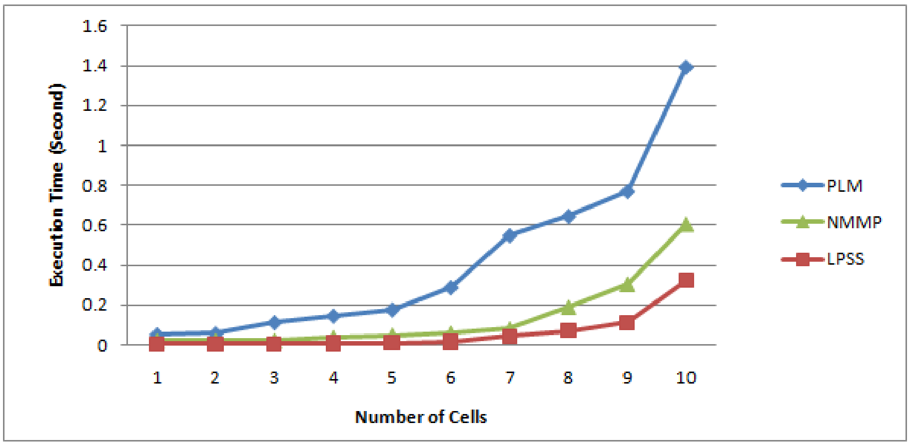

Figure 6.5: The Execution Time for LPSS, NMMP and PLM.

In comparison of the execution of the three techniques, the execution time for the proposed LPSS technique performs better. Figure 6.5 summarises the results of the LPSS execution time compared to the results of the NMMP and PLM execution times.

The LPSS technique outperforms both NMMP and PLM in every number of cells, but this is especially apparent when the number of cells increases. For example, when the number of cells is 1, LPSS technique requires about 4.22 ms, while NMMP and PLM techniques require 20.89 ms and 52.97 ms respectively. When the number of cells increases to 10, LPSS requires only 0.322 s, while NMMP and PLM require about 0.602 and 1.39 s respectively.

The mechanism of the LPSS technique depends on the virtual splitting of the cell into sectors. This virtual splitting does not affect the built-in database and structures when there is change in the physical serviced sector. Rather, the PLM acts as a “roundabout”. The real change in intersections between roads and physical features lead to costs for updating the database and structures, which are related to the user predictions. Also, the NMMP technique works on the whole cell area as a unit without splitting it, which leads to using manual filtering. This is done because a huge amount of data/information is delivered to the MU. Hence, the three techniques were designed to serve over low area resolution. As seen in Figure 6.5, expanding the resolution gives an increase of execution time for the techniques.

Furthermore, PLM has a large number of possibilities when a user wants to decide the next road. So, the user faces a larger number of possibilities than in the LPSS technique. The nature of the NMMP prediction technique depends on two levels of prediction as described earlier, which lead to more possibilities compared to the LPSS technique.

Finally, the overall number of possibilities in both the NMMP and the PLM techniques is larger than the possibilities in the LPSS, which decreases the correct prediction percentage and increases the execution time.

To complete phase 4, the prediction behaviour over period of time is considered one of the important factors in improving the prediction mechanism. The outcome of this behaviour provides a good measure for the robustness of the mechanism from the MU’s side. This is in addition to the ability to deal with challenges such as visiting a new location that has never been visited before, and utilising MU neighbours' behaviour. Figure 6.6 shows a description for the prediction success rate variations over a period of 180 days.

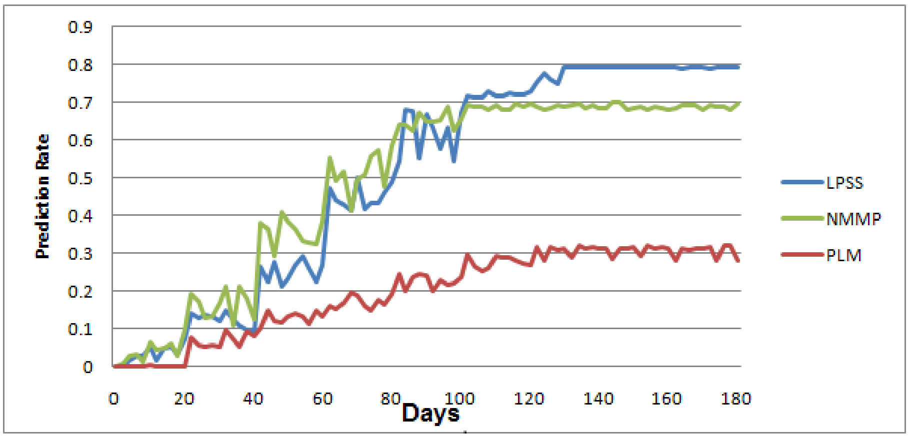

Figure 6.6: Prediction Success Rate According to Time for LPSS, NMMP and PLM.

At this point, two factors are needed to be considered: the robustness and the variation of the prediction success rate when the algorithm reaches the steady state. Moreover, there is a very tight relation between those two factors in of the sense that whenever the variation of the prediction success rate increases, the robustness will decrease, and vice versa.

The irregularity shown in figure 6.6 for all the techniques is caused from using the Random Way Mobility Model over low resolution. Moreover, LPSS reached steady state after 130 days although NMMP reached it after 100 days. This can be explained in the sense that NMMP has serving area as a cell which makes the decision point based on that cell while LPSS depends on a sector of a cell. The number of mobile users in the cell is greater than the sector which would make building the knowledge in a cell faster than building it in a sector.

Additionally, both NMMP and PLM are working with different procedures that depend on combination of two levels of prediction and road segments respectively, leading to prediction states that have never been handled before. This is in addition to what is noticed in figure 6.6 where there are very clear regressions after reaching the steady state by both mechanisms. The proposed LPSS mechanism is working on one level only. This contrasts with NMMP working on two levels, while PLM depends on making an extensive number of divisions, as shown in table 6.3. Table 6.3 which summarises the nature of LPSS, NMMP and PLM.

Table 6.3: Nature of Techniques for LPSS, NMMP, and PLM

	LPSS	NMMP	PLM
Number of Levels	1	2	1
Size of Divisions	Medium	Largest	Lowest
Serving Area	Sector	Cell	Raod segements

In this analysis, the performance was evaluated by adopting an evaluation methodology to gauge the impact of the enhancement technique on the accuracy prediction, memory usage, complexity cost, and prediction success rate over time.

6.3 Analysis of NRADP

This section describes the NRADP technique, walking through its details and phases. NRADP was introduced based on the developed ACO.

Corresponding to the prediction performance analysis, a phase of experiments was designed to evaluate the NRADP technique. It includes Phase-1: experiments to evaluate the prediction accuracy for each MU. Phase-2: testing the prediction success rate for 10 MUs over time. Phase-3: experiments to evaluate the search stagnation ratio over time. Phase-4: experiments to evaluate the memory usage and execution time.

In phase 1, The prediction success rate for each MU is tested over time. Figure 6.7 shows the prediction success rate for 10 MUs which use the MPAS and NRADP techniques. This figure shows that the highest prediction success rate for NRADP was 89% and the lowest was 48%, while it was 66% and 36% for MPAS. Consequently, the highest prediction success rate was related to the number of RA displacements. The highest number of displacements produced the lowest prediction success rate.

There are many factors that affect the prediction success rate. These factors are: the number of routing displacement, search stagnation and previous knowledge of the MUs' behaviour in the surrounding regions. The routing displacement is affected by

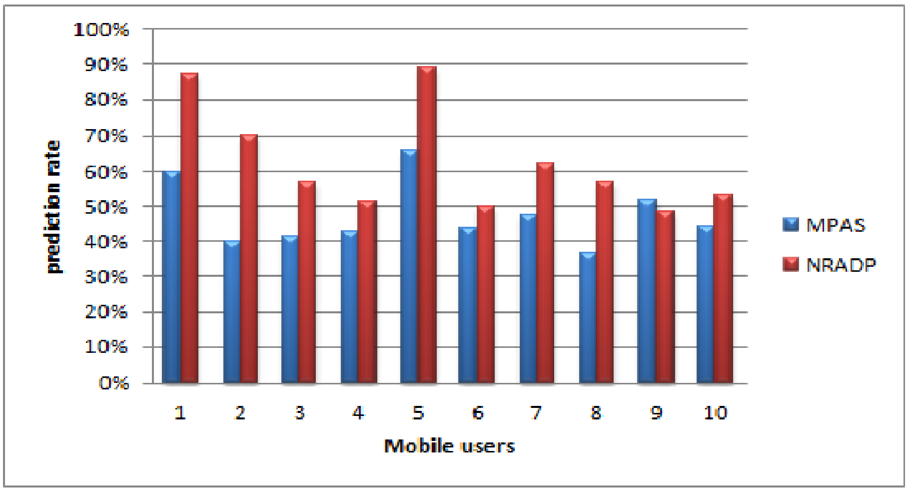

Figure 6.7: Prediction Performance for MPAS and NRADP Techniques for Each MU.

the number of areas that will be discovered. The core network consists of RAs which, in turn, consist of at least two cells. MPAS technique depends on the probability calculation at the cell level, while NRADP works on the RA level. Thus, the number of displacements for NRADP will be less than that for MPAS. Consequently NRADP shows better prediction results than MPAS. In addition, search stagnation is handled only by NRADP which aids in discovering new paths that represents better solutions for MUs. NRADP also reduces the blindness of a MU. The MU does not follow the previous discovered paths by other MUs. Therefore, the prediction success rate is enhanced. It is, on average, 62% for NRADP and 47% for MPAS.

MPAS creates a movement table for each MU whenever a displacement process carried out to assist the prediction process. Each movement table holds up to 50 records to describe the behaviours of the MU. That was not enough to provide the MU with the full knowledge about the behaviours of the MUs that reside in the same cell with respect to surrounding cells. On the other hand, NRADP supported the existing and fresh knowledge by suggesting equations 4.11, 4.12, 4.13 and 4.16.

In phase 2, the average of prediction success rate for 10 MUs is obtained. Figure 6.8 depicts the prediction success rate over time for both techniques. Each point in figure 6.8 represents the average prediction success rate for 10 MUs. As figure 6.8 shows, the overall prediction success rate for NRADP was better than MPAS.

It can also be noted that NRADP has less regression compared to MPAS, i.e. the NRADP prediction success rate is more stable than that of MPAS.

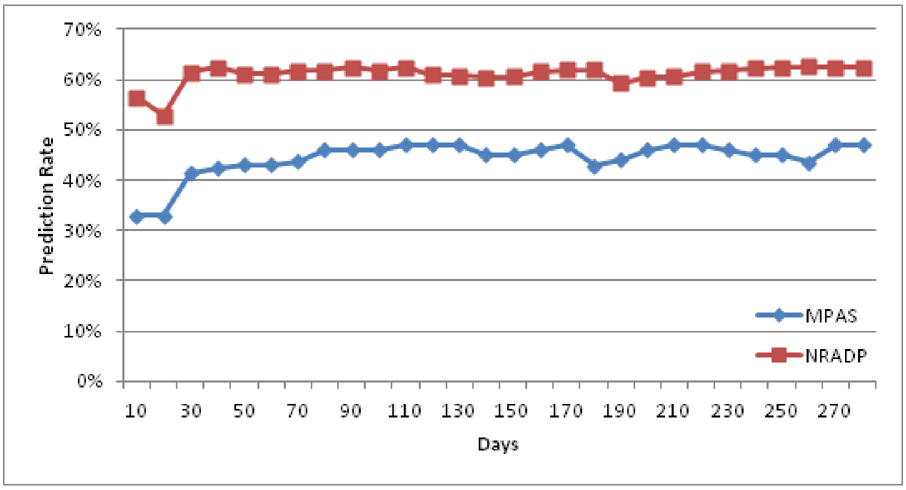

Figure 6.8: The MPAS and NRADP Prediction Success Rate for 10 MUs over Time.

Both techniques started with insufficient knowledge for next displacement, this is shown in Figure 6.8. After 20 days both techniques reach enough knowledge which is represented in the slight improvements in the prediction ratio over time.

MPAS shows a clear irregularity which can be explained from the use of the ant colony that suffers from the MU blindness, i.e. the mobile user keeping track of the other solutions that were created from other MUs. It was stated previously that the prediction rate was affected by many factors. The fourth factor is the weight of pheromone and visibility. The ACO method was improved to be used in NRADP.

While in NRADP, it is noticed that there is improvement compared to MPAS. Hence, the developed ACO is used in NRADP. The developed ACO depends on two factors: pheromone and visibility with two different weights. The improved version of ACO method depends on both factors by the same weight. Thus, this enhancement reduces the blindness of MUs. In Addition, for NRADP unnoticeable regression is shown after 200 days because the Developed ACO constantly explores new displacements for MU, this is discussed in phase 3 which the search stagnation is investigated.

In phase 3, the search stagnation was tested over long histories to obtain the ratio of search stagnation. Figure 6.9 explains the behaviour of MUs according to their search stagnation. Each point represents the average value for 10 MUs. The average value of search stagnation for NRADP was less than that for MPAS.

At the beginning of the prediction process, both techniques had the value of zero because all paths were considered new for both. As figure 6.9 shows, the value of search stagnation were increased overtime for MPAS producing increase in MU's blindness, which degraded the prediction success rate.

On the other hand, the value of search stagnation was oscillating constantly, i.e. it will never reach permanent stability state. The reason is that search stagnation represents the new area that has been visited by MU. This decreased the blindness of the MUs. NRADP used the MMAS algorithm as in equations 4.14 and 4.15 to guarantee the freshness of the pheromone over time as well as to prevent the MU from following any path blindly. The MPAS had never taken such cases into consideration.

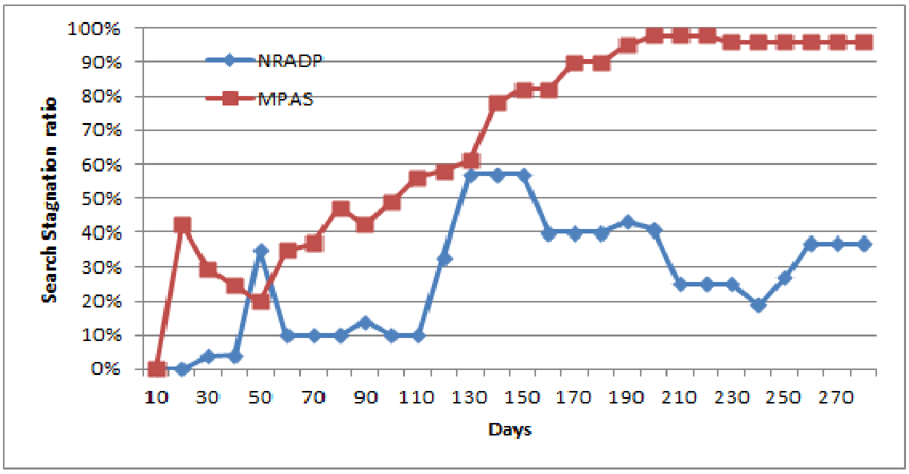

Figure 6.9: Search Stagnation Ratio for MPAS and NRADP over Time.

To complete phase 4, the experiments to evaluate the memory usage and execution time for both MPAS and NRADP were conducted for 10 MUs as shown in table 6.4. By running the experiments from 1 to 10 MUs, it was found that the execution time for NRADP was less than one second on average while for MPAS the execution time exceeded 30 s in average which is considered relatively very slow. Another factor as in the memory usage also showed that NRADP reserved less memory for the same range of MUs compared to MPAS, where NRADP consumed less than 25 kB on average, while MPAS used more than 29000 kB on average, see table 6.4.

Table 6.4: Memory and Time needed for NRADP and MPAS in the Prediction Process

Number of MUs	NRADP Time(Second)	Memory usage(kB)	MPAS Time(Second)	Memory usage(kB)
1	0.166	0.163085938	23.00662388	22467.39814
2	0.173	7.154296875	25.89657223	25289.61484
3	0.285	10.57045898	26.86357463	26233.95328
4	0.383	14.37119141	27.90411758	27250.10754
5	0.477	20.82143555	29.46295347	28772.40437
6	0.517	25.41171875	30.80820682	30086.12552
7	0.567	29.30253906	32.07564077	31323.86231
8	0.685	33.39042969	34.12452401	33324.72446
9	0.678	38.47426758	35.30505776	34477.58841
10	0.793	43.15126953	38.84320876	37932.81552
Average	0.472	22.28106934	30.42904799	29715.85944

Since MPAS is based on building a movement table during each prediction process, this means that the memory and execution time would be consumed by the repeated creation of this movement table and inclusion in the prediction process itself. Each movement table needed 6.515893043 s and 1632.065263 kB on average to be created. On the other side, NRADP does not need such movement tables during prediction processes since it used numerical variables to represent MUs' behaviours, see equations 4.11 and 4.12 and history freshness table is also used. The history freshness table in NRADP is built before the NRADP took place. Therefore, such values would not have any effect on the execution time and the memory usage of the overall prediction process.

6.4 Summary

This chapter introduced the NCPA analysis for cell splitting and finding MU's location, NCPA splitting tested over Pico, Micro, Macro and Rural cell for reducing a service area into sectors. Finding where the MU is located in a sector was tested over Micro cell. The implementations of the NCPA algorithm in terms of time complexity indicated that NCPA is efficient and usable for using in prediction techniques.

NRADP and LPSS were also investigated. The LPSS analysis was based on a simple mobility model: the Random Way Point model which does not have any prediction success rate to investigate the real prediction success rate that is offered from the introduced technique. NRADP is based on real datasets that are collected from the real world. The developed prediction technique has improved the prediction success rate and the performance by reducing the service area to a sector instead of a cell. This Illustrated that the ability to make a combination between LPSS and NRADP is because these prediction techniques can be worked independently. Thus, a mobility prediction scheme is achieved.

Compared with the current mobility prediction technique, the memory usage overhead and complexity time were reduced. Also, the prediction success rate and stability achieved compared favourably with current techniques. Experimental results showed that the developed mobility prediction techniques can be used over cellular communications networks and that these techniques can avoid the authentication traffic overhead for the network operators, the latency between requesting and responding to service for an MU, and reduce energy consumption of an MU, mobile device, as the mobile device's resources are not used by the developed techniques, saving the limited power of those devices. Generally, the developed LBSs mobility prediction techniques have the best performance.

Chapter 7

Conclusion and Future Work

This short chapter summarises the most important contributions of this research. Included are a number of suggestions concerning mobility prediction for Location Based-Services (LBSs) and cellular communications networks that require more research and improvement.

7.1 Conclusion

A literature review summarised research related to LBSs mobility prediction over cellular communications network in chapter 2 and 3. The following subjects were considered: LBSs issues, LBSs benefits and components, mobility states, mobility prediction, and cellular communications networks such as 2G, 3G and future generation cellular networks (4G). An extensive literature review was presented concerning research related to techniques used for the prediction of MU next displacements, specifically the Markov Chain Model (MCM) and Ant Colony Optimization (ACO).

Extensive investigation into existing LBSs mobility prediction techniques for a cellular communications network was performed as a step towards improving mobility prediction techniques. A mobility prediction scheme (Cell-Routing Area Multi-Levels Mobility Prediction) was developed. It relied on the combination between cell and Routing Area (RA) level. This scheme is used in the enhancement of the mobility prediction scheme and for remedies to weaknesses in current mobility prediction techniques.

An efficient LBSs mobility prediction scheme is suggested based on well-known probabilistic models and mathematical constructions. Prediction techniques that are used in the scheme are more efficient in comparison with the best-known techniques such as Prediction Location Model (PLM), New Markov-Based Mobility Prediction (NMMP) and Mobility Prediction based on an Ant System (MPAS). The suggested scheme provides four other characteristics.

1. The introduced Novel Cell Splitting Algorithm (NCPA) can be applied to pico, micro, macro and rural cells. The method can divide a cell into any number of sectors based on operator decisions.

2. The developed Location Prediction based on a Sector Snapshot (LPSS) evaluates all movement probabilities between sectors in the next RA before the MU enters it. The average complexity requirements for LPSS are smaller than PLM and NMMP techniques, a major goal of the project.

3. The New Routing Area Displacement Prediction for Location-Based Services (NRADP) specifies the next RA that an MU will visit. The NRADP is more competent when compared with MPAS.

4. The developed scheme is based on two different levels of prediction, LPSS for the cell level and NRADP for the RA level. The cell and RA prediction techniques work in such a way that if the RA prediction failed to predict the next MU's displacement, the cell prediction would perform the prediction.

The introduced mobility prediction scheme (Cell-Routing Area Multi-Levels Mobility Prediction), provides time to prepare services that may be needed by the user in anticipation of requesting them. This especially concerns services involved with complex computation which may need to extract data and to save time, to ensure that only desired services are available when requested. The cellular communications environment is considered a restricted dynamic environment. The restriction in such an environment is due to the limitations of the MU.

The following subsections summarise the contributions and outcomes of this research.

7.1.1 LPSS Cell Mobility Prediction

The NCPA was developed and used in the introduced mobility prediction at cell level (LPSS).

In this research, a dynamic cell splitting NCPA has been introduced. The NCPA used to accomplish the cellular cell splitting and finding the MU location were successful. Splitting a cell into smaller regions reduces the size of service areas compared with the original cell size, the amounts of data that are delivered to MUs are reduced and balance prediction success rate. These factors assist in improving LBSs mobility prediction.

As shown in chapter 4, the NCPA is applicable to pico, micro, macro and rural cells. Efficiencies in determining the location of MU movement is also achieved. As illustrated in chapter 6, the NCPA time needed 442041 ns for splitting one cell into eight sectors, while the execution time needed for 120 cells (Pico, Micro, Macro, and Rural) was 871290 ns. As seen, the execution times are equal to that referred to NCPA that does not depend on the radius for the splitting. Even though the NCPA execution time for splitting is insignificant, this operation is executed before the prediction technique is begun.

In this research, NCPA is used to split a Micro cell into eight equivalent sectors, with each quadrant containing two sectors. Thus, the time for finding a sector where the MU is located is an important factor to reduce the delay time in constraint environment such as mobility prediction for LBSs, whereas the NCPA finding time used during prediction process. The NCPA time needed for finding a sector where the MU is located varied from 3316 to 4038 ns in maximum where the cellular network size was between 1 and 120 cells, respectively.

NCPA analyses showed scalability, low execution time needed to split entire cells in a cellular and for splitting and finding MU's location. Thus, NCPA is worthy to become part of the common prediction techniques, where the performance of those techniques will significantly improve and assist the techniques to be more dynamic.

In this thesis, the new prediction technique LPSS was introduced based on NCPA algorithm. The mechanism of the LPSS technique depends on the virtual splitting of the cell into sectors. This virtual splitting does not affect the built-in database and structures when there is change in the physical serviced sector.

Chapter 6 has shown the LPSS is more efficient than NMMP and PLM. The suggested technique also provides other characteristics. For example, LPSS minimizes the computation cost, consumption of resources, and the over-all cost of the location management process. Also, the LPSS reduces the service area and the number of predicted routes during the MU trip. It does so by dividing the cell into eight equivalent sectors. In addition, the simulation of the three mobility prediction techniques offers the following three results.

1. The LPSS technique improves the location prediction probability over NMMP and PLM. The average percentage of correct predictions in the LPSS is more than 80% compared with 31% and 70% in NMMP and PLM techniques, respectively.

2. The LPSS average complexity requirements for execution time was only 0.059 s, while NMMP and PLM require about 0.14 and 0.42 s, respectively.

3. The LPSS usage space is smaller for the NMMP and PLM techniques. The LPSS technique requires 14.65 kB for space storage while NMMP and PLM require 27.77 kB and 121.91 kB, respectively.

4. The LPSS has a very light regression, where it is very clear that a lot of regressions take place in both NMMP and PLM after reaching the steady state.

The simulation results have demonstrated that the average prediction success rate, the memory usage, the execution time, robustness and regression degree of prediction success rate over time are improved when compared with the NMMP and PLM techniques.

In addition, the PLM does not allow a given user to visit each of the trajectories more than once for the whole trip. That means PLM is not a practical technique. LPSS does not suffer from this problem. Meanwhile, NMMP is based on the dependent hierarchical prediction process. This leads to increasing the messages passing on the network, delay time and overhead on resource in which it is avoided in LPSS.

Finally, it is acknowledged that the main factor for LBSs is the knowledge of the next location of a given user movement. This is satisfied more by LPSS than by either NMMP or PLM.

7.1.2 NRADP Routing Area Mobility Prediction

The NRADP was presented based on the enhanced ACO. The enhanced ACO was developed to be compatible for cellular communications network.

In chapters 4 and 6, the NRADP prediction technique is proposed and analysed to improve the prediction success rate for cellular communications network. This technique depends on the improved ACO method. Two types of visibility were defined: local and global. In addition, weight participation for factors, pheromone and visibility are balanced to enhance the prediction success rate through avoiding bias in factors selection. Alpha value was 0.5 and beta was 0.5. On the other hand, the prediction process in NRADP is limited by two thresholds: min and max which avoid as much as possible the search stagnation while the search stagnation is still unhandled in MPAS. Furthermore, NRADP works on routing area level rather than cell level. Thus, it decreases the number of displacements that decreases message passing and resources consumption. It also works on core network.

The simulation of the two techniques offers the following results.

1. The average execution time for NRADP was less than one second while MPAS exceeded 30 s which is considered not practical for use in mobility prediction technique.

2. The NRADP achieved a high prediction success rate, up to 89%, where the average resource consumed was less than 25 kB compared to 29000 kB for MPAS.

7.2 Future Work

There are many research issues relevant to the LBSs mobility prediction for cellular communications network which still need further research. New problems are likely to appear with the rapid growth in the technology of cellular networks. This thesis may be a possible starting point for further work and research in different areas. The recommendations for future research are divided into two categories.

7.2.1 Recommendations for Future Research Related to Mobility Prediction

Based on the research performed in this thesis, three areas of future research into LBSs mobility prediction techniques are recommended:

1. In LPSS, the Macro and Rural cells still need more investigation to determine how many sectors are suitable for both of them.

2. Software optimisation: the software implementation of the LPSS and NRADP can be further optimised for better performance.

3. NRADP needs more investigation in terms of MU's number that will affect the pheromone and visibility.

4. NRADP still needs more investigation for the ACO modifications that have already been done, and notice which one of these modifications can be applied in NRADP to improve the prediction ratio.

7.2.2 Recommendations for Future Research Related to Future Cellular Network

Based on the research performed in this thesis, three areas of future research into cellular communications network are recommended:

1. Due to the nature of battery-powered mobile devices, energy consumption is an important issue for mobile networks. Therefore, investigation of power consumption and how battery life is affected by use of the proposed techniques is desirable.

2. Testing by software simulation has proved that the proposed techniques are efficient and robust. However, real network validations are still needed. The results of real experiments would corroborate the effectiveness and robustness of the proposed techniques.

3. Mobility prediction scheme needs more investigation in terms of message passing between LPSS and NRADP, as well as to show the effectiveness of scheme for call admission, update location area, paging and the number of messages that may be reduced from knowing the next displacement of MU .

In conclusion, this study contributes significantly to LBSs mobility prediction. This study provides an important research reference for understanding the relationship between mobility prediction and cellular communications network. It provides a framework for the development of future cellular communication network.

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Appendix A

List of Publications

The following articles from this thesis have been published:

1. Daoud, M.; Ayesh, A.; Hopgood, A. & Al-Fayoumi, M. “A new Splitting-based Displacement Prediction Approach for Location-Based Services”, Systems, Man, and Cybernetics (SMC), 2011 IEEE International Conference on, 2011, 392 -397.
2. Daoud, M.; Ayesh, A.; Al-Fayoumi, M. & Hopgood, A. “Location Prediction based on a Sector Snapshot for Location-Based Services”, Journal of Network and Systems Management(JONS), Springer, 2012, DOI: 10.1007/s10922-012-9258-9.
3. Daoud, M.; Ayesh, A.; Al-Fayoumi, M. & Hopgood, A. “An Enhanced Ant Colony Optimization for Routing Area Mobility Prediction over Cellular Communications Network”, the 5th International Conference on Agents and Artificial Intelligence (ICAART), sponsored by INSTICC - Institute for Systems and Technologies of Information, Control and Communication, February 2013, Barcelona, Spain.

Appendix B

Network Structure

B.1 Network Simulator

The simulator provides a framework for building a network model, specifying data input and analysing output data. It is a discrete event simulator targeted at networking research. It is a widely used simulation tool for simulating inter-network topologies to test and evaluate various networking protocols.

The simulation tool supports a trace file that used to trace and analyse the packets for both wireless and wired networks.

B.2 Cell Structure

```
//This section explains the variables are defined inside a cell.
public class Cell
{
private int MCC; // Mobile Country Code
private int MNC; // Mobile Network Code
private int LAC; // Routing Area ID
private int CI; // Cell ID
private int signal_strength;
private int channel;
private int BSIC; // Base Station Identity Code
```

```
    public Cell(int MCC,int MNC,int LAC,int CI,int signal_strength,int channel,int
BSIC)
{
this.setMCC(MCC);
this.setMNC(MNC);
this.setLAC(LAC);
this.setCI(CI);
this.setSignal_strength(signal_strength);
this.setChannel(channel);
this.setBSIC(BSIC);
}

    public int getMCC() {
return MCC;
}

    public void setMCC(int MCC) {
this.MCC = MCC;
}

    public int getMNC() {
return MNC;
}

    public void setMNC(int MNC) {
this.MNC = MNC;
}

    public int getLAC() {
return LAC;
```

```
}

    public void setLAC(int LAC) {
this.LAC = LAC;
}

    public int getCI() {
return CI;
}

    public void setCI(int CI) {
this.CI = CI;
}

    public int getSignal_strength() {
return signal_strength;
}

    public void setSignal_strength(int signal_strength) {
this.signal_strength = signal_strength;
}

    public int getChannel() {
return channel;
}

    public void setChannel(int channel) {
this.channel = channel;
}

    public int getBSIC() {
```

```
return BSIC;
}

    public void setBSIC(int BSIC) {
this.BSIC = BSIC;
}

    }
```

Appendix C

Useful Source Code for Cell Splitting

C.1 Cell Splitting

public class CellSplitting {

//These variables are used to determine the limited for each quarter in a cell.
static final int ANGLES90 =90;
static final int ANGLES180 =180;
static final int ANGLES270 =270;
static final int ANGLES360 =360;
//These variables are defined for assisting the splitting algorithm
static int n,x,y,numberOfSector;
static double centerAngel,r,p;

//This function returns the centre angle for each sector, whereas the input parameter is the total number of sector.
static void setCenterAngel (double n)
{
centerAngel = ANGLES360/ Math.pow(2,n);
}

```
static double getCenterAngel ()
{
return centerAngel ;
}
// Find the total number of sectors in each quadrant.
static void setNumberOfsector(double n)
{
numberOfSector=(int)Math.pow(2,n-2);
}

    static void setX( int xLocal)
{
x=xLocal;
}

    static void setY(int yLocal)
{
y=yLocal;
}
static void setN(int nLocal)
{
n =nLocal;
}
static int getN()
{
return n;
}

    public static void main(String [] string)
{
setN(3);
```

```
setX(3);
setY(4);
setR(x,y);
setCenterAngel(getN());
setNumberOfsector(getN());
}
}
```

C.2 Finding the Location of Mobile User

```
public class FindingMobileUser {

    static final int ANGLES90 =90;
static final int ANGLES180 =180;
static final int ANGLES270 =270;
static final int ANGLES360 =360;
static int qi,s,numberOfSector;
static double centerAngel,r,p;

    //This function is to determine which quadrant where the mobile user locates
static int getQuadrant(double angelLocal)
{
if ( angelLocal >=0 && angelLocal <=ANGLES90 )
return 1;

    if ( angelLocal > ANGLES90 && angelLocal <= ANGLES180 )
return 2;

    if ( angelLocal > ANGLES180 && angelLocal <=ANGLES270 )
return 3;
```

```
    if ( angelLocal > ANGLES270 && angelLocal <= ANGLES360 )
return 4;

    return 0;
}

    static int getNumberOfsector()
{
return numberOfSector ;
}

    public static void main(String [] string)
{

    // to identify the sector where the mobile user locates
s=(getNumberOfsector() * qi)-(getNumberOfsector() -2);
System.out.print("s"+s);
}
}
```

Appendix D

Useful Source Code for Markov Chain Model Prediction

D.1 Historical Matrix Filling

//This function is used to fill the historical matrix from flat file. The file contains the movements of a mobile user according a Random Way Point mobility model.

```
    public FillMobileTracking(ArrayList<CellSector> mobile)
{
    int i=1,j=0;
CellSector temp,temp1;
MobileTracking newrecord=null;
while(i<mobile.size())
{
    if(i==1)
{ //This operation is to add a new record to the matrix if the record does not exist.
temp=mobile.get(0);
temp1=mobile.get(1);
newrecord=new MobileTracking(temp.getCellid(),
temp1.getCellid(),temp.getSector(),temp1.getSector(),1); mobilehistory.add(newrecord);
j++;
```

```
}
else
{ temp=mobile.get(i);
newrecord=mobilehistory.get(j-1);
//When the record existed in the matrix, the following code will perform to increase
the frequency of a movement.
if(temp.getCellid()==newrecord.getNewcell()&&
temp.getSector()==newrecord.getNewSector())
{
    newrecord.setFrequency(newrecord.getFrequency()+1);
mobilehistory.set(j-1,newrecord);
}
else
{ mobilehistory.add(new MobileTracking(mobilehistory.get(j-1).getNewcell(),
temp.getCellid(), mobilehistory.get(j-1).getNewSector(),temp.getSector(),1));
j++;
}
    } i++;

    } }
```

D.2 Transition Matrix Generation

/*Transition matrix is presented in this section. Constructing transition matrix is based on the history matrix. The following code presents how the developed technique deals with the target mobile user whereas the history of the mobile user is used to build the transition matrix for him/her.*/

```
    public void ReducingProbabilty() {
int i=0,j=1,fre=0;
MobileTracking tempi,tempj;
```

```
while(i<mobilehistory.size())
{
tempi=mobilehistory.get(i);
if(tempi.getStatus()==0)
{
fre=tempi.getFrequency();
tempi.setStatus(1);
mobilehistory.set(i,tempi);
j=1;
while(j<mobilehistory.size())
{
tempj=mobilehistory.get(j);

    if(tempi.getOldcell()==tempj.getOldcell() && tempi.getNewcell()==tempj.getNewcell()
&& tempi.getOldocatant()==tempj.getOldocatant()
&& tempi.getNewSector()==tempj.getNewSector()
&&tempj.getStatus()==0)
{

    fre+=tempj.getFrequency();
tempj.setStatus(1);
mobilehistory.set(j,tempj);

    }
j++;

    }
tempi.setFrequency(fre);
mobilehistory.set(i,tempi);
reducedhistory.add(tempi);
```

```
    }
i++;
} }
```

D.3 Prediction and System States

/*This section presents the extraction of system state, determine next state, predict next sector for mobile user and calculate the prediction rate.*/

```
    package LocationPrediction;
import java.util.ArrayList;
public class Prediction {
int total=0;
int accurte=0;
ArrayList<MobileTracking> mobileMovement=new ArrayList<MobileTracking>();
ArrayList<MobileTracking> TransitionMatrix=new ArrayList<MobileTracking>();
ArrayList<MobileTracking>nextState=new ArrayList<MobileTracking>();
ArrayList<MobileTracking>predictionsets=new ArrayList<MobileTracking>();

    //This function obtains the next state of the mobile user.
public Prediction(ArrayList<MobileTracking> predictionsets,ArrayList<MobileTracking>
mobileMovement,ArrayList<MobileTracking> TransitionMatrix)
{
this.mobileMovement=mobileMovement;
this.TransitionMatrix=TransitionMatrix;
this.predictionsets=predictionsets;
}

    /*This function is to obtain the prediction percentage for each sector around the
sector where the mobile user locates*/.
public void Highprobability(int oldCell,int oldSector)
```

```
{
int i=0;
while(i<TransitionMatrix.size())
{
if(TransitionMatrix.get(i).getOldcell()==oldCell
&& TransitionMatrix.get(i).getOldSector()==oldSector)
nextState.add(TransitionMatrix.get(i));
i++;
}
if(nextState.size()==0)
{
nextState.add(new MobileTracking(-1,-1,-1,-1,-1));
}
this.getHighestprobability();
}
public void getHighestprobability()
{
MobileTracking temp=null;
for(int i=0;i<nextState.size();i++)
for(int j=1;j<nextState.size();j++)
if(nextState.get(i).getFrequency()<nextState.get(j).getFrequency())
{
temp=nextState.get(i);
nextState.set(i,nextState.get(j));
nextState.set(j,temp);
}
}
//This function obtains the next predictable sector for the mobile user
public int predictionState()
{
int accurate=0;
```

```
int non=0;
MobileTracking temp=null;
int i=0;
while(i<predictionsets.size())
{
this.Highprobability(predictionsets.get(i).getOldcell(),predictionsets.get(i).getOldSector());
if(predictionsets.get(i).getNewcell()==nextState.get(0).getNewcell()
&& predictionsets.get(i).getNewSector()==nextState.get(0).getNewSector())
{
accurate++;
temp=nextState.get(0);
temp.setFrequency(temp.getFrequency()+1);
nextState.set(0,temp);
}
else
non=0;
nextState.clear();
i++;
}
return accurate;
}

    }
```

Appendix E

Useful Source Code for Ant Colony Prediction

E.1 Variable Definition and Manipulation

//The important parameters that are used in the Ant Colony Optimisation is declared in this section.

```
public class VariableManipulation
{
private double Pheromones;
private double Pheromone_lay_amount;
private double Visibility;
private double Beta;
private double Tau;
private double Alpha;
private double evaporation_rate;
private double m; for visiablility
public VariableManipulation(double ph,double phon,double vis,
double beta,double tau,double alpha,double evap)
{
this.setPheromones(ph);
this.setPheromone_lay_amount(phon);
```

```
this.setVisibility(vis);
this.setBeta(beta);
this.setTau(tau);
this.setAlpha(alpha);
this.setEvaporation_rate(evap);
}
public double CalcVisibility(int i)
{
if (i==0)
return 1;
else
return (this.getVisibility()*m);
}
public double CalPheromone()
{
return (this.getPheromones()*(1-this.getTau())+this.Pheromone_lay_amount);
}

    public double getPheromones() {
return Pheromones;
}
public void setPheromones(double Pheromones) {
this.Pheromones = Pheromones;
}
public double getPheromone_lay_amount() {
return Pheromone_lay_amount;
}
public void setPheromone_lay_amount(double Pheromone_lay_amount) {
this.Pheromone_lay_amount = Pheromone_lay_amount;
}
public double getVisibility() {
```

```
return Visibility;
}
public void setVisibility(double Visibility) {
this.Visibility = Visibility;
}
public double getBeta() {
return Beta;
}
public void setBeta(double Beta) {
this.Beta = Beta;
}
public double getTau() {
return Tau;
}
public void setTau(double Tau) {
this.Tau = Tau;
}
public double getAlpha() {
return Alpha;
}
public void setAlpha(double Alpha) {
this.Alpha = Alpha;
}
public double getEvaporation_rate() {
return evaporation_rate;
}
public void setEvaporation_rate(double evaporation_rate) {
this.evaporation_rate = evaporation_rate;
}

    }
```

E.2 Pheromone Initialisation

//Before the algorithm began the pheromone quantity for each routing area will be initialised by the following function.

```
public void initialPheromone(double Pheromone)
{
for(int i=0;i<RNt.Nt.RAs.size();i++)
for(int j=0;j<RNt.Nt.RAs.get(i).Lmemo.size();j++)
RNt.Nt.RAs.get(i).Lmemo.get(j).setPheromone(Pheromone);
}
```

E.3 Pheromone Updating

/*The process of pheromone quantity updating for each routing area is presented in this function. The new quantity of pheromone is affected by the old pheromone quantity and evaporation rate.*/

```
public double ProcessingPheromone(double originalpheromone,double evaprate,double pheromonequnt)
{
double temppheromone=0;
temppheromone=originalpheromone*(1-evaprate)+pheromonequnt;
return temppheromone;
}
```

E.4 Local Visibility Initialisation

//This function execute for each mobile user according to the mobile identification.

```
public void LInitialVisibility(int Visibility)
{
for(int i=0;i<RNt.Nt.RAs.size();i++)
for(int j=0;j<RNt.Nt.RAs.get(i).Lmemo.size();j++)
```

```
RNt.Nt.RAs.get(i).Lmemo.get(j).setCounter(Visibility);
}
```

E.5 Global Visibility Initialization

```
//This function execute for all mobile users.
public void GInitialVisibility(int Visibility)
{
for(int i=0;i<RNt.Nt.RAs.size();i++)
for(int j=0;j<RNt.Nt.RAs.get(i).Gmemo.size();j++)
RNt.Nt.RAs.get(i).Gmemo.get(j).setCounter(Visibility);
}
```

E.6 The Effeteness between Local and Global Visibility

```
//This function execute for each mobile user according to the mobile identification.
public double UpdateVisibility(int LocalVis,int GlobalVis,double P)
{
double Lall=P*LocalVis+(1-P)*GlobalVis;
return Lall;
}
```