AGENT BASED MODELLING OF AN EMERGENCY DEPARTMENT AND PATH PLANNING OPTIMIZATION OF A MOBILE REAL TIME LOCATION SYSTEM

by

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ABSTRACT

This research is directed towards improving patient care within a hospital's Emergency Department (ED) by providing support for health care administrators and policy decision makers. The work presented is an innovative automated data collection system, thereby freeing ED workers to focus on the most important aspect of their job: patient care. The thesis is organized as follows; patient data from the Winnipeg Regional Health Authority's Emergency Department Information System is used to provide insight into the patient flow processes within an ED. This process analysis was critical in developing an agent-based model of process flow (patients and staff) within an ED. From this point, emphasis was placed on illustrating the utility of an Agent Based Model (ABM) in the optimization of a mobile Real Time Location System (mRTLS).

Current data collection methods used for localization in health care facilities involving human data collection methods often tend to generate inconsistent and ambiguous data. To address these data collection problems, an automated ceiling mounted mRTLS is proposed. The system utilizes mobile Radio Frequency Identification (RFID) and is evaluated using ABM and optimized using metaheuristic genetic and simulated annealing algorithms. A prototypical agent model for an emergency facility was created using AnyLogic simulation software. The emergency department model is outfitted with mRTLS using mobile, ceiling-mounted RFID readers. Path planning and resource provisioning of mobile readers is accomplished using both a multiobjective genetic algorithm and a multiobjective simulated annealing algorithm. The genetic algorithm optimizes initial placement of static readers by finding areas where RFID tags are more frequently found. This generates the input parameters for the second algorithm, a multiobjective simulated annealing algorithm. The simulated annealing algorithm provides the first-cut path for the deployment of mobile readers. These paths are further improved by an A* search-based path planning algorithm,

which is used to find paths around walls and other obstacles. The results generated by the proposed model are a possible solution for implementing a ceiling mounted mRTLS using RFID for patient and asset tracking within an ED layout. The novel design implemented is a cost-effective system using fewer number of mobile readers that successfully optimizes and improves the coverage of real-time trajectory tracking of the RFID tags associated with the individuals or equipment.

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DEDICATION

This thesis is dedicated to Maa and Bholenath.

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Glossary

ABM	Agent-based model / Agent-based modelling
ED	Emergency Department
EDIS	Emergency Department Information System
WTBS	Waiting To Be Seen
TIP	Triage In Progress
FC	First Consult
WTA	Waiting To Be Admitted
TRN	Awaiting Transfer
PD	Pending Discharge
LOS	Length of Stay
DD	Discharge Disposition
DDS	Decision Support System
RFID	Radio Frequency Identification
GA	Genetic Algorithm
SA	Simulated Annealing
TSP	Travelling Salesperson Problem
RTLS	Real Time Location System
mRTLS	Mobile Real Time Location System
lmRTLS	Legalized Mobile Real Time Location System

Chapter 1: INTRODUCTION

An Emergency Department (ED) is a complex system that requires meticulous planning and well-organized policies to provide the best possible patient care. Efficiency in terms of time management, is highly essential in an ED as it directly relates to saving lives and improving the quality of care for patients. One of the possible solution to increasing the efficiency, was to keep track of patients, nurses, doctors, hospital equipment. Another option was to look for areas that have high dwell times and explore how to best track patients, hospital personnel and assets [1]–[3]. Knowledge of patient trajectories can then be used to improve or inform ED processes. Health care workers are often responsible for manually entering information for electronic record keeping in an ED. This is not ideal because their invaluable time could be used for other more important tasks. Using staff can also result in a loss in accuracy of data logging as it may fluctuate depending on the busyness of the ED and their experience with the assigned software. Precise data logging is necessary, as this is how most administrators decide on policies which can greatly affect efficiency. An ED can benefit from an automated system that seamlessly and accurately tracks patients, doctors, staff, assets and helps take the burden of recording off the health care workers.

The use of Radio Frequency Identification (RFID) has been suggested for tracking purposes in hospitals by many researchers [1], [4]–[7] These systems often require a large array of RFID based readers and depending on their transmission strength these could easily be bulky and intrusive if placed on the ED walls. One way to provide a cost-effective tacking system is to reduce the number of readers. By using mobile readers, it would be possible to use fewer readers while still maintaining adequate coverage. Therefore, a ceiling-mounted, track-based mobile RFID based Real Time Location System (RTLS) is proposed to keep track of patients, hospital staff and resources. Using ceiling mounted tracks allows the RFID readers to be mounted away from otherwise usable space and being mobile should allow for a reduction in the number of readers. These mobile readers or trackers can be mounted above the drop ceilings that are used in a vast majority of hospitals to hide the mechanical and wiring already present within a hospital. Alternatively, the system could be mounted on exposed tracks similar to those illustrated in Figure 1.

Figure 1: Exposed ceiling mounted tracks within an ED

All EDs typically have some means of collecting and maintaining data on patients, staff and/or resources. Within the Winnipeg Regional Health Authority (WRHA), ED data is mainly logged in an Electronic Data Information System (EDIS) which is implemented in all of the hospitals within the WRHA. Electronic Data Information System offers electronic patient tracking, display boards, lab results reporting, discharge instructions and other clinical documentation (See Figure 2). For EDs, wait time display boards collect information from the Decision Support System (DSS) extracts. The data fields recorded by EDIS waiting time boards include: registration time, age, severity of illness, influenza like infection, waiting to be seen time, treatment time, pending admission, pending transfer, pending discharge, discharge time, and length of stay. All of these data values are entered by the hospital staff by hand and thus, may suffer from missing and erroneous data problems. In addition, EDIS lacks some of the possibly crucial information such as tracking medical equipment (e.g., to reduce the time spent in locating the equipment if borrowed or leased).

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Facility	Age	Gender	Triage Score	ILI	MTA Appropriate	Registered Date	Triage Note Created	Triage Completed Date/Time	Time in WR (Hrs)	WTBS Duration	Direct Duration	First TIP
2	B	39	Male	2	0	No	10/1/09 8:59 AM	10/1/09 9:01 AM	10/1/09 9:02 AM	0.05	0.20		10/1/09 9:11 AM
3	C	88	Female	4	0		10/1/09 9:49 AM	10/1/09 9:50 AM	10/1/09 9:55 AM	0.12	0.53		10/1/09 10:21 AM
4	B	64	Female	5	1	Yes	10/1/09 10:30 AM	10/1/09 10:41 AM	10/1/09 10:49 AM	1.62	2.48		10/1/09 12:59 PM
5	E	81	Male	3	1	No	10/1/09 12:21 PM	10/1/09 12:23 PM	10/1/09 12:32 PM	0.42	0.58		10/1/09 12:56 PM
6	D	24	Female	UNKNOWN	0		10/1/09 1:03 PM			2.98	0.90		10/1/09 1:57 PM
7	A	52	Female	3	0		10/1/09 4:35 PM	10/1/09 4:36 PM	10/1/09 4:39 PM	0.27	0.43		10/1/09 5:01 PM
8	C	59	Male	2	0	No	10/1/09 6:43 PM	10/1/09 7:04 PM	10/1/09 7:10 PM	0.57	2.55		10/1/09 9:16 PM
9	B	22	Female	3	0	Yes	10/1/09 2:12 AM	10/1/09 2:20 AM	10/1/09 2:26 AM	2.08	4.90		10/1/09 7:06 AM

N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA
TIP Duration	First Consult	Consult Duration	First TBADM	TBADM Duration	First PD	Pending Discharge Duration	First TRN	TRN Duration	First WFT	WFT Duration	Discharge Date/Time	Total Length of Stay (Hours)	DischargeDisposition
7.78					10/1/09 4:58 PM	0.00					10/1/09 4:58 PM	8.0	AMB Home
53.55					10/3/09 3:54 PM	0.20					10/3/09 4:06 PM	54.3	AMB Home
1.18					10/1/09 2:10 PM	0.08					10/1/09 2:15 PM	3.8	AMB Home
21.72			10/2/09 10:39 AM	1.32							10/2/09 11:58 AM	23.6	AMB to Inpatient
2.08											10/1/09 4:02 PM	3.0	AMB Home
1.75					10/1/09 6:46 PM	2.48					10/1/09 9:15 PM	4.7	AMB Home
10.73					10/2/09 8:00 AM	0.30					10/2/09 8:18 AM	13.6	AMB Home
5.05					10/1/09 12:09 PM	0.00					10/1/09 12:09 PM	10.0	AMB Home

Figure 2 EDIS Data

To generate the data from which to investigate potential efficiencies in ED operations, an RFID based RTLS is proposed that includes RFID readers that detect the unique RFID tags attached to individuals (patient, staff etc.) and assets (medical equipment etc.). An RTLS provides real time data on location of patients and equipment which can be used to locate them quickly, and can also be stored for future analysis.

Cost effective deployment of mobile RFID readers of a RTLS for patient and asset tracking is a complex problem. Deployment problems, in general, tend to have three common characteristics:

cost, the contending cost objectives of fewer readers while maintaining high accuracy, and feasibility constraints which are discussed in detail in later chapters. As such, finding a set of mRTLS solutions that will lead to superior patient data collection and asset tracking while also minimizing cost is challenging. Some researchers have used Agent Based Modeling (ABM) based RTLS for tracking patients and assessing errors and uncertainty using low cost, fixed RFID readers [8]–[10]. These studies suggest that the error and uncertainty is inversely proportional to the number of fixed RFID readers used the greater the number of RFID readers, lower the errors and uncertainty for e.g. 1% error is equal to 99% accuracy.

However, by increasing the number of readers, the overall implementation cost will increase, thereby hindering the possibility of using such a system in EDs. To begin to find a solution that is cost effective and allows for improved resource utilization, an ED-ABM is presented comprised of patients, staff and resources as various agents. Through doing this, the aim is to provide a platform to build and test an improved data collection solution that can work with the existing data collection systems such as EDIS. Also, to optimize the overall cost of physical implementation by minimizing the readers required, while keeping the tracking errors to a minimal.

The overarching objective here is to improve efficiency in EDs by developing an autonomous mobile RTLS for data collection and resource tracking. As access to this type of environment is very restricted, an ABM of an ED is used to visualize, optimize and validate the proposed solution. The RFID based mRTLS is intended to reduce errors associated with more manual data collection processes. The design of an mRTLS is supported by exploring ABMs and validated with real data from an ED, where the agents are patients, hospital staff and resources. The same ABM can also be used by administrators to develop and test new policy ideas before putting them into practice.

Once validation (or partial validation) of a mRTLS for a particular ED layout using simulation methods is complete, then actual construction of a prototype mRTLS can then be examined.

There are some challenges with this kind of implementation, such as how to reduce the number of readers (e.g., which readers could be eliminated) and which paths the readers should take in order to provide maximum tracking and minimal loss of accuracy in estimating asset and patient locations. In addition, EDs are of various sizes and layouts, so one solution will not work for all EDs, However the methodology would still apply. In this research, three approximated ED layouts of different hospitals in Winnipeg are chosen. Each individual layout has its own nuances in terms of where patients and resources are most frequently found, as well as the best possible routes between these frequented areas. The use of the generalized optimization algorithms, when applied to a particular layout, will identify the regions of high traffic, and paths that connect them. Once these paths have been identified, it would then be possible to design the physical track-based solution for that layout that will be used by the mobile RFID readers to track patients, hospital staff and resources. In addition, the solution presented here allows for scalability as more layouts and EDIS type data can be added with a central objective of informing processes and potentially reducing waiting times in other EDs.

Two independent algorithms are implemented to resolve two nonlinear multiobjective problems. Both multiobjective problems have conflicting objectives, commonly known as trade-offs. The first optimization problem involves finding the minimum number of static readers while maintaining an acceptable error that is defined by the user or the administrator. This is accomplished by finding the busy points in the layout of the ED.

The busy points could be found by completely covering the ED with stationary readers without optimization. Then using a Genetic Algorithm (GA) the system can be improved to reduce the number of readers while also maintaining an acceptable level of error. Errors are defined as the time each agent (e.g., patient, hospital staff or resource) spends in the error state (non-tracked). For example, agents enter the error state when they change location prior to being read by a new reader. The agent will remain in the error state until that agent is found by a reader. Once it has been found, the agent will remain in the found state until another change in location happens. This definition of error is used in every case where error is discussed. An agent remaining in a known location such as waiting area will continue to be read and thus remains in a known location until they move.

The second optimization is to determine the minimum number of mobile readers that can be used while still maintaining a minimum or acceptable error rate. To this end, a Simulated Annealing (SA) algorithm which focuses on minimizing both the number of mobile readers and the error rate is used. Essentially the GA helps reduce the number of static readers while the SA algorithm considers mobile readers whose trajectories would compensate for a lower number of readers.

The premise of this work is the creation of the system to improve the quality of data recorded in EDs by exploring the use of automation technology that can provide more consistent data. Not only does automation help to remove the possibility of human error in data, it also allows for the healthcare providers to focus more on patient care, rather than spending time collecting and recording data. The proposed research outcome could be very beneficial. First, throughput of patients within an ED is a serious issue since delivering high quality health care depends upon it. Second, tracking of patients and medical assets is important as it helps speed up patient care by reducing the workload of health care staff. Third, it helps health care policymakers by providing accurate data for analysis. The ABM developed here enables administrators to design prototype models that would provide an enhanced visualization and evaluation of the complicated systems under study, this type of simulation is useful for testing new ideas before putting them into practise. An automated patient and asset tracking system is expected to deliver quality data that will benefit the staff in accelerating patient care and aid medical data analysts by providing them with data that is potentially less error prone. Finally, mRTLS is a non-intrusive automated mobile tracking solution, requiring no or limited input from medical staff. Ubiquitous sensor platforms such as cell phones could also be leveraged as part of an mRTLS [11]. Although the ABM and simulation presented here utilizes RFID, it may also be possible to use the location data currently collected by smartphones, as well at their built-in connectivity, as an extension to the system described here. It may also be possible to utilize either Bluetooth (BLE) and/or NFC instead of RFID, in order to make use of the ubiquity of cell phones [12]–[14]. While there would possibly be a reduction in location accuracy, only purchasing trackers, and minimal tags, may help to reduce the cost of the system even further.

Chapter 2: RELATED WORK

2.1 Concerns in Emergency Departments:

Overcrowding and long waiting times in Emergency Departments (EDs) are an ever-increasing problem. However, it is not simply a matter of providing more hospitals, or more doctors as this may not be economically viable. In order to understand the system, an initial analysis studied the flow of patients through the system in an attempt to identify areas or processes that are prone to problems. Minimizing wait times in EDs is a notoriously difficult problem.

The first step in analyzing the system is the acquisition of real-world data. To this end, the Winnipeg Regional Heath Authority (WRHA) provided data from their ED Information System (EDIS). The particular dataset, collected over the period of one month (October 2009), is comprised of 19,404 patient records from six EDs. The identity of each patient is anonymous with repeat patients recorded as separate data entries. In the proposed RTLS design, the EDIS data is used as an input parameter for the movement of patient agents through the ED-Agent Based Model (ABM) in order to develop an efficient data collection system. The 2009 data still holds its validity as the trends and time constants in EDs have not changed much over the years [15]. The system described here has been developed to be data agnostic; it is easy to replace the older data with an updated version. As such, for this work, even if the data available were from the present, the proposed RTLS system would still be modeled the same way. In addition, this work proposes an additional means of supporting data collection within a hospital environment via an RLTS platform. The advanced RTLS design attempts to demonstrate the benefits of improved or augmented data collection that can result in better justified decision making by the healthcare authorities [16] .

To gain an appreciation for patient flow within an ED, the system model was initially investigated with a multivariate linear regression model, which predicts multiple correlated variables in the ED dataset in an attempt to determine busyness factors of an ED. The data analysis results showed that time of arrival and triage acuity level of the patient are strong factors affecting busyness in EDs. This type of information on its own would potentially be helpful in testing possible changes, before policy changes were implemented in a real ED.

2.2 Methodologies

In the past, researchers used different methods in an attempt to predict individual waiting times and length of stay for a given patient. These methods also include the use of a discrete event simulation similar to the ideas being used in this research. The simulation designed by Harper et al. [17], Hoot et al. [18] and Jun et al. [19] showed promising results in accurately forecasting the waiting time and length of stay for a patient who is just arriving at an ED. These studies also made it possible to evaluate what-if scenarios for a given ED. This latter type of result is similar to the objectives of this study, showing how a given set of changes would affect an individual's wait time and length of stay. There are many ongoing efforts being made to reduce the waiting times and length of stay of patients in EDs.

For the purposes of gaining additional appreciation to the process flow within an ED, data from the WRHA EDIS system was used. The process flow and various factors affecting waiting time and length of stay in six EDs in the city of Winnipeg, were investigated. The aim was to build an ED simulation model using ABM that allows exploration of how changes in policy may affect patients' length of stay and waiting times. The preliminary work involved multiple regression analysis, in an attempt to identify main contributing factors in patient length of stay and waiting times. By manipulating the many possible variables, it is possible to see how changes made will affect patient's length of stay and waiting times in a given ED. This exercise provided useful insights into how an ED functioned and provided insights into the difficulties associated with policy-making by hospital administrators.

2.2.1 Statistical Methods

2.2.1.1 Time Series

Time series analysis is a forecasting technique used by McCarthy et al. [20] and Tandbgerg et al. [21] for evaluating the effect of overcrowding on wait times in EDs. Time series can be used to predict emergency demand, length of stay, forecasting overcrowding as shown by Brown et al. [22], and Schweigler et al. [23] and even hospital processes such as patient movements in hospitals as demonstrated by Lin [24]. The study conducted by McCarthy et al. [20] demonstrated that crowding increased the median wait times for high acuity levels. The time series analysis study by McCarthy et al. [20] measured the changes between the effects of overcrowding from the 50th to the 90th percentile of wait times. The time series predictions provided useful information about the consequences of overcrowding on wait times. Rather than examining the individual effects of distinct variables such as overcrowding and boarding on wait times, the purpose of their research was to investigate the overall effects of changes in multiple, system wide hospital variables. The study conducted by Tandberg and Qualls et al. [21] found that the most accurate forecasting technique to estimate ED volume was the simplest moving average model that explained 42% of the variance. However, the time series models could only explain 1% of the variation in the length of stay and acuity levels. Overall, the time series analysis centered its efforts in estimating the number of patients and effects of overcrowding rather than forecasting the effects on an individual patient.

2.2.1.2 *Multiple Linear Regression*

Many evidence-based studies have demonstrated the applicability of multivariate regression on hospital forecasting. Regression modeling is used by many researchers to solve different problems within an ED. Issues such as estimation of overcrowding have been studied by Miro et al. [25], Weiss et al. [26], Fatovich et al. [27]. The quartile regression was used to study ambulance diversion by Schull et al. [28] and regression analysis was used to study demand for services by Rotstein [29], Asaro et al. [30], and McCarthy et al. [31] and length of stay Yoon et al. [32].

In an analysis conducted by Asaro et al. [30], a multivariate linear regression was used in four-hour time periods. They used independent variables such as arrival time, time of day, admission percentage, nurse staffing, inpatient bed utilization to estimate the impact on dependent variables such as length of stay, wait time, treatment time and boarding time. The regression coefficients of the independent variables had a one-to-one relationship with the dependent variables and were measured against the baseline time period from 4am to 8pm. Not surprisingly, results showed that increases in the number of ED arrivals, admission percentage, in-patient bed utilization and boarding admitted patients increased waiting times [33].

Multivariate regression is used in this research. In contrast to the study conducted by Asaro et al. [30], where the wait time data is transformed to improve the linear relationships with the independent variables, these independent variables are used later as control parameters within the simulation model. By allowing the user control of these variables, it is possible to observe how a set of changes will affect the dependent variables such as wait times and lengths of stay. Most research papers [25]–[33] use a purely statistical method for finding the factors that affect patient wait times and lead to increased lengths of stay. By allowing control of various contributing factors, the designed model is expected to be able to accurately predict how these given changes would affect wait times and lengths of stay.

2.2.2 Simulation and Modeling Methods

Unlike an analytical approach, a simulation approach allows analysis of the interdependence of processes within a complex system. Simulation models aid in analyzing the interactions between humans and the system processes in critical or stressful situations. Simulation approaches are also useful in identifying emergent characteristics of the system. Wang et al. [34] noted that simulation software can model entities separately in order to analyze the initial effects during a surge of incoming patients.

2.2.2.1 Analytical Approach

In order to simplify modeling tasks, analytical modeling provides abstractions through mathematical parameterized functions. Analytical approaches, such as queuing theory, evaluate the utilization of available resources in relation to requirements. In a normalized system, when utilization exceeds one, no steady state solution can exist as stated by Winston [35]. Li and Howard [36] designed an analytical framework that used a system theoretic approach to address patient flow and quality of care, such as length of stay and patient outcome. The analytical model proposed by Li and Howard suggested structures such as parallel, re-entrant, split, and closed structures to solve the problem of ED overcrowding and provide better ED efficiency. Under tight resource constraints, such as when the available capacity in the ED is less than the number of patients in the waiting room, then the highly generalized queuing theory imposes its own limitations and makes it difficult to get a deeper insight into ED complexity [37]. Similarly, a queuing theory model with restricted assumptions does not support the building of real-world models, as queuing theory models are already an abstraction. Overly generalized models of queuing theory underestimate certain aspects such as delays and bottlenecks in systems similar to EDs [37]. The details and variability under constraints can be modelled more efficiently using ABM to generate more accurate results. However, queueing theory and agent based modeling methods together may provide a powerful combination to design and help manage ED operations and can verify system sensitiveness to variation in underlying parameters [8], [37], [38].

2.2.2.2 Discrete Event Approach

Discrete event modeling (DES) has been used in many fields to help in organizing and visualizing the functioning of many systems, with varying success. The probabilistic distributions of inputs used by discrete event simulation can help with analysis, and can be used to identify process loopholes, and interrelationships in the inputs. Besides simply showing queue length, process times and utilization rate, the simulation model can be used to understand process bottlenecks and help in decision making (what-if scenarios) as presented by [17]–[19] Although discrete event simulation is a powerful forecasting predictor and a testing tool for future policies implementations, it may still not be the most appropriate approach for estimating waiting times in EDs. Although DES enables the construction of complex models apt to the problem, healthcare problems are in general an exception [39], DES was originally designed for modeling industrial systems with physical infrastructure with predictable interactions [40]. However, such strict assumptions might not be able to correctly estimate the solution in cases of emergency situations such as a patient surge. In DES simulation, the uniform movement and functioning of entities makes it potentially unrealistic for EDs. This can be mitigated by integrating DES with Agent Based Modeling to allow human-like movement through the DES [41].

2.2.2.3 Agent Based Modeling/Simulations Approach

Agent Based Modelling simulations are comprised of autonomous entities, each with different behaviors and roles that interact with the environment and each other within a complex system. Agent Based_Modeling allows modeling of unpredictable behaviour of the individuals in emergency scenarios such as surge, thus providing an insight into an overall impact on the entire system. Thus, Agent Based Modeling is a reasonable choice to model and simulate real-time individual movements and processes in a complex dynamical system such as an ED. The ABM based model or paradigm can be explored using various agents (patients, doctors, staff, medical resources or patient or asset tracking devices), interaction rules and system structure (layout of ED) that are the key aspects of time critical healthcare systems such as EDs. The flexible system structure and autonomously behaving active micro-entities provide a leverage to applying the ABM approach. Furthermore, a modelling technique such as ABM, could be integrated with real-world data collected from existing data sources such as EDIS, crowdsourcing, social media general information and Smartphones. This provides a better opportunity for even greater information integration in order to build stronger frameworks known as data-driven ABMs [42]–[46].

Patient flow can be examined to determine which factors contribute to restrictions in the flow of patients through the ED system. With the main restrictive factors identified, ABM techniques can then be used to better predict how changes may impact the throughput of the system, specifically to see how changes made will affect patient waiting times and length of stay.

Agent Based Modelling techniques have been used in evaluation of policies and work flow in ED such as Laskowski et al. [47]. Taboada et al. [48] used an ABM as a decision support tool for an ED. An ABM approach is flexible enough to analyze many different complex open systems. Another application of an ABM is in augmenting the electronic medical records using data from a modeled RFID system as reported by Laskowski et al. [8]. Cabrera et al. [9] designed a decision support system using a Moore state machine-based agent to optimize the performance of an ED by proposing an index to minimize length of stay of each patient in the ED. The focus of much of the work undertaken here is directly related to ABMs for EDs.

2.3 Real Time Location System (RTLS) in EDs:

An outline of real-time location system (RTLS) applications in patient tracking and asset localization is presented in this section. In this section the related literature is reviewed by categorizing it, in order to provide insight to research directions in automation using RTLS technology for better patient outcomes in Emergency Departments (ED). The section evaluates localization technology, the issues associated with tracking objects using radio frequency (RF) signals along with other technologies and analyzes the various approaches used for solving localization problems. The characteristics of various localization techniques are then examined to compare different solutions and systems. In this section the applicability and efficiency of deploying fixed RFID readers is also discussed with the view of introducing cost-effective mobile readers. The work concludes with the proposal of a cost effective and efficient solution for deployment in healthcare facilities.

The collection of ED data is a vital component of patient care. The decisions based on data such as priority setting, allocation and leveraging of resources, comprehensive planning, service delivery, and performance evaluation depend on collection of both qualitative and quantitative data [49]. Examples of gathered data include medical history, registration of events, monitoring and the collection of data related to treatment procedures up to the final decision after diagnosis. Additionally, using a real-time localization system would allow for real time patient and resource localization and tracking [44]. This would also aid in improving patient care by locating medical equipment quickly, such as frequently misplaced Intravenous (IV) pumps [50], in EDs.

Errors and inconsistencies are frequently found in manually collected records. These error prone data collection techniques need to be addressed as they influence patient care outcomes as demonstrated by Tsang et al. [51], where researchers examine the recorded data including medical records, vital events registration, and safety quality surveillance, recording of treatments in progress, overall length of stay and discharge or admittance disposition, to show that data collected manually frequently contain errors and discrepancies.

As the data give insights to accessibility issues and hurdles encountered by staff and patients, an automated system to collect the data, one that would be much less error prone than current manual methods, would have a beneficial effect on patient care. This same system would also be useful for real-time resource and patient tracking, in turn helping improve patient care and overall efficiency, for example by reducing the time it would otherwise take to locate specific pieces of equipment.

While the focus in this chapter will be RFID in particular, there will also be discussion about some other possible technologies which could be useful in patient and resource tracking in an indoor environment. EDs are indoor with many obstacles including walls and other electronic instruments that may cause RF noise which could lead to more difficulty in using RF as an indicator of position.

Once the various technologies have been covered, then discussion of the various techniques that are used to estimate the position of a particular tag, including some discussion as to how well a given algorithm fits within our ED scenario will be presented. Discussion will be elaborated for some possible deployment methods, including both static and mobile readers.

Other requirements for an ED environment are that solution be nonintrusive and not affect the treatment procedures or cause any inconvenience to the critically ill patient or healthcare personnel. One study in particular discusses various implementations of RTLS for hospital environments [52].

A well-designed, tested and implemented solution for automated data collection within an ED should be more effective and efficient than methods of manual data collection. Due to these factors, RTLS spending in healthcare is expected to increase [53].The healthcare providers predict that the RTLS market worth may go up to 8.09 Billion USD by 2022 [54]. Using an automated system not only removes the possibility of human error, but also allows healthcare professionals to focus on the most important part of their job, the reason many chose the health care field, helping people.

2.4 Motivation for creating a mRTLS

Since manual data collection has shown to be error prone, automated data collection methods should be continually examined, as tracking of patients and assets using automation should be more accurate, and many researchers have found this to be true. The view is that error prone data collection techniques, and issues therein, require improvement as they can affect patient care [55]. Thomas et al. [56] as well, have shown that inaccurate data can have adverse effects on patient outcomes and the efficiency of resource allocation in the ED environment. Researchers such as Hirshon et al. [57] examined techniques used for recording data in healthcare facilities like EDs. However, the collected data is not without its limitations. There had been several cases of medical mistakes extending from error prone data leading to a large (rough estimate of 44,000 to 98,000) number of fatalities as reported by Institute of Medicine [58]–[60]. In fact, many researchers believe RFID/RTLS applications in medical institutions can help reduce medical errors and reduce labour [6], [61]–[63]. For instance, in the case of locating or verifying prescription medication, a highly accurate localizing system is needed or it could be life-threatening for the patient under treatment [64]. An RTLS system can also help in locating medications using RFID-based location systems [65] to ensure inventory is up-to-date with no recalled or expired or counterfeit drugs accidently administered to the patient [66]. In the paper published by Wicks et al. [63] he stated that RFID data collection automation leads to improved communication of patient details amongst healthcare staff with reduced errors. The researchers attempted to focus on the issues and benefits of RFID implementation in the hospitals. The proposed RTLS for ED has the capability of further integration of RFID tags on patient with the tag on prescribed drugs so that the nurses can administer the correct dosage to the correct patient. Revere et al. [62] surveyed the significance of using RFID in various hospitals and other industries in United States. The authors assessed the potential of using RFID integrations to patient supply chain within the hospital can enhance efficiency in healthcare processes, service excellence and convenient access for patients. The researchers strongly recommended that with the continuously increasing load on healthcare, medical errors can significantly be reduced by incorporating RFID technology contributing towards improving patient care [8], [44], [62], [63], [67]–[71]. The proposed RTLS for ED attempts to integrate the RFID with EDIS with the aim to design a cost effective and precise system desirable for patients, healthcare personnel and asset tracking.

Selection of the localization technology, or a combination of technologies is an important consideration in designing a solution. A technology that might be good for one application may not be as effective for another application as it may not meet a particular user requirement, or it may focus on a different area of interest. For example, designing RTLS for patient tracking in an ED may not need exact spatial and temporal accuracy where room level accuracy may suffice. However, many of the available RTLS solutions are unsuccessful even at room-level accuracy

[52]. All of these papers have shown several different ways in which automated systems are effective, efficient methods of improving data collection, not just in EDs, with many using RFID technology[8], [44], [62], [63], [69], [70], [72]–[75] In addition, this work builds upon many of the opportunities arising from the inertia within IoT. The main idea here extends the advances being made in IoT in general, in that, for the proposed mRTLS the readers or data collection entities are mobile. It is not unreasonable to anticipate that many mobile IoT systems will be applied in other areas in the future as well.

2.5 Data Collection Systems in EDs

Quantitative and qualitative data collection is the key to appropriate decision making. The detailed health records include medical history, important measures, registration, monitoring, and treatment progress. The patient's overall length of stay and admittance or discharge are also recorded. Crucial patient details can be collected using methods that can be either manual like maintaining paper charts, semi-manual such as EDIS or semi-automated (for instance incorporating technologies like RTLS)

However, manual data entry is known to be least accurate followed by slightly more accurate EDIS type systems which attempt to provide some automation and ease entering data for staff. Augmenting data collection with RTLS appears promising. Researchers have also advocated the use of RFID over existing tracking procedures [76]–[78]. There had been reports indicating discrepancy and inaccuracies when human intervention is involved in the data recording processes unintentionally affecting patientcare [55], [79]. These include, healthcare resources such as time management of expensive medical personnel and underutilized or misplaced emergency equipment [80]. In an effort to solve the ongoing problem of accurate medical data collection, an automated tracking method is proposed that attempts to capture accurate location details with the least possible error. The proposed RTLS system is oriented towards data recording of patients, healthcare professionals and medical assets. At this time, due to unavailability of the medical assets and/or healthcare professionals' related data, the designed model is limited to patient data only. However, the proposed design can be further integrated with additional data for resource tracking and utilization. A high-level view of an RTLS in an ED is shown in Figure 3. For example, the ED ABM developed here can reasonably easily be integrated with asset tags representing equipment and simulations can be undertaken to determine the overhead incurred by not knowing the location of assets as opposed to having their location known.

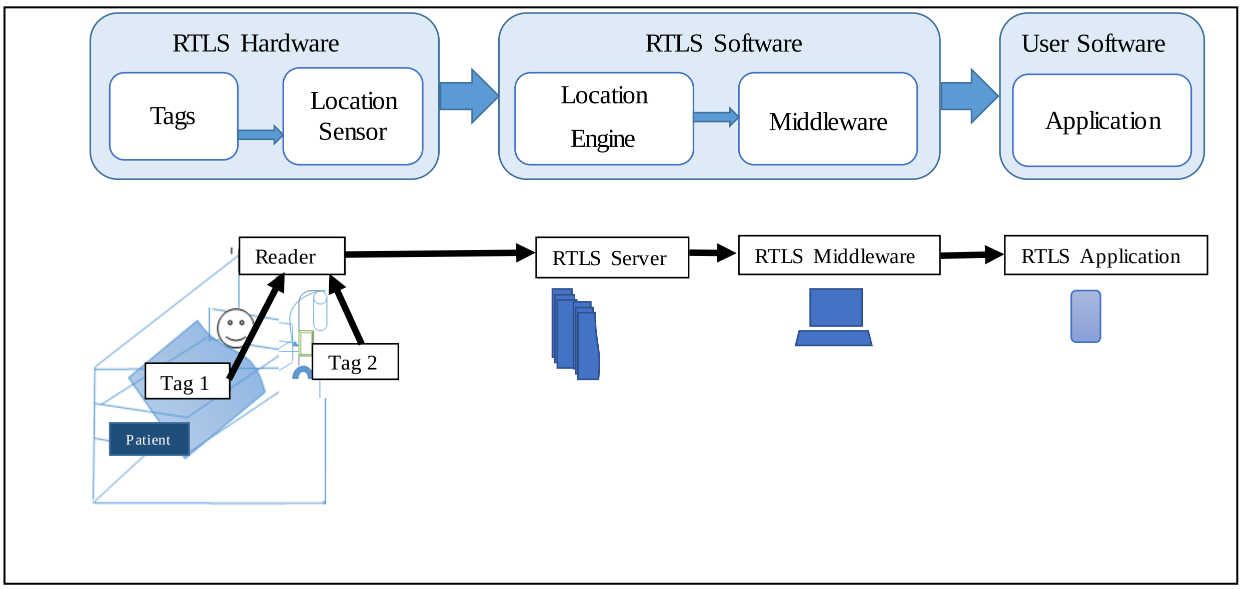

Figure 3 A high-level view of an RTLS in an ED

Hirshon et al. [60] analyzed the data collection methods used in healthcare facilities such as EDs. One school of thought is to increase the automation of current data collection systems. Automated data collection methods are expected to improve the accuracy and reliability of data, thus improving analysis and aiding in efficient policy making, thereby improving ED throughput and patient care outcomes. Many researchers believe RFID applications in medical institutions can help reduce medical errors and reduce labor [61], [81]–[84]. As such, many conject that RFID systems may also have the potential to improve the efficiency of medical services and improve patient outcomes.

Many scientists and researchers such as Nelson et al. [85] have explored various asset tracking means to improve throughput and resource utilization. Among the wireless technologies, RFID and RTLS have been suggested as leading contenders to aid in automated data collection [86]. Ferrer et al. [87] discussed the use of RFID tracking technology in monitoring various environments. Ferrer et al. [88] demonstrated that the provisioning of real-time data collection with RFID aids in logistics and resource tracking. Radio Frequency IDentification data collected in a Texas hospital were used to generate data for infection control, automated discharge and improved workflow, as reported by Baum [89] and Ward et al. [90]. This provides an indication that high-quality healthcare data can be obtained using wireless automated data collection techniques that are more precise, reliable and time saving for all involved. While commercial tracking systems are available and evolving, they are expensive solutions each with their own limitations. It is reasonable to suggest that some form of commercially hardened RTLS will be employed within EDs in the near future.

Simulation and modeling are generally used for visualizing and assessing process flow of complex systems and has been used in this manner by other researchers. Miller et al. [91] have used simulation experiments to demonstrate improvements to ED throughput. This supports the conjecture that simulation tools can accurately represent complex systems like EDs.

In the case presented here, simulation and agent-based modelling is useful as an inexpensive exploration and validation tool for optimizations that may be made attainable through deploying RTLS. Using AnyLogic simulation tools, an Agent Based Model of an ED was developed. Using patient flow data acquired from Winnipeg Regional Health Authority (WRHA), the solution obtained by our algorithms is validated, without the need for expensive hardware installations or other survey type data collection. The EDIS patient flow data was used to effectively bootstrap or augment the ABM to being a more reasonable model as opposed to a more generic ABM that is not regulated by real data.

The mobile RFID reader system proposed here is also not without difficulties of its own. The deployment of mobile RFID readers and the network planning to achieve two objectives is a non-linear multiobjective optimization problem. Guan et al. [92] demonstrated that deployment of RFID in large scale environments requires solving a complex network planning problem. Bandyopadhyay et al. [93] have developed a simulated annealing-based multiobjective optimization algorithm (archived multiobjective simulated annealing - AMOSA) to find a solution to this problem. These types of methods will also be applied while addressing the mobile RFID reader network planning problem. In this thesis, the proposed system first optimized and then further improved and thereby, successfully implementing considering obstruction similar to real world settings.

2.6 Underlying Technologies

The technologies used here are mainly categorised into radio frequency (RF) based and non-radio frequency (Non-RF) based.

2.6.1 Radio Frequency Identification (RFID) (RF based)

Radio Frequency Identification (RFID) uses radio frequency to communicate by transmitting and receiving data to and from RFID tags to RFID readers using a specified frequency and protocol. The RFID technology can be applied various environments that require tracking and identification of people or items. For instance, healthcare environment can deploy RFID readers to track patients doctors, nurses, equipment, medication [67], [84], [94]–[98] associated with RFID tags. Three kinds of RFID tags are considered, each with their own power source (or passive), range and cost. Figure 4 shows the types of RFID tags with different individual characteristics.

Passive tags usually operate in Low Frequency, High Frequency, Ultra High Frequency, or Microwave frequency bands. The smaller range (around 1-2m) and expensive readers makes passive tag option less useful in certain applications unless augmented by additional antennae. Use of bulky antennae (phased or directional) to increase the range (up to 60m) requires more space for installation. In space constrained environments such as healthcare facilities, this might be an issue. Passive tags do not have their own power source, instead relying on energy from the transmitted RF signal to process and transmit a response. This means that tags will be cheaper than using semi-active or active tags. For example, PINC solutions uses low-cost passive RFID tags and mobile readers on vehicles and drones to track tagged objects [99].

Semi-Passive tags are similar to passive tags but with the addition of a battery power source. The auxiliary battery enhances the range at which a reader may detect a tag. However, a large number of disposable batteries can be one of the environmental issues that can be addressed by using energy harvesting power source solutions, or through the use of rechargeable batteries [100], [101]

The addition of a power source results in a higher cost for active tags versus passive ones, however, active tag readers are usually less expensive than comparable passive tag readers [102]. Kimaldi created a system which identifies hospital personnel by using an active RFID tag worn as a wrist band or attached to a key ring [103]. This RTLS tracks more than one tag at the same time using a reader capable of reading multiple tags at once. The system operates in the microwave band with static or fixed location readers. SpotON [104] and LANDMARK [104] are few of the well-known systems that use active RFID tags for object location. Axcess [105] uses active RFID tags to automatically identify tags of interest to rapidly respond in case of a disaster.

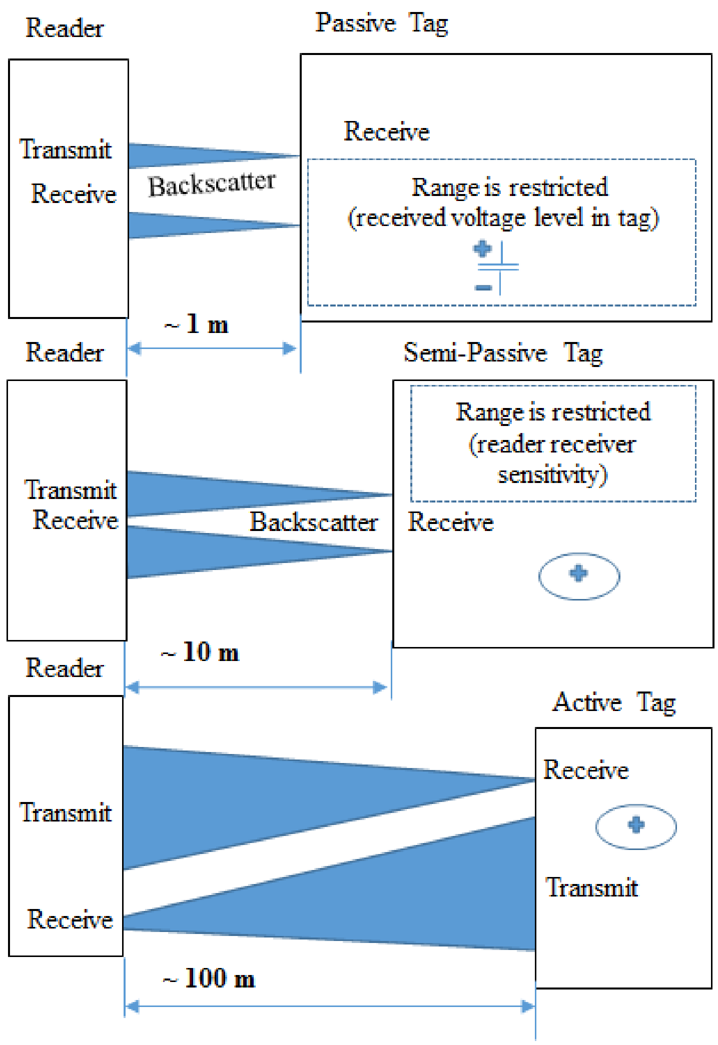

Figure 4 Types of RFID tags

2.6.2 Near Field Communication-NFC (RF based)

Like RFID, Near Field Communication (NFC) uses radio signals and is known as a improved version of RFID. Near Field Communication uses the same principle as RFID but the reader has to be in extremely close range; approximately within 4 inches. Of the available, previously discussed technologies, most are viable options, but due to NFC's exceptionally short range, it is not applicable for the proposed application in this thesis.

2.6.3 Bluetooth (RF based)

The operating industrial, scientific and medical (ISM) band of 2.4-GHz is used in Bluetooth based location sensing. In Bluetooth tracking systems, small transceivers detect Bluetooth tags [106], [107] with a specific tag identification number. The range is usually around 12-15 meters. The Topaz system is one of Bluetooth location solution that provides 95% accuracy of 2 metres . However, the cost of Bluetooth tracking system might prove to be more expensive, as both readers and "tags" would cost nearly the same and require both a power supply and expensive hardware. Wang et al. [108] reported that various antenna types, device types and relative positioning and proximity of devices, of Bluetooth detectors causes many spatial errors, meaning that Bluetooth based measurements are inaccurate, especially when compared with passive or semi-passive RFID tags which offer a similar range. A potential solution to using Bluetooth would be to use the patient's personal phone or device. In this case the patient's phone would not need a special app but rather just have its Bluetooth on, and the MAC address of the device could be acquired at registration and associated with that patient. There are many difficulties associated with this type of solution, not the least of which is privacy issues and mobile device battery life although many places no offer reasonable access to recharging of devices.

2.6.4 Bluetooth Low Energy (RF based)

Similar to Bluetooth, BLE operates in 2.4 GHz and provides almost similar communication as Bluetooth. The major difference lies in its power consumption. Bluetooth Low Energy offers low energy operation due to its characteristic of remaining in sleep mode unless data transmission is in progress. The Kontakt.io system [109] uses BLE Beacons that allows assets, wheelchairs and expensive equipment tracking, whereas the Centek system [109] offers BLE operated work flow RTLS in a hospital. Bluevision [110] even offers insight to inventory management and allocation of staff. Frisby et al. [111] implemented a tracking system using a combination of Bluetooth receivers and BLE beacons to detect physicians' locations accurately. Overall BLE RTLS seems like a viable option for choosing as a technology within a healthcare environment [112].

2.6.5 Cellular (RF based)

In cellular systems, target location is assessed using signal strength derived from the standard cellular signal providers. The cellular based localization could have an the accuracy of range of 50 to 200 meters [112]. Although there has been some work in developing a more accurate, indoor localization system using cellular, this involves a much more expensive setup including several base towers in close proximity to the building [112] or pico-cells within a building..

2.6.6 4th Generation (4G) communication: Long Term Evolution (LTE) (RF based)

The 4th Generation (4G) communication is form of enhanced mobile radio communication. 4G Long Term Evolution (LTE) are making progress in the RTLS field [113]. With an increasing number mobile subscribers, indoor positioning using LTE signals is becoming viable [114]. Given the high cost associated with equipment, it would likely not meet the economical requirements of the RTLS systems presented here.

2.6.7 Wi-Fi (RF based)

Wireless Local Area Network (WLAN) or Wi-Fi (IEEE 802.11) is another location tracking option. With a 50 to 100 m range, no length of stay (LOS) requirement, location sensing using WLAN is most widely available, as it can make use of access points already available [115]. In emergency healthcare applications, integrating WLAN with other localization technique would be useful. Active RFID and Wi-Fi based RTLS used for tracking, managing and analyzing mobile entities such as patients, staff and equipment in hospitals have been investigated [116], [117]. The Zebra system [117] is a ultra wide band (UWB) and Wi-Fi based RTLS used for tracking and managing medical assets and operations flow optimization. One of the successful implementations of the Zebra system is in an aerospace asset tracking application [66]. Some Wi-Fi based RTLS are reported to being capable of tracking infection spread by tracking patient and utilization of rental assets. One such RTLS system is Centrack [118] that uses cloud services. It has been successfully installed in hospitals [119]. A potential difficulty with Wi-Fi for the application developed here would be the cost in providing Wi-Fi tags to all patients.

2.6.8 Infrared (IR) (Non-RF based)

Infrared localization is achieved using a sensing unique identifier low-cost IR signals by IR receivers. The Active badge technique [120] is one such localization solution that uses IR badges that emits IR signals to be traced by a reader (every few seconds). The accuracy is dependent on nearness to receivers therefore dense placement of receivers affects system accuracy. The requirement of multiple receivers might increase the cost of the solution. Security is another issue with specific infrastructure requirement and scalability limitations. Also, fluorescent light and sunlight can interfere with the transmitted IR signal. A Versus Systems solution, an IR and Wi-Fi based RTLS, demonstrated the effectiveness of their system by addressing the Intravenous (IV) pump hiding problem and its replenishment in a hospital [50].

2.6.9 Computer Vision (Non-RF based)

Computer vision uses visual information to estimate the position of the objects by measuring angles to landmarks using a camera [121], [122]. Large image databases are then used in the matching process. Cameras are the only requirement for this kind of localization which might be an advantage but the need of a large image databases are a disadvantage. Simultaneous Localization and Mapping (SLAM) is an autonomous localization of the moving objects (robots/vehicles) which works by creating a map to find its own position without any precompiled image database [123]. Indoor pedestrian SLAM that has been implemented using short range laser scanner and inertia measurement units works best when sensors were placed on the shoulder and hip area [124]. The authors intended to achieve real time and precise pedestrian location. However, sensors attached to patients may seem to be bothersome [125] and acceptance of wearable cameras is still unpredictable for patients in EDs [126]. Furthermore, an SLAM system based on vision still faces accuracy and error issues due to environmental factors such as light and visibility [127]. In addition, SLAM is typically used by a robot so that it can determine its own location. In the case of patient or asset localization it is more important that the ED data collection system knows the patient's location than for the patient to know their own location. Computer vision is based on cameras that are certainly easier to integrate with the hospital infrastructure such as EDs, but the major difficulty lies in security and in the accuracy of detection, particularly when there is constant movement from one treatment area to another [128]. However, computer vision based system are expected to work really well in cases of detection in intensive care units where it can detect healthcare worker's hand hygiene compliance and personal protective equipment adherence to control the spread of infections [128], [129]. Furthermore, the quality of the images is still limited at night when patient detection is covered with blankets and when the complexity of tracking methods such optical flow or stereovision are implemented [128], [130]. With the aim to capture the maximum number of patients or assets, computer vision even when combined with RFID, seems like a complicated solution. Computer vision has its own set of limitations particularly in multiple object tracking when there are a large number of people [131]. Additional tracking algorithms are required to be implemented in vision-based systems that can efficiently track not only face but other features as well. Kinect and RFID based system was used to accurately track patients in real-time effectively [131].

In an attempt to minimize the cost and enhance the coverage, the selection of a technology and the devices used and their implementation, makes a significant difference in the overall cost of the system. This encourages the use of a cheaper alternatives, for instance inexpensive and unobtrusive RFID tags and readers that seems to be the best fit for a hospital environment such as EDs. However, the overall cost and efficiency of the RTLS system can only be estimated once all of the components of the tracking technology, its placement strategies/network planning and optimization techniques are carefully implemented. The RTLS development begins with measuring, evaluating and selecting the type of technology in alignment with the major design goals followed, leading to the optimized system which is briefly discussed here.

In any event, independent of the technology used for readers and tags, the mRTLS system described and presented here could be adapted. All it would require is similar modeling and simulation to aid in justifying deployment.

2.7 Data-driven Agent-based Modeling

The overall aim of data-driven modeling is to develop as accurate a model as possible using real data to the greatest degree possible. A major advantage of an ABM is the capability to feed real data into the modeled system. With the growing availability of research data, the model complexity can be further assessed in great detail including links to different data sources such patient data, medical assets data, and healthcare professionals' data and so on. Incorporating real data improves the validity, reliability and strength of the proposed model. However, the major limitation of using real data is that it is available in several different formats usually derived from distinct sources. Data-driven modeling techniques have effectively been applied in various areas including modeling EDs or hospitals [132]–[139]. Data driven modeling and computational intelligence are proven to be applicable in many cases [134], [138]. Data driven modeling aims at making use of actual available data to model the system in order to determine the loopholes or congestion in the existing scheme that impacts the performance of the entire system. The major advantage lies in the mining of the inherent characteristics of the various elements or by introducing new enhancements and assessing their impact on the system as a whole. The role of data-driven modeling is to make the model as accurate and valid as possible. A potential disadvantage of a data-driven model is that in grounding the model, unexpected or emergent behaviour may be difficult or impossible to observe, as the model is continually grounded. Also, one has to be mindful of experimenting with what-if scenarios as only certain aspects of the original data may still be valid. For example, if a data-driven model correctly models and simulates the ED under a process flow of A, then using the same data for a process flow B would be difficult to justify. It may be that only the arrival rates and service times of specific sub-processes would be usable while modeling process B.

The preliminary ABM model developed here emulates the progression of the treatment of patients within EDs. After outlining various processes involved, the functions and parameters are defined in a way that all of the treatment phases are taken into account in order to achieve the actual functioning of ED in the developed model. Once a properly operational ED model is established, the correctness of the designed model is tested by entering preprocessed EDIS data by means of input parameters stored in a csv data file. The developed model is then assessed for its validity and checked for any overlooked or incorrect processes of treatment present in the actual data but not being accurately captured in the model. The model is run multiple times to verify the generated output data and checked to see if it represents the same as the actual data that has been used to initialize the model. Subsequently, the process of extending the model towards the proposed RFID based RTLS begins after the model has achieved operational correctness.

In an attempt to explore the impact of a new RFID based data collection system on ED-ABM model, the model is run several times to measure the effect of the augmented stationary RFID-RTLS system. The proposed RTLS design, once optimized using evolutionary algorithms (EA), is iteratively tested under several scenarios, for instance corner cases. Corner cases include the scenarios such as impact of covering an entire layout of the ED-model with the maximum number of readers or none. Also analyzing the influence of changing the course of treatment by changing state diagrams or controlling the number of patients moving through the system.. The process of elimination (i.e., by removing one sensor at a time) was also tested to find out how removing readers one by one impacts the overall tracking of the patients. All of these what-if situations were tested to evaluate their impact on the ED model in terms of tracking accuracy and uncertainty or error. Ultimately, an optimized RTLS system was developed that tracked the maximum number of patients transitioning through the system using fewer readers and the generated complete data set of the patient trajectories within EDs. The data produced through implementing the augmented RTLS in an ED captured the process of patient flow more carefully thereby eliminating ambiguities and automates the data collection. However, there is still scope for improvement in the data quality and cost by making the next effort of optimizing the trajectories for mobile readers. The initial design allowed movement between the most active hotspots, but determining near optimal trajectories among active areas is a potential source of improving the quality of data capture still further.

Extending the RTLS model in order to further improve the system requires finding the best route that can connect all the optimum static hotspots while optimizing the objectives of minimizing the RFID tag tracking error and minimizing the number of readers simultaneously. This problem is related to the travelling salesman problem [140]. The best tracks are explored by implementing metaheuristic algorithms, an advanced level technique to determine, build or select using partial search algorithms such as Simulated Annealing (SA) that might provide adequately good solutions. As the model ran on the data derived from the EDIS dataset to follow the actual timestamps of patient flows, the proposed mobile RTLS captured the locations of patients while they moved through various treatment areas. The near optimal tracks or trajectories were produced by the Simulated Annealing (SA) algorithm further improved the tracking using even fewer readers than realized by the previous stationary RTLS design. The proposed system design was then confirmed by running the ED-ABM model to verify the quality of output data generated by the enhanced mobile RTLS system. The improved mRTLS design in the ED-ABM model was further tested for various ED layouts in order to evaluate the modeling performance and potential improvements that a mobile RTLS may provide. At this point it was important to note that the trajectories for the mobile readers are "as the crow flies" or direct point to point. The iterative testing was repeated for an optimized number of readers and the process of elimination of readers in order to reach the desired coverage for accuracy and cost. This was verified by the generated output data collected over several runs of the augmented model. However, the practical application of the proposed mRTLS system was only feasible if the actual infrastructural barriers of the building are considered.

Infrastructure modeling and path planning without the presence of some obstructions is unrealistic. Furthermore, in an effort to credibly model an ED, the augmentation of ED-ABM model with actual physical obstacles in the environment becomes a necessity. Upon finding the optimized tracks for the moving readers, the ED-ABM model could be enhanced by introducing walls separating different areas. The permissible or legal routes are ones that take into account the presence of walls within the layout of the setting. An implementation of the A* based path planning algorithm finds a legal path for the different layouts that avoids walls or obstructions.

2.8 Stationary RFID RTLS

In this section additional details of a stationary or static RFID RTLS are provided. Communication between a reader and a tag occurs within a limited range so in order to achieve complete coverage over the entire area, the deployment of static or fixed readers in high traffic or high density areas becomes a necessity [141]. The ad-hoc communication is established wirelessly between multiple static readers and RF-tags to form an RFID network. An RFID network cost and complexity is primarily based on the number of static readers in order to achieve a goal of tracking efficiently [92]. Reader positioning, possible deployment locations, reader type such static or moving, and reader parameter configurations contribute towards the planning a well operating RFID network in practical scenarios such as EDs. A well-planned RFID network also resolves technical issues such as reader interference [92]. Guan et al. [92] applied a genetic approach to determine an optimum configuration for RFID readers to achieve a coverage of 92%. The researchers evaluated their genetic algorithm implementation of a discrete model of RFID network with a Tabu Search technique and found a reduction in the interference values.. In this thesis, for the proposed RTLS design, an attempt to determine optimum locations of RFID readers was achieved by implementing a genetic algorithm with two competing objectives. The aim was to achieve the optimization of two individual objectives, accuracy and cost, simultaneously instead of attaining the objectives in a hierarchical fashion optimizing only a single objective at a time

[92]. Concurrent optimization of multiple objectives often generates compromised trade-offs or non-dominated solution sets that are not provided by single objective optimization. However, optimizing against a single objective might give in-depth insights into the problem to the decision maker. However, most practical problems require attaining multiple goals such as maximizing profit, minimizing loss etc. [142].

Laskowski et al. [8] designed an ABM for patient tracking including the assessment of error/uncertainty of a low cost, fixed RFID readers in an ED. The limitations associated with the fixed RFID readers in this study relates to a degree of uncertainty or error that depends on the number of readers provisioned in the ED. An issue addressed here is the high cost and maintenance associated with a large number of static RFID readers deployed in the ED. Many researchers are making efforts to reduce the number of expensive RFID readers by using reference tags which are passive RFID tags at a known specific places [143], [144]. Manzoor et al. [144] presented an indoor position algorithm that uses a grid of passive RFID tags that were placed at calculated distances (as neighbours). Their technique provides information about the proximity to an unknown tag and determines the final position of the tracking tag. However, smaller inter-tag spacing between the inexpensive reference tags is able to minimize the linear positioning error but adds to the cost and time [143].

The research studies of Anusha et al. [145] support replacing expensive static or fixed RFID readers with fewer mobile readers to save on the deployment cost of the RFID system. Furthermore, these researchers believe that using moving readers to get complete coverage periodically is a better alternative to full coverage by fixed readers at all times. The automated coverage planning tool (known as RFIDCover) addresses the problem of the placement and movement patterns of mobile readers by identifying the number of mobile readers to give complete coverage within a specific time. The tool uses a zigzag mobility model to move through aisles in the supermarket and using a least square optimization function to generate layouts that determines placement and movement pattern of the readers. However, the RFIDCover tool is limited to rectangular layouts similar to warehouses, so their model may not be applicable to other layouts such as EDs. The proposed RTLS design is not layout specific and has a possibility of broader applications. Further, the multiobjective optimization benefits the decision maker in a wider scope. More importantly, the work of Anusha [145] does not involve any interaction with agents such as patients or mobile equipment. In their scenario, the tags are static and immobile while the readers are mobile.

Factors affecting the reading performance of a mobile reader and its evaluation is complicated. There is not much research published about mobile RFID systems, so designing a mobile RFID based RTLS for EDs is a challenging task. However, research from disparate sources can be used to support the potential of an mRTLS for an ED. Xie et al. [146] conducted research to effectively identify a large number of tags in practical settings using a mobile reader. The researchers claimed to have developed a continuous scanning algorithm that reduced the scanning time by almost fifty percent with lower energy consumption for their application. Their probabilistic model optimizes parameters for identifying a large number of multiple tags. Xie also considered mobile tags but differentiated from the work here as those tags were constrained to conveyer belt systems. However, there are other aspects of mobile RFID readers, such as those moving on tracks, that have not been discussed. In the proposed mRTLS, the novel idea of using a ceiling mounted tracking system is designed on which the mobile RFID readers will traverse. The advanced mRTLS system optimizes the tag identification by covering the high tag tracking areas with the view of infrastructure limitations such as walls as well. The proposed design also implemented a probability detection model to determine the probability of locating RF tags based on its presence within the tracking range or vicinity of the mobile readers.

Anusha et al. [145] and Xie et al. [146] are of the view that the expensive deployment of fixed readers gives a broad coverage. However, complete coverage might not be essential in real world, and practical applications may then take advantage of mobile readers.

2.9 Evolutionary Algorithms based Optimization for RFID Systems

The application of evolutionary algorithms (EA) to address multiobjective and constraint-optimization issues has shown promising results in several research studies. The studies conducted by Guan et al. [92] and Seo et al. [147] support solving RFID network planning optimization problems by evolutionary algorithms. Guan et al. [92] applied a genetic approach to overcome complex problems such as interference of multiple readers, undesirable mutual coverage and variability in the propagation environments. Guan et al. [92] are of the view that uplink signals from tags to readers should be taken into account while solving the complex RFID network optimization problem.

Seo et al. [147] designed a genetic algorithm-based resource allocation for RFID system to resolve the reader to reader tag collisions and interference complications. The system designed by Seo et al. [147] optimized RFID resource allocation and the related tag recognition issues. Weijie et al. [148] analyzed RFID network features and multiobjective optimization built on genetic programming. These multiobjective genetic programs or algorithms typically generated the best fit layout/deployment of static readers.

In my work, the proposed implementation incorporates multiple algorithms in order to optimize the RTLS system. The development of a design begins with Genetic Algorithm (GA) optimization to identify hotspots. In order to get a more optimal coverage, the hotspots are then connected via mobile readers to achieve the routes with the least acceptable error. As the hotspots are assumed to be multiple locations or cities where the reader or the salesman visits, the problem appears similar to the travelling salesman problem (TSP). Simulated annealing (SA) is implemented for this modified TSP problem to optimize the path or tracks on which the readers traverse. To improve the path, another path-finding algorithm known as A* is employed, to generate a realistic path considering obstructions such as walls within the simulated healthcare environment.

Seo et al. [147] addressed the resource allocation problem (RA) or the problem of assigning frequencies and timeslots at the same time in order to decrease interference amongst readers. They implemented an optimization solution to maximize the system performance by solving the problem of RFID reader-to-reader interference based on distance, frequency and operating time of readers using a genetic algorithm. Seo et al. believe that their RA-GA technique performs better than one that does not use any resource allocation technique. However, their solution is based on a single objective problem formulation instead of a multiobjective focus, which is one of the major limitations of the RA-GA method. Most real-world problems are multiobjective in nature. Their algorithm's performance is only compared with a random reader deployment and not with other optimization techniques for reader deployment such as simulated annealing. Another issue lies in the actual applicability of RA-GA in practical settings such as EDs as no real-world environments are tested. Seo et al.[147] and Weijie et.al. [148] discuss the use of mobile readers in future research. The novel concept proposed in this thesis addresses the applicability of a multiobjective simulated annealing algorithm for mobile RFID based RTLS complex environments such as EDs.

Weijie et.al. [148] developed an automatic optimization tool using multiobjective genetic programming, that attempts to optimize the deployment of RFID readers. The author does encourage the concept of using mobile readers instead of static ones in order to reduce the cost of the system but this is not implemented in their present design. The researchers focused on coverage overlap between readers (reader collision), initial distribution of readers (load balancing) for complete coverage and reading accuracy in specified areas. The proposed mRTLS design in this thesis attempts to replace a large number of fixed readers with fewer mobile readers to make the system more budget friendly.

Weijie et al.[148] examined their automatic optimization algorithm applicability in an ideal square working area and not in a more realistic RFID deployment scenario such as in EDs. The performance of these types of algorithms needs to be evaluated for more realistic environments with areas separated with walls or obstructions. The proposed mRTLS design in this research attempts to address the concern of optimized RFID deployment in practical hospital settings that includes infrastructural boundaries such as walls.

2.10 Mobile RFID RTLS

Mobile RFID data collection systems in general are relatively few in number and are considerably fewer as they may relate to an ED. Mostly, these are expensive solutions with least information about its effectiveness in the real time healthcare environment. There have been studies that use RFID enabled robots or mobile devices. Xie et al. [146] supports the idea that the efficient use of mobile readers may cover the area sufficiently, with the advantage of reduced cost of deployment due to fewer readers being required. Similarly, in order to address the issue of reducing cost and reducing patient and asset localization uncertainty in an ED, a mobile RFID/RTLS system is proposed here. The proposed mobile RTLS aims at minimizing the cost by reducing the number of readers while minimizing the error in tracking the RFID tags in an ED. A significant difference here from most mobile RFID systems is that the readers in the ED would be ceiling mounted as a means of keeping the system as non-invasive as possible to the normal operations of a busy ED. This in effect further constrains the mobile RTLS problem, making it more challenging.

2.11 Metaheuristics Algorithm based Optimization for RFID Systems

A heuristic uses guided trial and error to find a solution whereas meta, as in metaheuristics, implies a higher level. Metaheuristics is an approach that directs heuristics to discover a better solution. There are various metaheuristic algorithms, such ant colony optimization, evolutionary computation, simulated annealing. However simulated annealing and its variants are seemingly more popular optimization techniques. The metaheuristic algorithms allow broader searching capability.

Researchers have demonstrated the advantage of using multiobjective simulated annealing (MOSA) over a well-known multiobjective genetic algorithm (MOGA) such as Non-dominated Sorting Genetic Algorithm II (NSGA-II) by [149] that accepts the best or dominating solution. An efficient MOGA like NSGA-II may not be the best option to solve all problems all the time [150], [151]. Furthermore, the authors believe that MOSA may not work in the same fashion as a single objective SA or EA in terms of having a lesser likelihood of getting caught at suboptimal region due to acceptance of worse solutions. The researchers attempted to include the key SA characteristic of acceptance of worse solutions than the current one in multiobjective SA in AMOSA. However, certain limitations still remain, such as integration of the designed algorithms with other systems or algorithms, for practical scenarios where the algorithm can be applied. As future work, the authors claim to be still working towards convergence properties of the designed algorithm, parameter selection and application to real life domains. Their algorithm's applicability in scenarios like RTLS deployment in EDs seems limited at present. A novel concept in this thesis is the implementation of multiobjective genetic and simulated annealing algorithms for a practical setting such as an ED. The proposed algorithms optimize the mobile tracks generated from preliminary RTLS with static readers and is then augmented with mobile readers. Different parameters are tested to examine the convergence of the developed algorithm in the ED-ABM RTLS model and evaluate the model design.

2.12 Proposed mRTLS Path: A Mobile RFID Reader based RTLS

A RFID RTLS was developed that used mobile readers and delivered a near optimal path for actual deployment of a minimal number of mobile readers. The RFID augmented ED model and the two proposed multiobjective algorithms are used for developing path planning strategies. The two objectives achieved for the proposed agent-based model were used to minimize the number of RFID readers (i.e., minimize the cost) and to maximize the coverage.

The designed agent-based model helps verify the optimal path planning of the mobile and the fixed RFID surveillance system while achieving both objectives of minimizing cost and errors. The proposed model was optimized using genetic and simulated annealing algorithms (GA and SA). The algorithms effectively optimize the RFID mobile reader network. As an example, on one representative ED layout, the number of readers was reduced from 27 in the full static reader deployment case, down to an average of 14 static readers using the GA which was and further reduced to 6 mobile readers on fixed tracks or segments. On an average, over nine runs, the GA optimization was able to minimize the RFID tracking error using fewer readers. The optimization experiment is explained in detail in Chapter 5. It was concluded from the parameter variation experiments that the optimized solution minimized the cost by using fewer readers was and achieved sufficient coverage that was determined based on by maintaining a minimum error rate comparable to a greater number of static readers. There are obviously unavoidable tracking errors in any RFID tracking system but an mRTLS system based on mobile readers may offer a cost-effective alternative with acceptable error rates.

Potential future work includes deploying and testing of the proposed RFID based mobile tracking solution in a controlled and monitored environment. This would done using mobile RFID readers that would traverse on the optimized paths on the ceiling mounted tracks . While the number of readers and segments is small in the current study, the work can be extended to much larger instances. The general framework explored here is also applicable to envisioned scenarios beyond tracking within hospitals, but where the mobile readers are not on tracks but may be drones within an IoT environment where drone path planning may still be required.

2.13 Legalized RFID RTLS

Research that had been published to date mainly discusses modeling the RTLS in ED settings or indoor RFID enabled mobile robot path planning [8]. However, no work has been published that models a moving RFID reader based RTLS design optimised by incorporating multiple objectives that takes into account the presence of practical infrastructural barriers such as treatment areas in a hospital setting.

The proposed mRTLS model determines the admissible or legalized path or the tracks on which the mobile reader will traverse within hospital environment such as EDs, for instance, the presence of walls and their impact on the mobile track in terms of designing cost effective moving readers for hospital environments. As mentioned previously, these types of obstructions also tend to constrain the problem, which in general is known to increase the difficulty associated with any optimization.

A layout can have legal or permissible boundaries within the system that separates various key areas of interest with physical obstructions such as walls within EDs. In order to design a tracking system that considers the presence of physical barriers and traverses through allowed areas, obstacle avoidance algorithms can be applied. The admissible search algorithm A* search was implemented to optimize the path in an ED layout encompassing walls.

2.14 Summary

The proposed RTLS is a RFID based system with goals of using reasonably priced and wearable RFID tags on the patients, healthcare personnel and medical equipment in order to capture their location and flow in an ED of a hospital. A set of ceiling mounted mobile RFID readers installed to navigate on optimized tracks is proposed to identify and track patients, medical staff and assets. The aim is to design a RTLS for an ED environment that minimizes the cost by using fewer mobile readers instead of static readers while maximizing the tracking accuracy by making all the readers move on optimized paths, planned using evolutionary, metaheuristic and legalized search algorithms. .The proposed RTLS design evolves from static reader placements to mobile readers and finally achieving legalized paths for moving readers. The details of each advancement in design is described in detail in Chapter 4, 5 and 6.

Chapter 3: Agent Based Modeling for Emergency Department

Pure statistical analysis cannot accurately predict individual patient wait time or treatment time, as missing data can cause potential bias in the estimate of parameters [152]–[155]. However, its use as an ancillary method that provides information of individual patients such as arrival timeand waiting time during different phases of treatment is useful within an ABM. Using all available data, statistics and ABM would enable a much more realistic model which could then be used to predict how arrival rates and other independent data could affect individual waiting times and length of stay. In this study, EDIS data for six facilities in Winnipeg was used as input to develop and run an ED-ABM model that emulates the patient flow within an emergency department. The proposed model attempts to provide a benchmark design specification for installing and modeling a patient and asset tracking system for a critical environment such as a healthcare facility. The long-term objective of the modeling is to improve the process of collection of data related to patients and assets by means of an optimal mobile RTLS design. This aligns with the concept or practice of better data collection techniques and prevention of missing data before delving into advanced statistical analysis, by envisioning a system that mitigates against missing data which otherwise diminishes the power of statistical analysis [153]–[155].

The simulation model developed here uses the AnyLogic simulation and modeling tools. These tools make it easier to simulate the flow of patients within an ED. These tools were also very useful for constructing a three-dimensional simulation to help visualize the functioning of the system. These types of modeling efforts are also aligned with Building Information Modeling (BIM) methods where 3D modeling combined with simulation are used to improve large scale infrastructure design [156]. The simulation is driven using data acquired from EDIS, imported from an Excel spreadsheet. The data is limited to patients only, and does not include any indication of hospital resources. This admittedly restricts the model's capability. Model improvements would require data on the number of nurses, doctors and other staff as well as resources such as number of available beds, specialty equipment and other devices. This is not a fundamental difficulty but rather a technical or logistical constraint based on the data that was available.

3.1 ED Simulation and Model Definitions

Each patient is an individual agent following the treatment process flow of the ED, as shown in Figure 5, model initially begins with a patient entering the waiting room. This event is generated based on the arrival time or registered date and time as it was recorded in the EDIS data set. For some facilities, this also corresponds to the triage time From there, the patients proceed to triage. If the value for time at which triage was completed is the same as the registered time, then the patient will immediately return to the waiting room, otherwise the patient will wait at triage until the triage time has expired. Once triage is completed, the patient will attempt to occupy a treatment room. If a room is available, then the patient will seize that resource, and move to the treatment room location defined in the visual representation. If a room is not available, the patient will remain in the waiting room until one does become available. Once a patient arrives in a treatment room, he/she then enters the Waiting To Be Seen (WTBS) state. Once a doctor is available and arrives in the treatment room, the patient then transitions to the Treatment In Progress (TIP) state. There is then the possibility of the patient requiring a consultation with a specialist in the hospital (i.e., First Consult (FC)). For the sake of simplicity and due to requiring other data, combining the TIP states and the FC state as one was necessary, since the patient receives both of these services without changing locations in the simulation model. Upon completion of TIP/FC the patient then enters either the Waiting to Be Admitted (TBA) state, the awaiting Transfer (TRN) state or the Pending Discharge (PD) state. This state is dependent upon the final disposition of the patient. If the patient is going to be admitted to the hospital, then they are going to enter the TBA state. If the patient requires transfer to another facility, then the TRN state will be chosen.

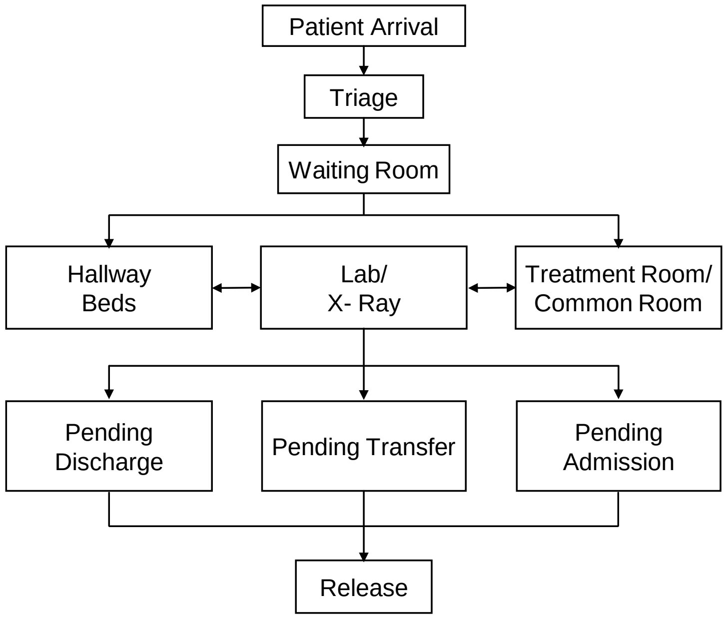

Figure 5 The simplified flow diagram of patients in ED simulation model

3.1.1 Graphical Representation

One of the best ways of understanding any dynamical system is by watching it work. While sitting in an ED is definitely helpful, this is not always efficient or permissible, especially if what one is interested in viewing is a certain specific series of events. This is where a graphical representation of the simulation and modeling system is helpful. One is able to view the system from an overhead view to see how patients move through the system. This is also very useful in demonstrating what-if scenarios, and presenting the model to others. In my work, the built-in graphical system of AnyLogic simulation tool is used. These tools provide three dimensional (3D) models an example of which is shown in Figure 6 and the scene and camera functionality associated with the model.

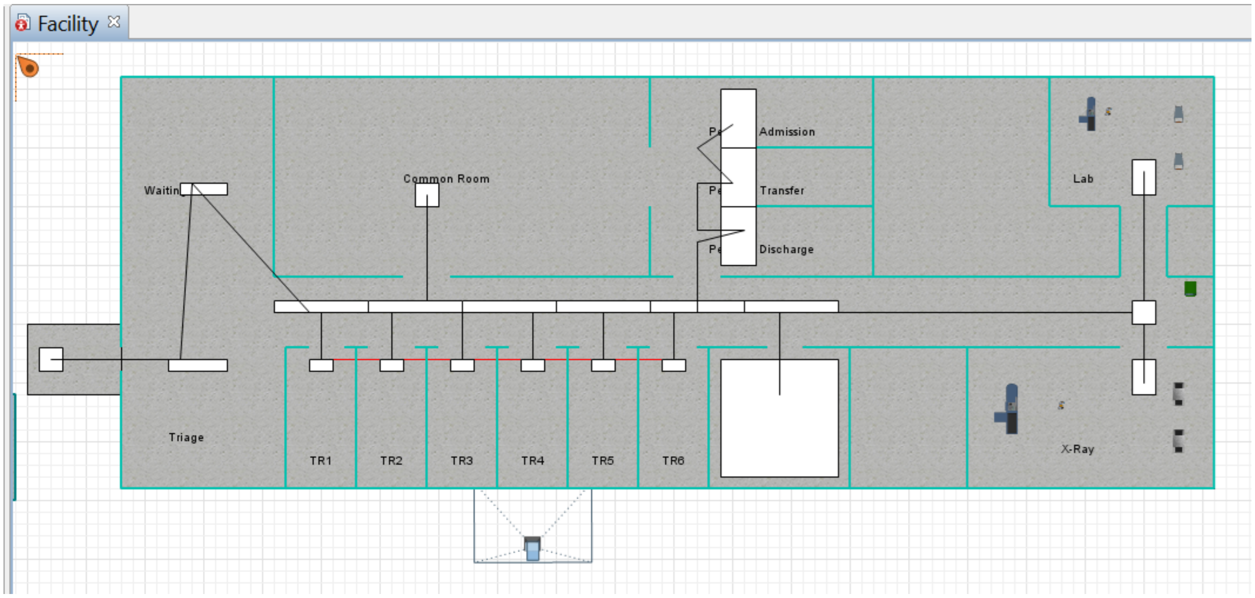

Figure 6 Overview of the simulation model layout

Using a Java based OpenGL graphics engine, the simulator creates the 3D models associated with the patients, doctors, nurses and other resources which is shown in Figure 7 .

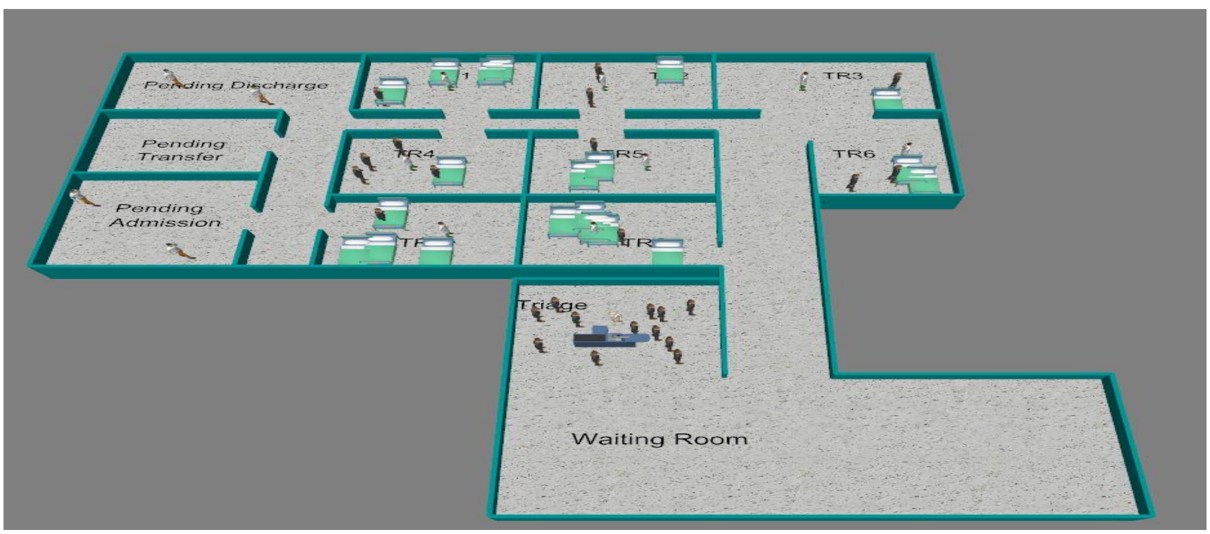

Figure 7. Hypothetical 3D simulation model

The simulation tools also have facilities for defining the movement of an individual patient through the system. This was done using a polyline, where the polyline definedthe segmented path which a given object, either a nurse, a doctor or a patient, follows in order to proceed from one location to another. This must also be modeled correctly in order for the simulation to be as accurate as possible. If the time it takes a doctor in real time to move from location A to location B differs greatly than that which it takes in the simulation model, then the accuracy of the model will be lacking.

With the essential portions of the model defined, it is also possible to add several smaller, detail-oriented touches to the graphical model. Items such as walls, floors, and rooms can be added to the scene in order to make the simulation more visually appealing and life-like. While these details are not required by the simulation model in order to function correctly, they do add a level of detail to the graphical model that may aid others in understanding the system model.

3.2 Simulation and Preliminary Results

In order to validate and verify that the underlying ABM was functioning as expected, the model is run using the EDIS data set.

For example, running the EDIS data for the month of October 2009 through the simulation model as shown in Figure 8showed that Triage Score 3 has the highest Length of Stay (LOS). Also, the time period between 6:00 pm to 12:00 am has the maximum number of patients who are WTBS in the ED for facility C. The WTBS in facility C was 1.318 hours and was as expected.

The WTBS, on average, takes the most amount of time of all processes in the ED. These results help validate, by accurately matching the dataset timestamps, the preliminary ABM as the results were as expected. Also, are similar to that from the statistical analysis of the EDIS data. The designed ABM produces observations similar to the EDIS data as one would expect, implying that the model and state charts reasonably capture ED behaviour providing micro and macro face validity [157].

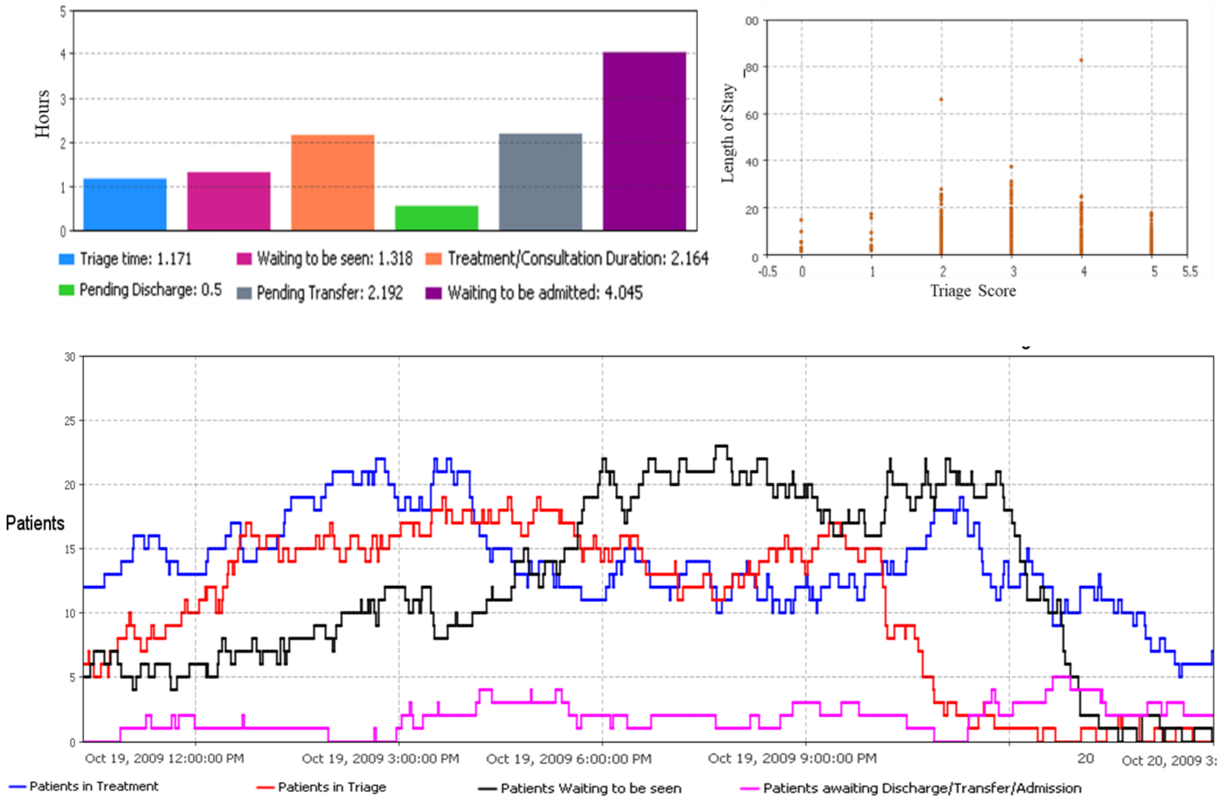

Figure 8 Real-Time data processing and analyses for Facility C

In future work, the ability to relocate a patient to a given specialty service location for services such as X-Rays, MRI, CT scan, and other diagnostics can be included. However, the current data is lacking the necessary information to implement these features in the simulation model. Data detailing the number of services available, relative locations of the services and staff requirements for service will be required. With this additional data, it is possible to implement a much more accurate simulation model by adding a number of resources and their locations. These resources would become variables that the user could manipulate, giving even greater flexibility in tuning the system. These types of data inclusions would be required for any analytical or simulation model.

One issue with these types of simulations is that it is difficult to model human behavior. While it is possible to add nurses and doctors as resources, these resources will behave in the same manner every time the simulation runs. This is not realistic. Humans have good days and bad days, each with different characteristics; productivity can increase during good days and it can also decrease on bad days. This could have an effect on the accuracy of the designed model.

Perhaps in the future, some statistical analysis of average performance of humans can be accounted for in the model to improve the realism of the model. The busyness of the ED itself could also be a significant factor in a person's behavior potentially compounding the waiting times [26], [158]–[162]. These types of human behaviours are arguably easier to model with an ABM than through aggregate techniques, as each individual has its own agency.

To this point, EDIS data has been analyzed and various descriptive statistics are available. The goal of EDIS is to improve patient flow by better using technology to know where people and resources are and allow the analysis to help better understand potential bottlenecks. As a means to this end, the EDIS data was used to govern the flow of patients in ED ABMs. These ABMs produced similar descriptive statistics, providing confidence in the ABM as accurately reflecting patient flow in an ED. This then serves as a starting point for explorations into the technology to augment and further data collection. In the next section the possibility of using RFID as a means to collect additional patient flow data as well as providing a means to track resources is introduced. Although not without criticism, having the ABM provide similar statistics as the original data set helps verify that the model is reasonably accurate in that a person considering the EDIS data set directly or the ABM would perceive similar observations. The visualization also contributes to the face validity as the agents behave as expected if one were to physically observe an ED.

3.3 Adding RTLS and mRTLS

During the course of the preliminary investigation, the uncertainty of the data and the perceived issues with its collection also inspired the development a means of filling some of the gaps in data collection that may improve the model. The creation of an automated system to collect and record patient, staff, and asset data through an ED would improve the quality of data, while also reducing the workload of ED staff. This led to the idea of incorporating a tracking system using RFID and to verify its ability to augment the data of the EDIS in the ABM, prior to real world deployment. In Figure 9 a snapshot visual of patients' movement patterns is provided for their time in the ED, where their movement based on the real data from EDIS. The data is essentially a record of the start and stop times of the events that a patient would experience. These times also include arrival and discharge times. Essentially this is representative of an agent's EDIS schedule and its state machines. The descriptions and definitions of events and statecharts are provided in the appendix. Although not included or addressed here, the visualization shown in Figure 9 also shows a cluster of patients at triage, where it is a more realistic scenario that patients tend to social distance themselves. It is these types of details that can be easily extracted form a visualization and subsequently readdressed in the ABM to make it even more realistic.

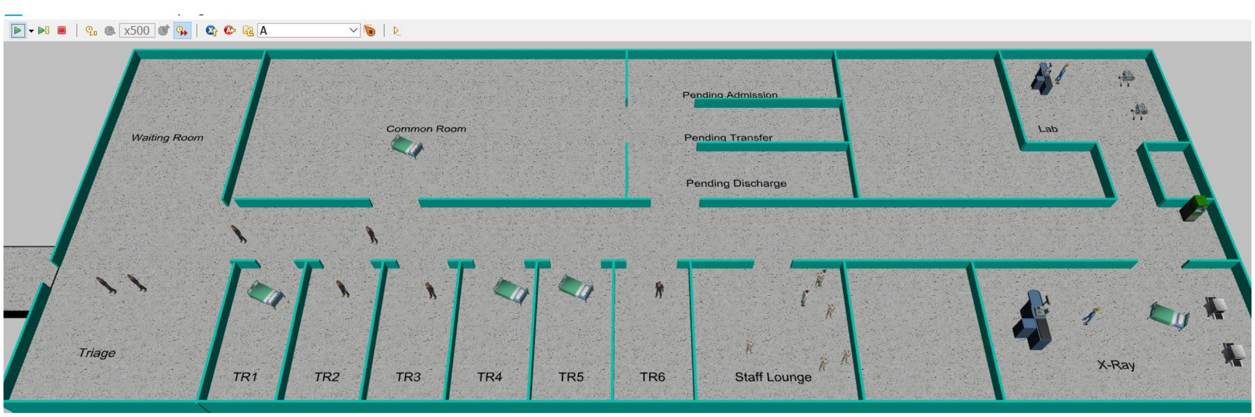

Figure 9 EDIS driven ABM with similar statistics

In the top-level hierarchy shown in Figure 10, initiates with the source as the starting point in the ED ABM model and generates six main agents and are defined as Facility agents. These are patients from facilities from A to F and their timestamps at different stages through the treatment process that is based on the EDIS dataset (an Excel file). The space, network type they will belong to, variables, initialization functions, events specifying their action (behavior) are defined before they exit through the sink where they are removed from the model and disposed from the system.

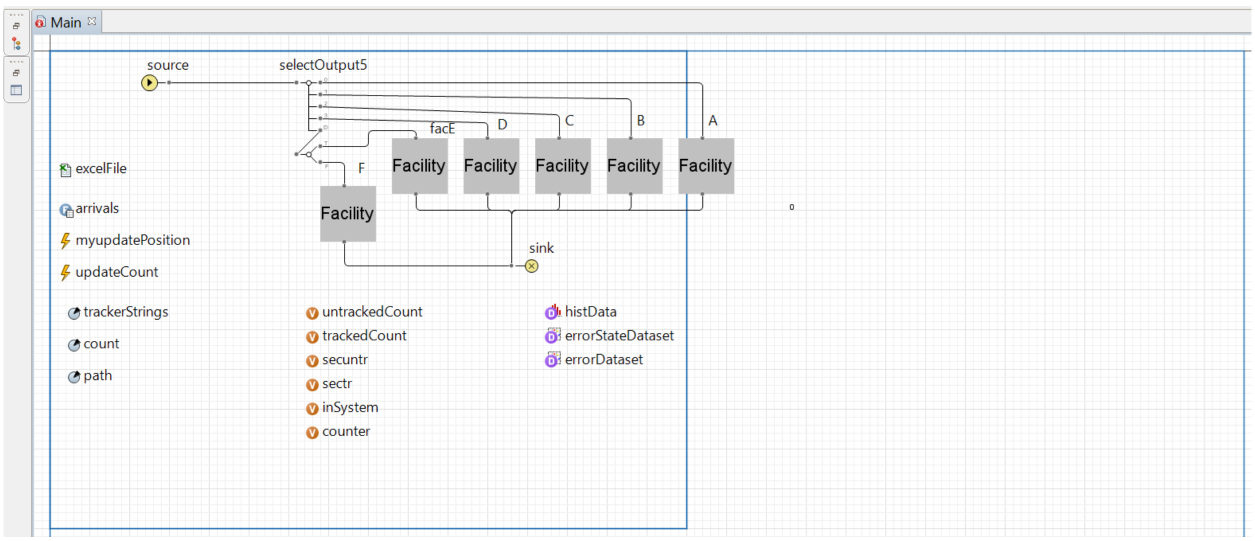

Figure 10 Top level Main hierarchy with six facilities

In Figure 11 the network of the modeled process is shown in which includes a physical space movements of agents and resources (these can have individual speeds and can be changed). A typical network is a group of interconnected nodes and paths where a node is a place of stay for agents while a path connects the node on which the agents can move from origin node to the destination node (typically a shortest path).

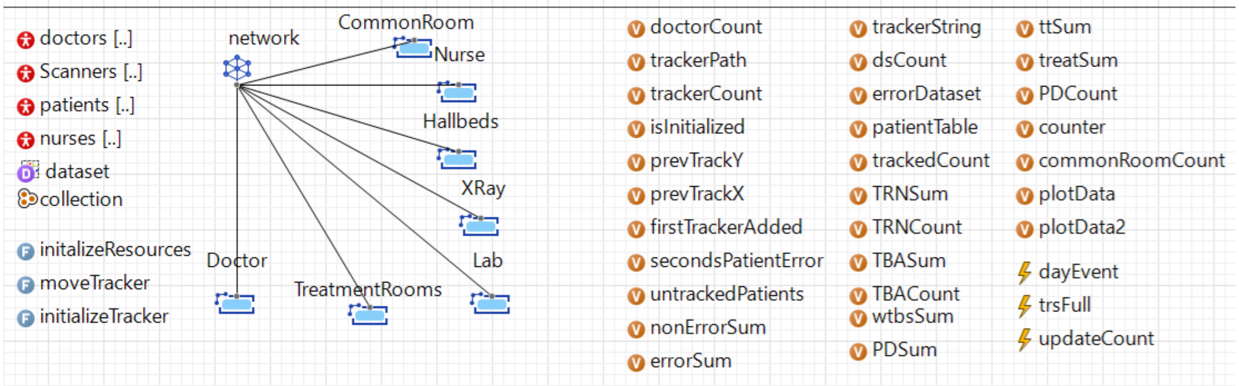

Figure 11 Network of treatment areas and resources

In Figure 12 the statechart are illustrating the states and transitions of a patient agent. Event and time driven behaviour can be defined through a statechart construct. Transitions can be triggered by messages received by the statechart, by timeouts/rates, and by Boolean settings that can lead to state change, activating a new set of transitions (hierarchical or comprised of other states and transitions). Here the state machine was used to show the state space of the algorithm, events initiating transitions between states and their subsequent actions. There is a statechart class in the AnyLogic simulation library that constructs a statechart object and calls the defined functions internally.

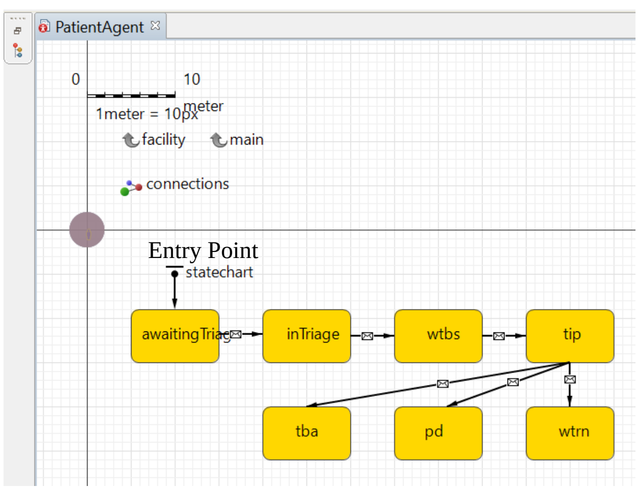

Figure 12 PatientAgent state machine

The Figure 13 continuously scanning behavior of the RFID readers is shown schematically (trigger transitions) by the RFID readers' agents. The entry point indicates the initial state of the statechart. This also uses an advanced type called internal transition which is enclosed within a state including both entering and exiting end points of the transition. The Reader state machine makes use of this useful feature for implementing background jobs such as scanning patients, doctors and nurses which remain uninterrupted while the key action of the composite state is going on. In Figure 14 doctor and nurse agent state machines is shown. These simple statecharts have only a basic functionality at this point. However, when the data related to the healthcare staff becomes available the relevant states and transitions can be expanded.

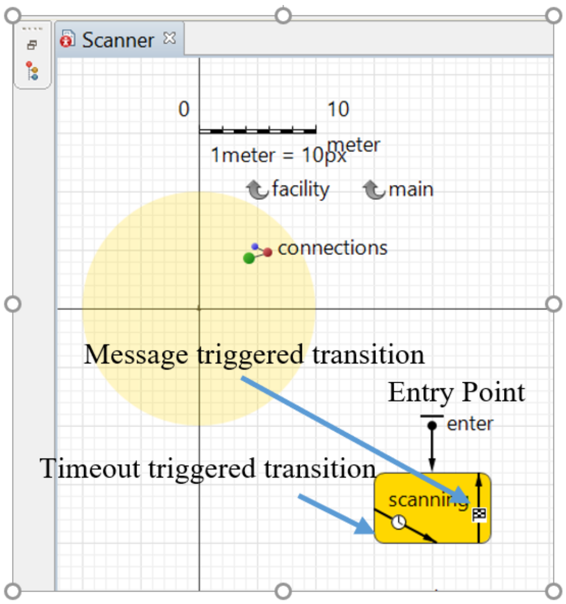

Figure 13 Reader Agent state machine

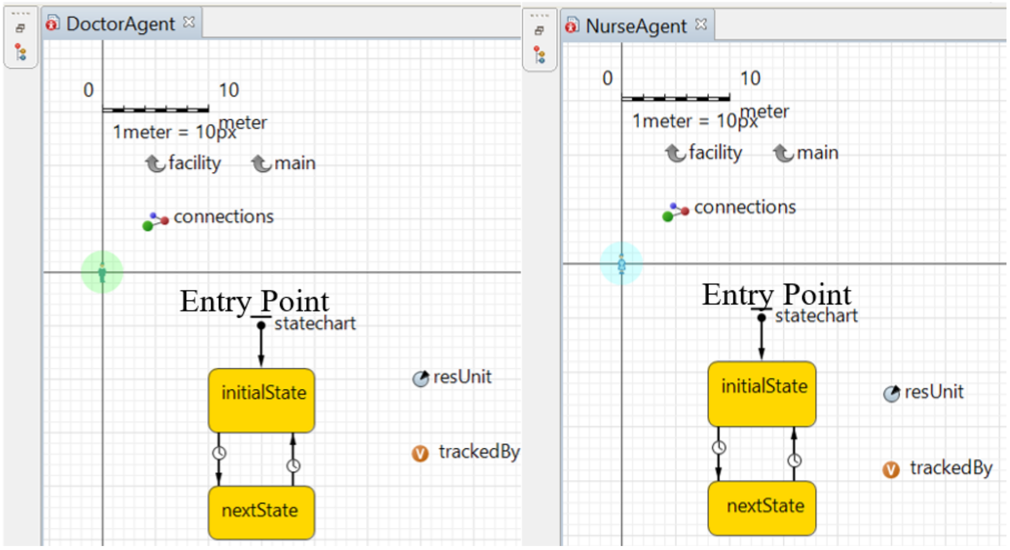

Figure 14 DoctorAgent and NurseAgent state machine

In Figure 15 the detailed network of the model is shown for each facility agent that includes the patient arrival, their movement through various stages of treatment processes and finally getting discharged from the facility. Various modeling library blocks which are used to capture the complete processes of an ED. One such block is called delay, which is used to show the delays each agent for a specific amount of time such as the waiting time, the triage time, treatment times, etc. in this work. The delay blocks animate the agents both while moving and staying at a specific position. The capacity of these delay blocks, such as the number of patients in the waiting room, can be defined and changed dynamically.

The ABM imposes a movement pattern based on a physical topology or ED layout. In an mRTLS, a patient initially arrives in the triage room and gets tracked by the moving mobile reader running on the ceiling tracks. The identity and timings of each individual tag is maintained by all of the mobile readers in a central repository. The reader data would be backhauled (getting the data) over an existing wireless protocol such as 802.11.

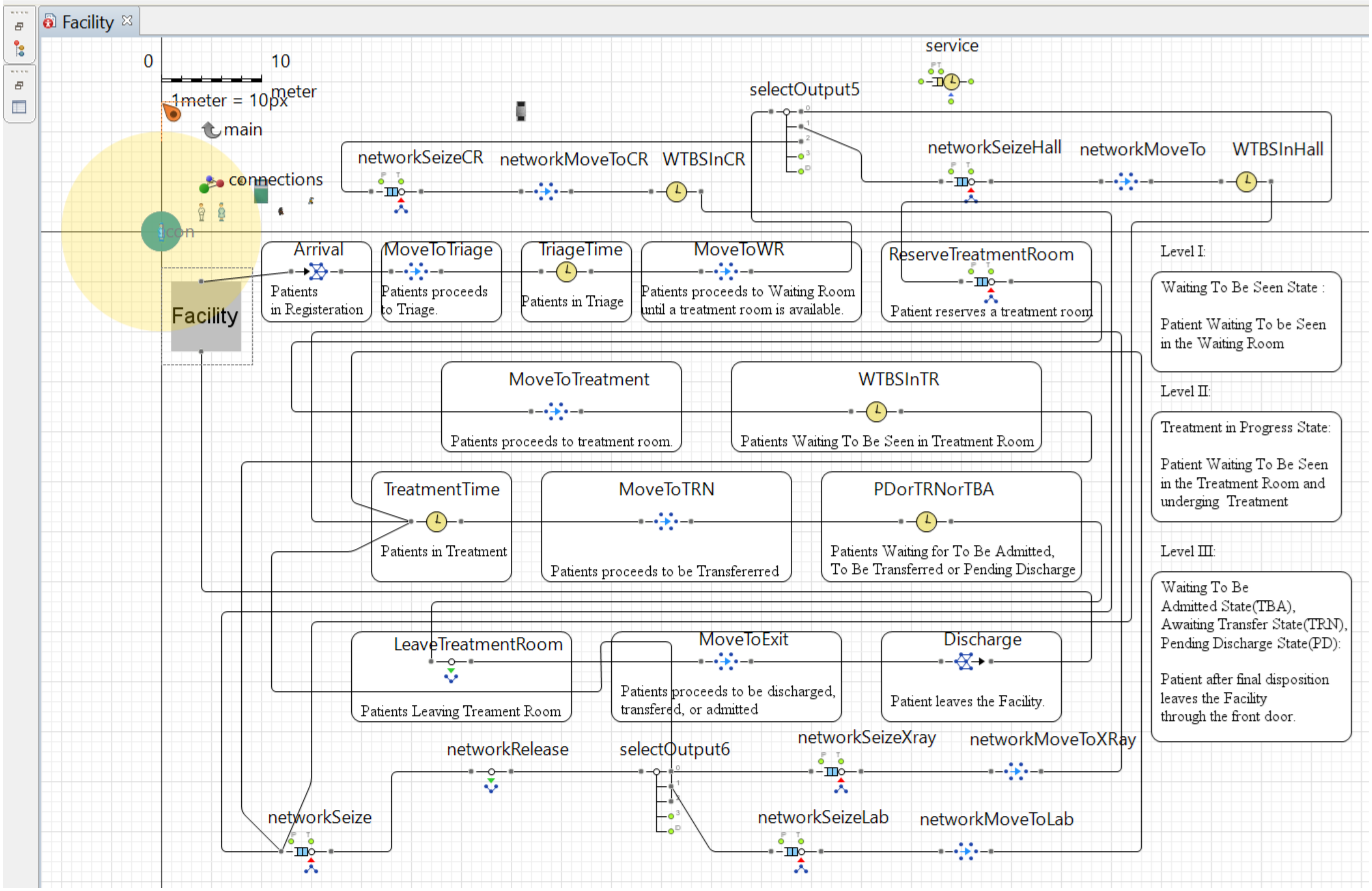

Figure 15. Overview of the simulation model and graphical representation

A layout was created for the facility, which could be modified to be applicable to any real-world existing or envisioned future ED floor plan. Installation of fixed RFID readers to obtain adequate coverage is costly primarily due to the number of readers that would be required and the space and layout constraints in the health care facilities. The initial placement of the readers is shown in Figure 16.

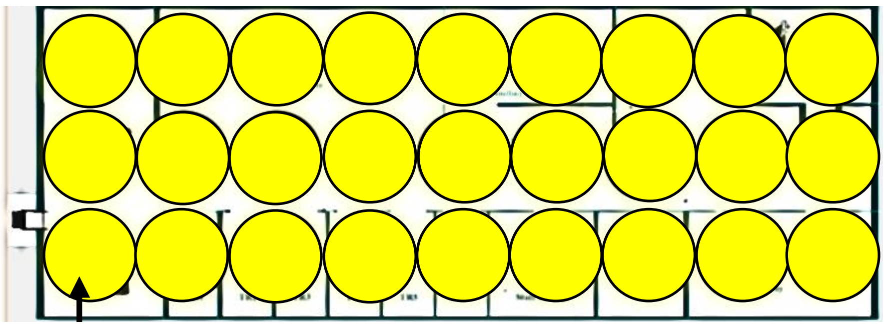

Figure 16 Initial placement of 27 static readers

Mobile readers, on the other hand, act as patrolling devices to track resources and patients instead of waiting for the resource to come within the range of fixed ones.

3.4 ED ABM Summary

At this point in time, the ABM is essentially a data driven simulation tool with little agency embedded. The agents moved from one location according to a schedule provided by best estimates from the EDIS data set. The utility of the ABM could be extended by allowing for the insertion of additional patients whose WTBS, TIP and LOS were governed by the distributions extracted from EDIS data. With the addition of these conditions, agents within the model are affected through delays that would be incurred if the capacity of a resource were exceeded.

For example, if a scheduled TIP were to start, but a treatment room was no longer was available as a consequence of an inserted patient occupying the room, then that scheduled agent's TIP would be delayed. This in turn would ripple through the system. This type of feature has not been added to the ABM at this time as the main purpose of the current ABM is to facilitate the optimization of mobile RFID readers where actual movement patterns, extracted from the EDIS data, are of primary modeling importance.

The optimization of the designed RTLS ABM is accomplished using an evolutionary algorithm such as a genetic algorithm. To minimize the two contending objectives, specifically error in patient tracking and quantity (i.e., the minimum number) of readers used for it, a multiobjective genetic algorithm is applied. In the following chapter a genetic algorithm-based optimization is introduced which elaborates on the multiobjective implementation for the augmented RFID based RTLS on ED-ABM.

Chapter 4: REAL TIME LOCATION SYSTEM

Beginning from the late 1960s and 1970s, studies based on biological evolution were published. In 1970, J. Holland studied self-adaption behavior in natural and artificial systems and introduced the concept of genetic algorithms (GA)) [163]. A genetic algorithm is a robust search and optimization mechanism useful in optimizing complex systems [164]–[167]. Genetic Algorithms are known to be efficient for problems involving multiple dimensions or objectives in particular [168]–[170]. Genetic algorithms are inspired by natural evolution and use Darwin's paradigm of selection, competition, reproduction and survival of the fittest [171]. A population of individual feasible solutions is created. The fitness of each individual solution is calculated using a fitness function. Fitness forms the basis for the selection of parent solutions for combining genes to produce offspring, thus creating the next generation. The process is analogous to natural selection where the fittest survive to reproduce and the weak die off. As such that the population of solutions is the same size for the new generations to follow. In a well-designed GA, the population is expected to converge to a near optimal solution by following the evolutionary process [172]. However, genetic algorithms can be computationally expensive and infeasible if the population size is too large, as the population size is a significant factor in convergence time and accuracy of the solution [173]. The inherent difficulty of the problem itself and the cost function calculation may also lead to computational inefficiencies.

The ED ABM was originally designed to visualize EDIS data, and subsequently be used to test the accuracy of initial versions of an RTLS for patient localization data collection in an ED. The preliminary ED ABM model aims to locate all the high tracking areas or the hotspots where the patients are mostly identified while going through different phases in the treatment process within the simulation. In an effort to find near optimal locations for RFID readers in an ED layout using the genetic algorithm optimization technique, the entire layout was initially covered with fixed RFID readers as shown in Figure 16, demonstrating the maximum coverage with a maximum number of readers. This required a few definitions and parameters to be established, such as the scale of the layout model, and choosing a range for the readers. The scale for the model is defined as one model unit is equal to 10 centimeters. In other words, 1 meter = 10 model units so 5 meters will be equal to 50 units. Approximately 27 readers with a reception or tracking range of 5 meters (i.e., radius = 5 meters or 50 model units, and a diameter = 10 meters or 100 model units) are required to cover the dimensions of an ED layout with a width of 930 and a length of 350 model units of AnyLogic simulation software. This is shown schematically in Figure 16 of the previous chapter. Of course, it is possible to utilize a more realistic RF model of an RFID reader and an area with a measured or known RF profile. Based upon the principle of insufficient reason, the underlying assumption of a somewhat isometric and fixed range is a reasonable starting position for this work.

4.1 Error Model

There are numerous approaches that researchers have used to model the determination of patient location, and its real time accuracy [174]. Laskowski et al. [8] designed an ABM of an ED to capture uncertainty or error in terms of trajectory difference inferred from readers with respect to actual positions of the patients within the simulation. However, their model design is limited to fixed readers that add to the cost in order to get better coverage or trajectory accuracy due to additional readers. Fixed readers also result in “dead zones”, which are areas where there is no coverage, due to the fact that the reader coverage is generally semi-spherical, while most rooms and buildings are irregular or at best rectangular.

In the proposed model the recorded error is based on the time a patient or resource spends in an unknown location. When the patient is registered within the range of any reader, the error would be zero, and the approximate position of that patient is recorded. When a patient moves from its recorded, or known, location, while beyond the range of the readers, the error begins to accumulate in time. Simply, the error is the total time the patient's location is unknown. In the case of a mobile reader, if a patient remains in its known location, but is not within range of a reader, it is still in its known location, and therefore error time does not accumulate. Error is recorded for each of the patients and added up for all the patients to generate total error in the system. This error model is plausible as typically the time constant for a patient's movement in an ED is often many minutes or even hours within a given location.

4.2 Acceptable Error

Every system will have some error and the proposed design is no exception. The acceptable error value is user defined, as the acceptable error is determined by the problem to be solved and can be varied depending on the accuracy desired by users or administrators. However, there are trade-offs associated with achieving higher precision, that included adding more readers, which will increase to the cost of the system. In the work presented here, the acceptable error is defined or set as the amount of time that the location of patient, moving through ED, is unknown as a percentage of the average time per patient (i.e., average of all the patients). A threshold of 95% accuracy was selected for acceptability, and was chosen as it's a smaller round number. However, the acceptable error value can be tweaked by the users of the system depending on their own custom requirements.

Chao Bian [170] conducted research on improving of RFID tracking accuracy for personnel in Seven Oaks General Hospital ED in Winnipeg. The researcher's system involved data cleaning, system optimization, sensor fusion and simulation and was able to establish the best accuracy of about 87% tracking. In this thesis, an attempt is made to improve the situation for any ED or healthcare facility and get even better accuracy in patient tracking. The proposed system implemented in the presented work begins with the selection of acceptable error as a percentage of average error per patient. The precision can be varied based on the requirement of the problem and user's requirement.

4.3 RTLS Optimization based on a Multiobjective Genetic Algorithm: Definitions

The genetic algorithm and its variations are some of the more robust techniques to achieve global optimization when designed correctly based on the problem [164]–[167], [175].

The initial statistics of the ED ABM using EDIS data before the ED ABM model is augmented with an optimized RTLS model is shown in Table 1. The error values with no readers (Table 1) and complete coverage with all fixed readers (Table 2) is estimated. The travel time from one location to the next (and/or additional time to go to Lab or X-ray room) is approximately 2.5% (nearly 13.8 minutes per patient) of all the patients in all the six facilities. This is added in the RTLS augmented ED ABM simulation model that is driven by EDIS data.

The initial scenario when no/zero readers are used is summarized in Table 1. In this table a comparison of the total error values and the total non error values when the entire EDIS data is running through the designed ED ABM without RTLS model before optimization. Without an RTLS there is no localization of patients as illustrated by the "no readers" table below.

Table 1 Initial ED ABM Statistics with no static readers in the system

No Readers *(No Optimization)*	**Total Error** *(seconds)*	**Total Error** *(hours)*	(%)
EDIS	523278720	145355.2	100
EDIS + (ED ABM)	536620886	149061.36	102.5
	13342166	*3706.2*	*2.5*

The layout of the ED ABM simulation, with no readers in the ED, is shown in Figure 17.

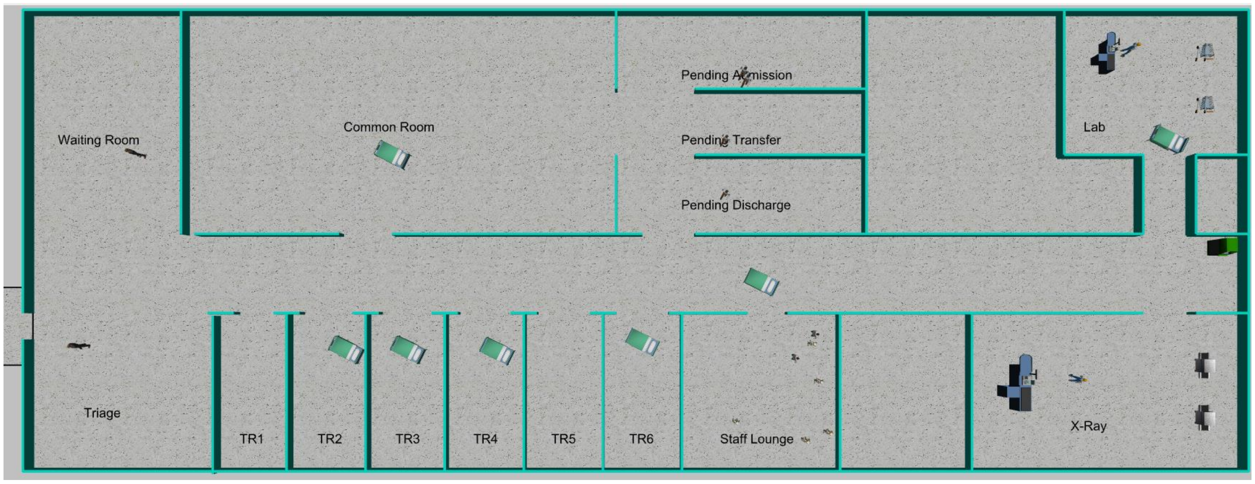

Figure 17 Initial ED ABM model simulation with first scenario of having zero readers

Table 2 examines the second scenario with full coverage with the static readers (i.e., 27 readers in this case) when EDIS data is used as input and passed through the designed ED-ABM initially and then through augmented version of RTLS model prior to optimization. However, the full coverage for the other EDs will vary depending on the size of the layouts that are discussed later in this thesis in chapter 6.

Table 2 Initial ED ABM Statistics with complete coverage with all 27 readers in the system

All 27 Readers *(No Optimization)*	**Total Error** *(seconds)*	**Total Error** *(hours)*	**%**	**Total Non-Error** *(seconds)*	**Total Non-Error** *(hours)*	**%**
EDIS + (ED ABM) + RTLS	2341782	650.5	0.45	520936938	144704.71	99.6%

In Figure 18 the ED ABM with pre-optimized RTLS that is completely covered with static readers for full coverage of ED layout with 27 readers here.

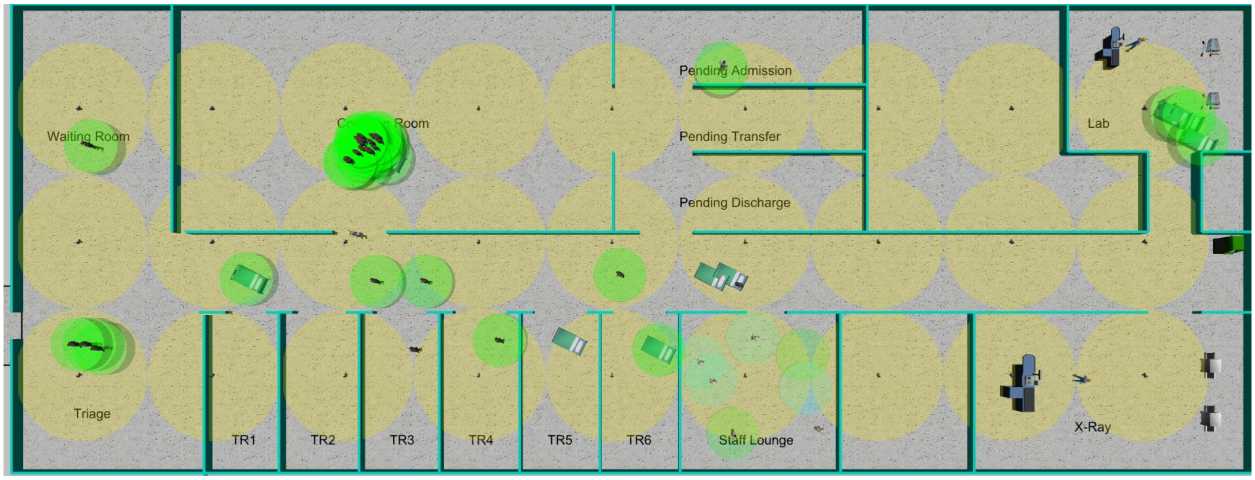

Figure 18 Complete coverage with 27 readers ED ABM model simulation

4.3.1 Search Space

The search space can be defined as the set of all feasible solutions among which the desired solution resides [176], [177]. With a GA, one looks for the best solution among a number of feasible solutions that is represented by one or more points in the search space [178]. As searching for an optimum solution in general is a complex problem. Due to the complexity of the problem under study, compromise with a suitable, sufficient or a "good enough" solution is made based on the requirements, using methods such as genetic algorithms and simulated annealing. The genetic algorithm, described to reduce the number of fixed readers and simulated annealing is used in the next chapter is used to optimize the number and the paths of mobile readers.

The search space is a simple calculation, as it is using a binary string 27 bits in length. A "1" in bit location x would imply that the location would contain a reader while a zero would imply the absence of a reader. The total number of static readers required to cover the entire layout of the infrastructure, with no or minimal overlapping coverage is 27. This means the total number of possible solutions is 2^27 or 134,217,728. This search space is dependent on the layout of the facility; larger facilities will require more readers to cover, thus expanding the solution space. In the general case, one can describe all possible solution spaces as 2^nwhere n is the number of static readers necessary to entirely cover the layout. One could also allow for a placement of readers in close proximity of a uniform distribution of readers, for example if each reader were confined to von Neumann or Moore neighbourhood. In the case of a Moore neighbourhood, the search space balloons to 10^n.

4.3.2 Initialization: Population size and Randomness

The traditional way to generate the initial population of readers is using a pseudorandom number generator [179]. Among the many methods that can be used to generate random numbers, the principle ones generate either a true random number or a pseudorandom number. The former measures physical occurrences such as thermal noise or quantum phenomena whereas the latter uses computational algorithms [180]. The pseudorandom numbers are often preferred as long sequences of seemingly random numbers can be generated that are determined by a seed value or key (an initial value). The apparently random sequence can be reproduced based on the seed value. The effectiveness of using a PRNG algorithm, used for generating pseudorandom numbers, is known to be well-tested and verified [181]. There are other less established methods such as a quasi random sequence that produce points try to cover the feasible region in an optimal manner [182], [183]. Maaranen et al. [183] use quasi random sequences to generate initial populations for genetic algorithms, as selection of an apt PRNG confers better performance to a GA [184]. A PRNG suitable to the problem under consideration was chosen to generate the initial population of the GA implementation in AnyLogic. The dependence on initial population makes GAs susceptible to early convergence, making them unable to find globally optimal solutions as they get stuck in a local maxima. The initial population generated should use a proper PRNG and appropriate population size. When designed correctly based on the problem at hand, the genetic algorithm and its variations are one of the more robust techniques to achieve global optimization [164]–[167], [175].

After many experiments, the initial population size of 96 appears reasonable for the problem under study. In Figure 19 a possible initial solution used in this part of the work is shown. However, a good initial population and its size is difficult as it is problem specific in nature [181], [185], [186].

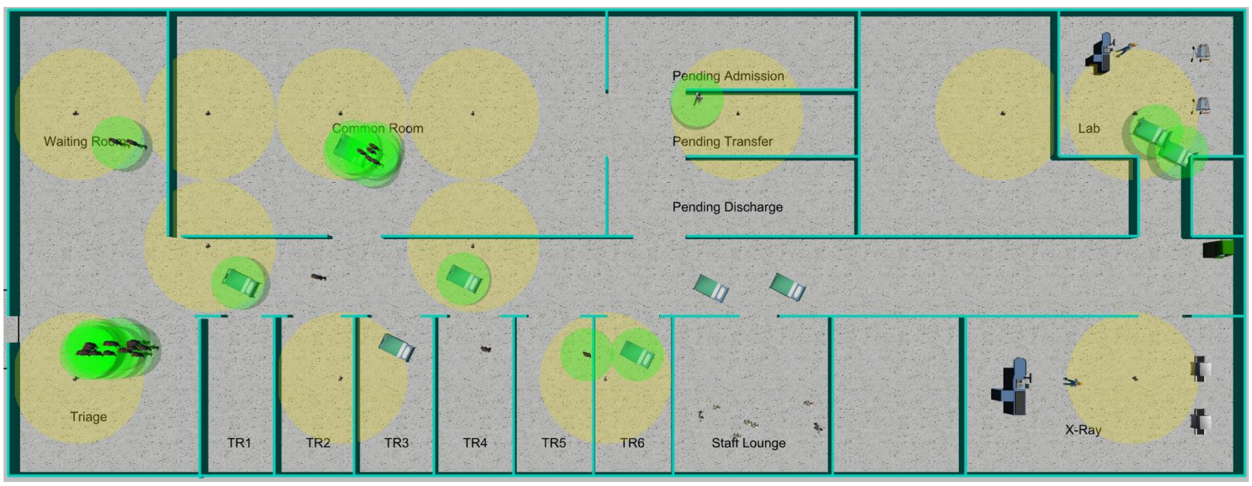

Figure 19 Initial possible solution (111101011010100000101010001)

4.3.3 Chromosomes and Genes

In GAs, a chromosome is a set of parameters that defines a proposed solution to the problem that the genetic algorithm is attempting to solve [175]. The set of all solutions is known as the solution space and from the initial population, the solutions are selected based on fitness, and used to create a new population [164]. This process of reproduction to create new populations continues until a predetermined generation count is reached, or a solution meeting some predetermined condition or specification is found.

The encoding of chromosomes is problem dependent. In order to provide complete coverage of the ED layout model used here, 27 static readers are used. Therefore, a 27-bit binary String object is created that associates each index to the location of a fixed reader in the ED Model layout. Using genetic algorithm terminology, the 27-bit string is a chromosome and every bit is a gene, which represents a potential location of a static reader and whether or not a reader is actually placed there. The standards chosen to represent a reader as being present is with the value “1”, and not present with the value of “0”.

4.3.4 Fitness Evaluation

The assessment of fitness is the key component of a GA. In the case of multiobjective fitness estimation, fitness is calculated based on trade-offs where increases in fitness of one objective results in decreases in fitness of another objective. In the work presented here, there are two competing objectives, firstly to minimize the amount of time a patient or resource spends in an unknown location, and secondly to minimize the cost of the system by reducing the number of readers required. These objectives result in a trade-off, where the increase in fitness of one objective results in the reduction of fitness in the other objective. By example, if one wishes to reduce the cost of the system by using fewer readers, it would intuitively result in an increase in the error value, and vice versa.

The following are a few numerical definitions, all taken from or calculated from the EDIS data provided. There was a total of 16,110 patient records. There is a total time spent in the ED for all of the patients of 523,278,720 seconds. The data includes records from six different facilities. From these values, one can calculate some averages, such as the average time in the ED per patient

$$\frac{523{,}278{,}720}{16{,}110} = 32{,}482 \; seconds \; or \; 9.02 \; hours \qquad (1)$$

Not only is it necessary to attempt to strike a balance in the objectives, consideration must also be given to resolve the large difference in magnitude between the two values. Since the error value ranges from 0 to 87,213,120 seconds, and the tracker count value ranges from 0 to 27, this will lead to a situation where changes in one objective can overpower changes in the other objective. As discussed by other researchers [149], [187], the fitness function must account for cases where one objective is dominating and/or indifferent to the other objectives.

$$(\mathrm{f_i}, \text{where } \mathrm{i} = 1, 2, \ldots \mathrm{n}) \tag{2}$$

For any two objectives $\mathrm{x_1}$ and $\mathrm{x_2}$,then

$$\mathrm{x_1} \text{ dominates } \mathrm{x_2}, (\mathrm{x_1} \succ \mathrm{x_2}) \text{ if}$$

$$\mathrm{f_i}, (\mathrm{x_1}) >= \mathrm{f_i}, (\mathrm{x_2}), \text{for all } \mathrm{i} = 1, \ldots \mathrm{n}$$

$$\mathrm{x_1} \text{ indifferent with } \mathrm{x_2}, (\mathrm{x_1} \sim \mathrm{x_2}) \text{ if}$$

$$\mathrm{x_1} \text{ does not dominate } \mathrm{x_2}, \mathrm{x_2} \text{ does not dominate } \mathrm{x_1}$$

A quick referral to the problem shows this may be a possible issue, given that the range of values for $errorValue$ is much larger than the $trackerCount$ value. This means one will have to use a normalizing function to be able to combine these values into a single fitness function [188].

The fitness function is:

$$\begin{aligned} \text{Fitness} = {} & ((errorValue \;/\; \text{indv.facility.patientCount}) /\; 1624.10) \;/\; 5.0) \\ & + (trackerCount \;/\; 27.0) \end{aligned} \tag{3}$$

32482 seconds is average time per patient, error rate of 5% of average is 1624.10 seconds, and the division by 5 is done to normalize the value in a range to match with the *trackerCount* where *errorValue* is the total number of seconds the patients spend in error state. This means that if two patients are in the error state for one second each, the $errorValue$ would be two, whereas if a single patient spent two seconds in the error state, the $errorValue$ would also be two. $TrackerCount$ is self-explanatory; it is the number of trackers, or readers, in the system. The division is used to normalize the values, and to make it possible to equally weight the two objectives.

The denominator in the *trackerCount* side of the equation is the maximum number of static readers possible in the tested layouts. The denominator in the *errorValue* side of the equation is calculated similarly to the *trackerCount* side, in that beginning with the average maximum possible error, in this case, with 16,110 total patients, with an average time in the system of 9 hrs for a total possible *errorValue* of 523,278,720 seconds. If one divides that by six, for the six different facilities, since each solution is checked against only one facility at a time, one is left with a total of 87,213,120 seconds. This results in the values for *errorValue* having much less of an influence on the overall fitness of a solution than the *trackerCount*.

4.3.5 Survivor Selection

A new population is created by selecting the best fit individuals from the previous generation and creating offspring. Based on Darwin's evolution theory, the best fit individuals that survived the previous generation will be selected as parents to create offspring for the new generation in a process known as crossover. The crossover is the basis of GA as it is analogous to biological crossover of genomes in reproduction. There are many techniques to select the parent chromosomes such as roulette wheel selection, rank selection, steady-state selection, elitism and others. Elitism, a method of selecting the best individuals, to create the next generation is used here, as elitism has been shown to increase the performance of GA [189]. Elitism also reduces the chance of losing the best solutions if they are discovered in early generations [190]. The use of an elitism strategy has demonstrated improved performance, particularly in multiobjective genetic algorithms [191], [192]. However, the best results are achieved when strategies of natural selection and elitism are used together [192].

In this work, the new population is created by selecting the better fit chromosome/solution as the parents for subsequent generations, using a survival ratio of 0.5 in the selection process.

4.3.6 Crossover

Crossover is a genetic operator that brings variability in the population by means of creating a new generation from the previous generation by creating offspring solutions from parent solutions.

In this work, uniform crossover is applied. This randomly chooses a gene from the first or the second parent chromosome as shown in Figure 20. In the uniform crossover method, both the parents contribute at the gene level. The collaboration ratio can result in an either equal contribution from each parent or it can be random mixing [193].

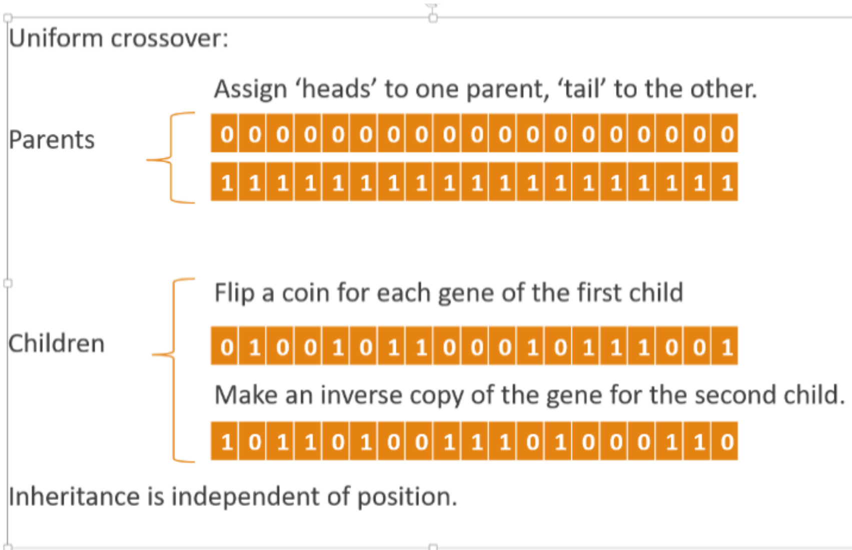

Figure 20 Uniform crossover

A 50% crossover is used in is GA implementation, which enables an enables an equal mixing ratio of characteristics from both the parents. However, a 50% crossover probability can take longer for the algorithm to run compared to other crossover operators and is more complex for parallel implementation in particular [193]. As the GA is implemented to run on multiple cores in

AnyLogic simulation software, the time taken to run the algorithm for a uniform crossover operator is accelerated. This speed increase-on multicore systems has been noticed by other researchers as well [193].

4.3.7 Mutation

The variability in the population is facilitated by applying mutation, which is an arbitrary change in the chromosome or genome. The selection of a mutation rate is a significant factor, as it introduces diversity to the search space in a GA. However, a very low mutation value prevents any change in the population whereas higher mutation rate delays GA convergence towards an optimal solution and makes the search more random. A mutation rate in the range 0.5% to 1.5% has been shown to be reasonable [194]. The rate of 1.5% mutation -was chosen after a series of -tests in the range of 0.5% to 1.5% mutation rate for the convergence to achieve the optimal solution. Another explanation for the use of selection of a 1.5% mutation rate lies in the fact that several runs of GA showed better a diversity in the population in this range as compared to 1% or lower. However, on increasing the mutation rate (unlikely to happen in the human evolution process), the GA did not perform better or show- any improvement in results, as too many varied individual solutions (or larger search space) in the population takes a longer time to reach the optimum level or even may not meet the desired expectation of a plateau of optimized solutions.

Mutation is introduced in the chromosome or solution by swapping the corresponding gene. In the GA implementation, a 1.5 % chance (as explained in previous paragraph) of a mutation occurring for each gene in a chromosome is used. The mutation operator is applied to each chromosome of one randomly selected gene after crossover.

In this study, there are 27 bits of genes representing 27 potential locations for the ED-ABM-RTLS model forming a single chromosome or an individual solution. The 27-bit binary string representing the genetic sequence allows the recognition of higher traffic areas or locations that are associated with presence of RFID tags attached to the moving patient agents. As the ED-ABM-RTLS model is driven by the actual data from the EDs, the simulated model recognizes the occurrence of such prominent patient waiting areas. Then, the implemented genetic algorithm integrated within the AnyLogic simulation tool initialized and generating the 27 bits for the binary genetic sequences starting from 96 random individual solutions forming the initial population. The GA's inherent processes of selection, crossover and mutation associated with each iteration evolves the individual chromosomes into an improved version of the solution strings based on the fitness values forming the next generation with new population. The RTLS aims at minimizing the time for which the patient's location is not known by installing fewer readers. The fitness function is calculated by the weighted sum method that adds the two conflicting measures of error (or the time for which the patient agent's location is not known) and the number of readers (reader agents) with the respective weights associated with each one. The selection criteria decide on the basis of best fit individual with the lower fitness value (lower fitness function value means better fit individual solution) indicating a reduction in error value and the quantity of readers. Once the better fit parent chromosomes are identified, the GA applies crossover to create a new offspring solution that is based on the probability of inheriting the best traits from both the parents with the prospect of a better solution for RTLS for ED-ABM. In the succeeding iteration, along with other fit individuals, the offspring solutions are added based on fitness resulting in better possible solution outcomes. The GA introduces diversity in the population by mutation. Mutation is accomplished by probabilistically flipping a gene arbitrarily in a chromosome to create a new individual solution that helps the GA to avoid local minima by increasing diversity. This provided an opportunity to obtain a better solution that might have otherwise slipped through. After each

GA iteration or generation, the next generation of population continues the same steps in the following generations until the desired solution is attained. This best solution significantly lessens the unknown time for location of patient agents or error using a smaller number of readers. The complete flowchart of GA is discussed later in section 4.6.

4.4 Static Parameter Variation Experiment

AnyLogic allows a designing custom parameter variation experiments to run models with different parameter settings specific to the model requirements. The gives the opportunity to analyze the impact of different model parameters on the model and provides an insight on the overall model behavior. The random factors of stochastic models can be assessed by using fixed parameters in the experiments.

The complex RTLS model simulation is configured using parameter static variation experiment comprising 4000 individual model runs by changing root object parameters. The experiment is defined by implementing Java code for all the components of experiment setup specific to GA-based RTLS model comprising execution code for initial setup, before each experiment run, before simulation sun, after simulation run, after iteration and after experiment.

4.5 Simulation and Results

An RFID tag detection probability model is implemented to capture the RFID tag reads in the simulation. When the patient enters the reader's range, the possibility that they will be tracked depends on the probability detection model that is designed based on approximated RFID reader operation.

The detection model attempts to probabilistically detect the RFID tags associated with the patients. The implemented methods are defined in the probabilityDetection function created in the class for reader agents in the ED-ABM-RTLS model. As the maximum range of RFID reader is 5.0 meters in this study, the probabilityDetection function detects with probability of 100% up to half range (in the range 0 meters to 2.5 meters) and linearly degrades to a 50% probability from half range to full range (in the range 2.5 meters to 5.0 meters). After full range, the read probability quickly degrades to 0.

The Figure 21 shows the probability of detection depending on the location of RFID tag on the patient. An AnyLogic element called Scale is used to set scale (i.e., proportion of pixels of animation to the actual units of length). The scale is defined graphically and the pixels in one metre is defined as the number of pixels divided by 10.

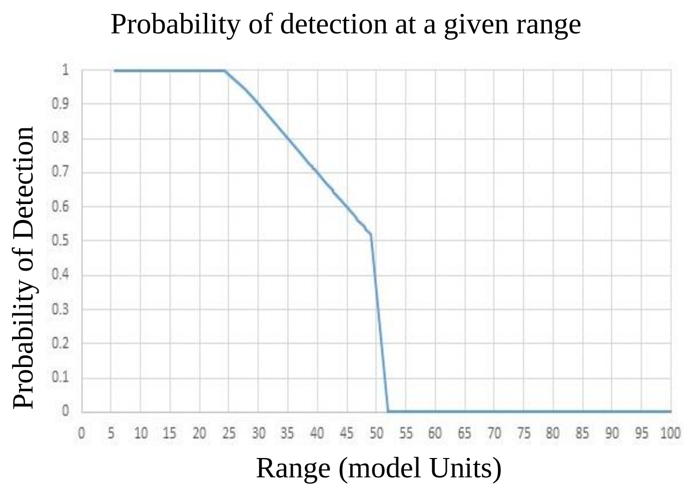

Figure 21 Probability of detection at a given range in metres (1 metre = 10 model units)

In the designed model 5.0 metres is 50 model units. If the patient happens to be within its full tracking range from zero to two and half meters then she or he is certainly tracked. In the case where the patient's location falls beyond the range of two and half meters but within five meters, then the reader is likely to detect the patient with a linearly decreasing probability from 100% to 50% probability.

The Table 3 shows the error values with complete coverage achieved of nearly 99.6 using fixed readers with no optimization and provides the coverage of 99.4% with almost half the number of readers after RTLS optimization.

Table 3 RTLS Data

Data	**Readers**	**Error(E)** *(seconds)*	**Non-Error (NE)** *(seconds)*	**E** *(%)*	**NE** *(%)*
EDIS		**523,278,720**		-	-
Completely covered layout fixed readers	27	2341782	534,279,104	0.4%	99.6%
EDIS + (ED ABM) + Optimized RTLS	**14**	**2954779**	**533,666,107**	0.5%	99.4%

Table 4 illustrates the multiple runs of optimized RTLS on the same ED layout that gives an approximate number of minimized readers that gives almost an average coverage around 99.5%. The results show that the optimization algorithm is consistent in finding the high tracking areas or hotspots in the same layout over multiple simulation runs for all the six facilities from A to F. The facility D data gives the best solution overall. Each facility individually has its best solution as well. However, the RTLS system optimization process in not without its limitations. The total time to complete one parameter variation experiment in the simulation is approximately 216.7 hours (or nearly 9 days) on 8 cores with 8 logical processors machine (Intel(R) Xeon(R) CPU E3-120 V2 @ 3.60GHz). An attempt was made to improve the runtime by rewriting the optimization algorithm using Java multithreading and run in parallel on 8 with 8 logical processors and 8 cores with 16 logical processors machines to reduce computation time. The total time to complete one parameter variation experiment in the simulation is approximately 67.2 hours (or nearly 3 days) on 8 cores with 16 logical processors machine (Intel(R) Xenon(R) CPU E-52620 v4 @ 2.10GHz 64-bit operating system, x64-based processor). Using 8 cores with 16 logical processors the simulation runs progress in parallel for all the six facilities reduced computation time by almost one third.

Table 4 Multiple ED ABM RTLS simulation GA runs over 100 generations

Simulation runs for 4800 iterations each							
Sims	**Fitness** *(norm.)*	**Tracker String**	**Generations**	**Facility**	**Readers**	**Error** *(seconds)*	**NE** *(%)*
1	**0.006917174**	**1010010010011110001111110001**	**78**	**D**	**14**	**2954779**	**99.4%**
2	0.006896888	1010010010111110001111110001	65	D	15	2261665	99.6%
3	0.006908465	1010010010011110001111110001	81	D	14	2940384	99.4%
4	0.006905597	1010010010111110001111110001	84	D	15	2277273	99.6%

When the simulation was run for 200 generations (Table 5), the number of readers were further minimized to almost 12 to 13 readers (average 12.5) with the almost 99% coverage (average 98.7%). The fitness over 200 generations' plots for each facility is given in the appendix. However, it took almost 20 days to run one complete simulation on an eight-core machine.

Table 5 ED ABM RTLS simulation GA runs over 200 generations

Simulation runs for 9600 iterations each							
Fitness *(norm.)*	**Tracker String**	**Generation**	**Facility**	**Readers**	**Error** *(seconds)*	**Patient Count**	**NE** *(%)*
0.000907	**1010010010100010001111110001**	**104**	**A**	**12**	**6519923**	**3139**	**98.8%**
0.048194	1010010010111010001111110001	34	B	14	11127496	3547	97.9%
0.007517	1010010010101010001111110001	76	C	13	4875891	2445	99.1%
0.005923	1010010010100010001111110001	80	D	12	5022734	2187	99.0%
0.012469	1010010010100010001111110001	41	E	12	5148801	2028	99.0%
0.038272	1010010010100010001111110001	159	F	12	9653980	2764	98.2%

The overall fitness of reader static locations over 100 generations and 200 generations is shown in Figure 22 and Figure 23, respectively.

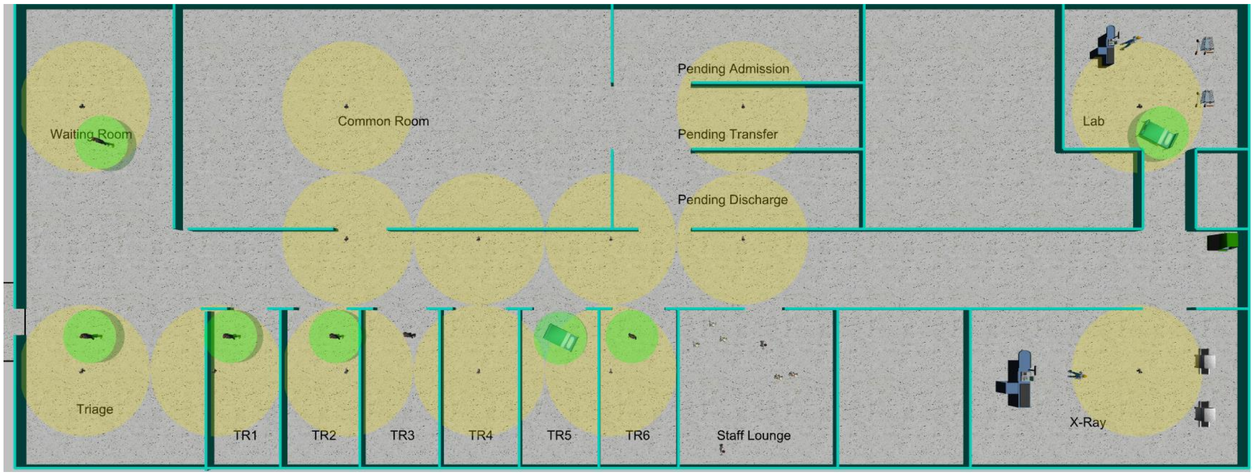

Figure 22 Optimized RTLS (1010010010011110001111110001) simulation screenshot for 100 generations of GA

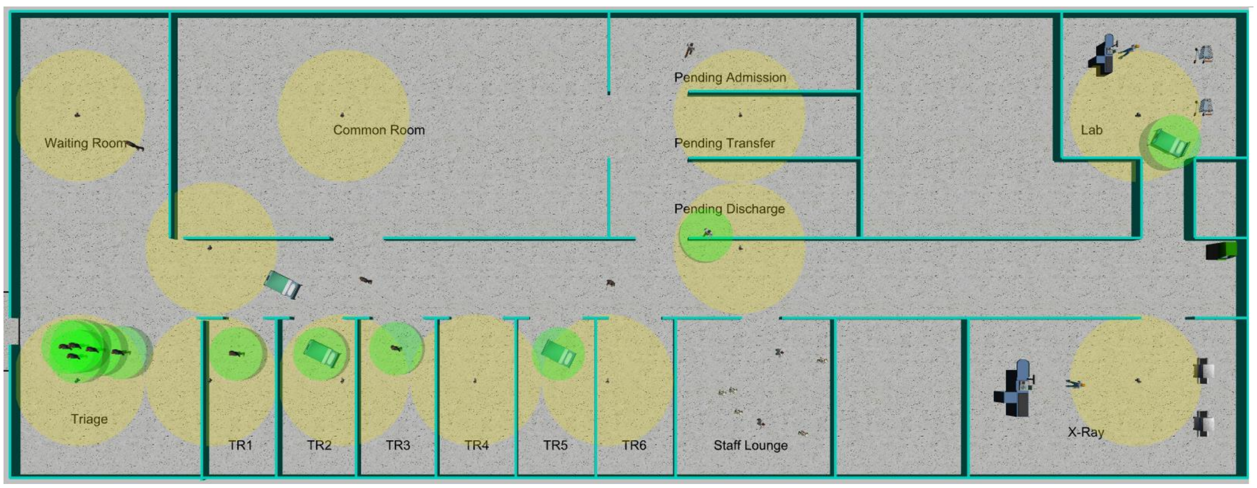

Figure 23 Optimized RTLS (1010010010100010001111110001) simulation screenshot for 200 generations of GA

The

Figure 24 demonstrates the convergence in the form of a plateau or almost stable solutions, indicating potential results that are significantly the better or the best fit.

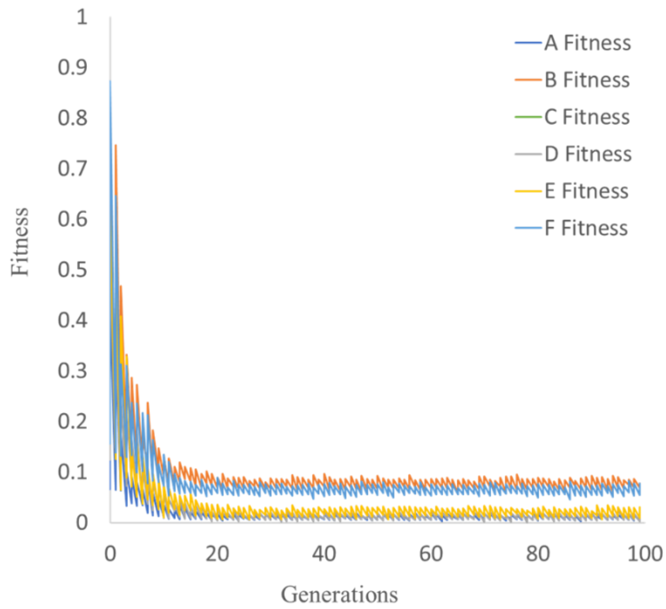

Figure 24 GA Fitness evolution over 100 generations overall for all individual facilities)

The performance of the GA is verified for a benchmark example: a square with flow simply left to right. The high tag tracking areas are expected to be in a straight line as the best locations after optimization. Table 6 gives an insight for the performance of optimized RTLS in a different flow of patients that are moving from left to right in a square ED layout and verifies the accuracy of the algorithm. The best solution is given by the facility A with almost 99% coverage using only eight readers in straight line as expected.

Table 6 Benchmark example statistics

MOGA performance on Benchmark example**	**Readers**	**Error (E)** *(seconds)*	**Non-Error (NE)** *(seconds)*	**E** *(%)*	**NE** *(%)*
EDIS		523,278,720	-	-	-
EDIS + (ED ABM) + Optimized RTLS (Patients moving from left to right in a square ED layout)	8	6497224	516781339.9	1.24%	98.75%

The performance of the GA is also analyzed for different facilities for the benchmark example. The significance of the tracker string all being the same verifies that the high tracking locations or the hotspots remain the same even when different data from each individual facility is run through the optimized RTLS model in the same square ED layout. Table 7 and Table 8 displays the best solution that is selected and performance of optimized RTLS over multiple runs respectively.

Table 7 The best solution selected out of multiple simulation runs

Tracker String	Fitness	Generation	Facility	Readers	Error *(seconds)*	Patient Count
000000000111111101 000000000	0.508619019	48	A	8	6497224	3139

Table 8 Multiple RTLS Simulation runs

Tracker String	Fitness	Generation	Facility	Readers	Error *(seconds)*	Patient Count
000000000111111101 000000000	0.508619019	48	A	8	6497224	3139
000000000111111101 000000000	0.558595416	21	B	8	9070864	3547
000000000111111101 000000000	0.682253647	34	C	8	9199445	2445
000000000111111101 000000000	0.60929016	20	D	8	6675129	2187
000000000111111101 000000000	0.646746802	42	E	8	6929420	2028
000000000111111101 000000000	0.590100044	36	F	8	7916967	2764

The plots of comparative values of error, readers and fitness are included in the Appendix that shows values for error, reader quantity and fitness for individual facilities for the benchmark example discussed here.

4.6 Conclusions and Summary

A multiobjective genetic algorithm (GA) is designed using static parameter variations to find the high traffic areas of the agents and asset flows. Through this algorithm, an optimized layout of static readers is obtained. The optimized solution, in the form of a reader location string from the GA, shows areas of frequent traffic within the facility (Figure 25).Based on the tracker or reader string (genetic sequence), the locations of most active fixed readers is determined. These locations will be used as endpoints in the path segments followed by mobile readers. The proposed GA algorithm finds the best or new best placement of static readers for this specific floor plan as illustrated in Figure 25 (with 100 generations) and Figure 26 (with 200 generations).

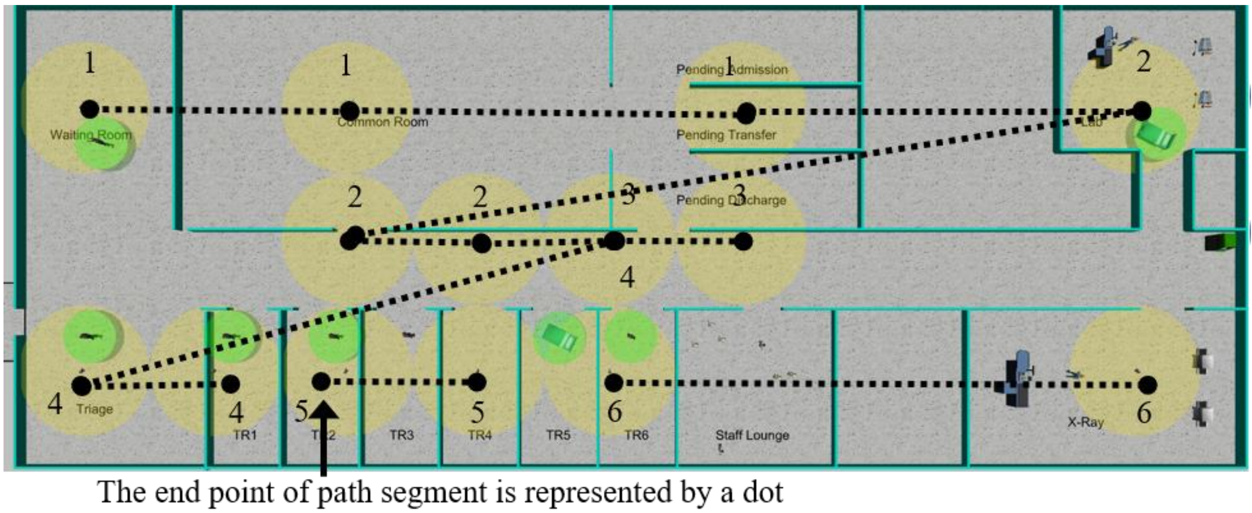

Figure 25 Parameter optimization of a static RFID reader model using a GA (100 gens.) that illustrates the high RFID read areas

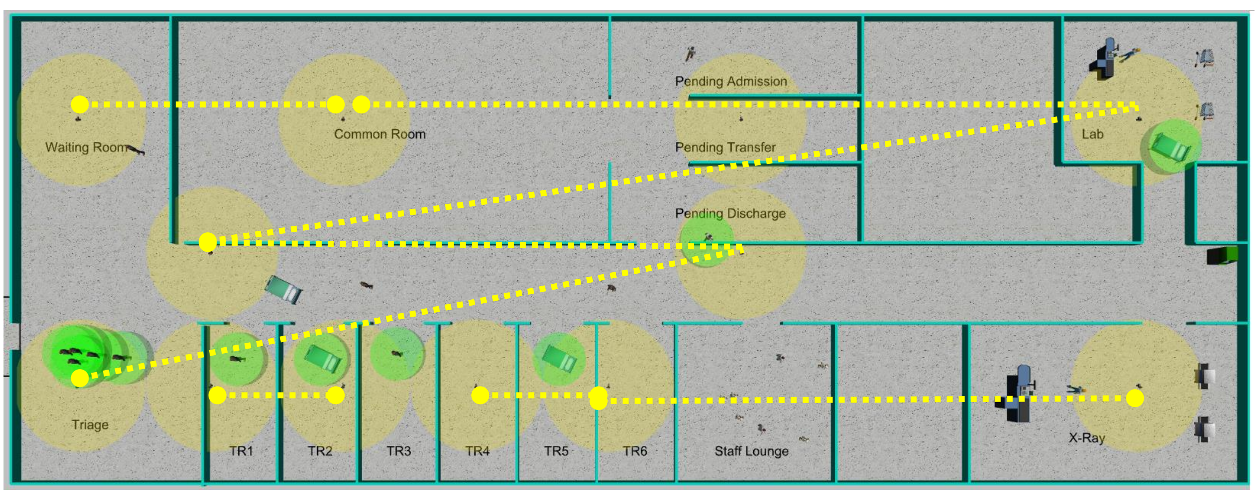

Figure 26 Parameter optimization of a static RFID reader model using a GA (200 gens.) that illustrates the high RFID read areas

The improved solution, in the form of effective reader locations in the form of trackerStrings found from the GA, shows areas of frequent traffic within the facility. The proposed algorithm implementation successfully identifies all the high tag tracking areas in the designed ED model layout that can be effectively used for other layouts. This can be done by designing a new layout and configuring it with the designed algorithm using the AnyLogic simulation software.

With the areas of high traffic defined, the next step is to optimize the ordering of these hotspots into a path for mobile readers to follow. To accomplish this task, making use of a simulated annealing algorithm appears to be proficient to help in finding a path using a minimal number of readers, while still keeping an acceptable error rate. Figure 27 shows the genetic algorithm near optimal solution as an input to simulated annealing based optimization.

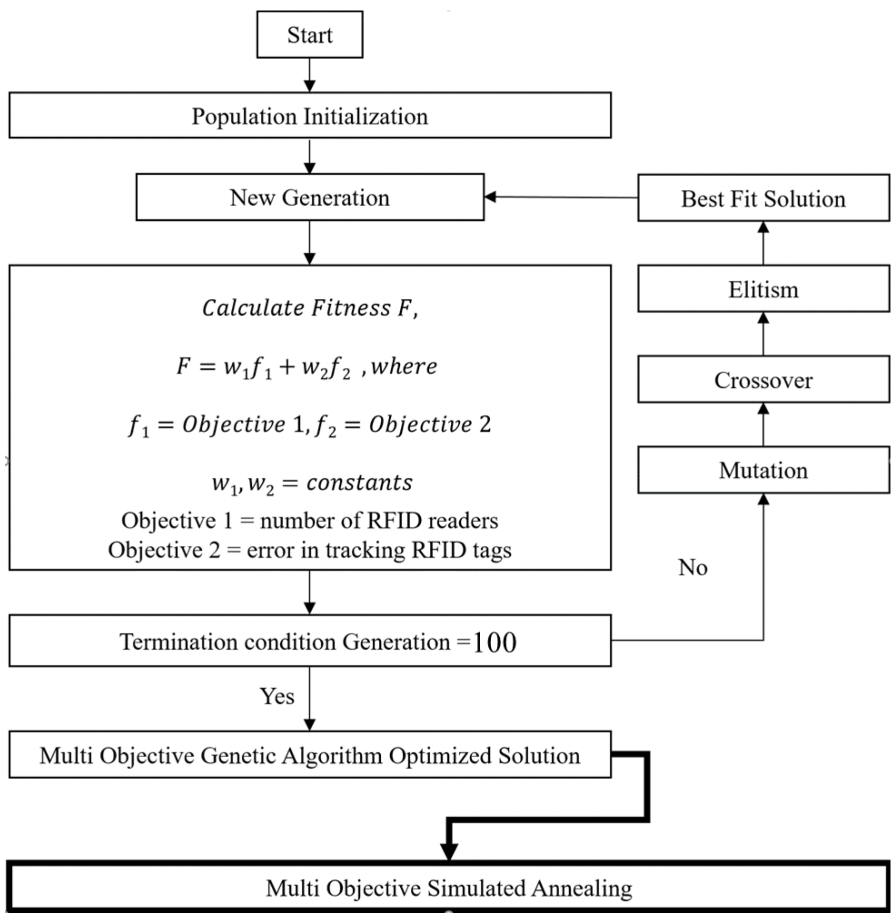

Figure 27 The optimization process (GA followed by SA).

The details are provided in the next chapter of the thesis.

One could argue that the high traffic areas may also be readily apparent from an ad hoc or best guess which is again reasonable. The GA however provides evidence-based decision support and quantitative insights into the error associated with optimizing the number of static readers and their location.

Chapter 5: MOBILE REAL TIME LOCATION SYSTEM (MRTLS)

Research work presented in this chapter demonstrates that a new optimal or near best solution consisting of static readers obtained from a genetic algorithm can be used as initializing parameters to a simulated annealing (SA) algorithm to acquire global minimization for a problem similar to the traveling salesman problem [44]. Simulated annealing will be used to provision mobile trajectories or paths for mobile readers.

The genetic algorithm optimization provided the initial static reader locations, referred to as hotspots. With the hotspots identified, the next step is to find a path between them that results in a further reduction in the error rate and/or number of readers required. This reduces the problem to a variation of a well-known combinatorial optimization problem, the classic travelling salesman problem (TSP). A standard TSP can be specified as the problem of finding least expensive path starting from starting from city i to city j in the tour of k multiple cities, where k is equal to the total number of cities [195], [196].

The problem here is slightly different. The weights assigned to each edge of the graph, or the distance travelled between cities in the general TSP problem definition, are not individually available due to there not being a directly associable change in error resulting from the inclusion or exclusion of a single edge; there is only a total value for a given solution. As in the presented problem, the distance traveled is not the cost in this case, rather it is the number of readers and localization errors. Also important is reducing the number of readers required, when compared with using static readers located at the hotspots. With these considerations, the equation used earlier to equally weight the two objectives, the seconds in error state and the tracker count, gives a good metric for evaluating solutions. This allows for optimization not only for the path the mobile readers take, but also in how many readers are operating on that path.

A study by Wang et al. [197] applied the TSP concept with Dijkstra's algorithm for optimal path planning for a robot. Jang et al.[198] developed paths for minimum flight time and cost for unmanned aerial vehicles with remote sensing capabilities by transforming the problem into a dynamically constrained TSP with neighborhoods.

To avoid pitfalls associated with genetic algorithm optimizations, another metaheuristic is used. A stochastic search and optimization technique known as simulated annealing is implemented, as it uses significantly less memory than a genetic algorithm to find a reasonable solution in smaller runtime [199].

5.1 Mobile RTLS Optimization based on Simulated Algorithm: Definitions

Simulated annealing was chosen due to the ease of implementation, and on the basis of various research studies conducted that shows simulated annealing can be used to efficiently solve a TSP problem. Sales et al. [200] successfully applied simulated annealing in a robot path planning problem. Simulated annealing and fuzzy logic based automatic controllers for navigation and path planning of mobile robots developed by Martínez-Alfaro et al. [201] also show promising results. This gave confidence from the beginning that the applied methodology would produce acceptable solutions. Other variants using SA have been considered. The problem under study may be solved by combining simulated annealing with machine learning methods for boosting convergence and route planning [202]. Perhaps, reinforcement learning would be the most appropriate machine learning technique which can learn policy for paths to follow that can be extended as future work for routing the path of mobile readers. Machine learning was not further considered in this work as the mobile reader optimization problem is not a more of a ML type of classification problem but rather a problem better suited to iterative improvement.

5.1.1 Graphs

The algorithm description includes concepts such as vertices, edges, path and trees that are used in graph theory [203]. A graph is a collection of nodes, also referred to as points or vertices, and edges, also called arcs or lines, connecting the nodes that have weights, or costs, incurred when moving from one node to another. In our study, the nodes are the hotspots found or pruned by the genetic algorithm, and the edges are the paths followed by the readers. More general graph theory can also involve directed edges, where it is only possible to traverse in one direction, as well as different costs for the same edge, dependent on which direction the edge is traversed. Our case does not use directed edges, nor does it involve the use of different costs based on the direction of traversal.

An undirected graph is a graph with only one edge between a pair of vertices and no loops [204]. A simple graph can be a complete graph if each individual vertex is joined by an edge to each other vertex [205].

$$Complete\ Graph\ with\ n\ vertices\ and\ \frac{n(n-1)}{2} edges$$

Formally, a graph is illustrated as a pair of sets (set of vertices V, set of edges E). V can be a set of cities, people or websites [206]–[208]. In this research, V is the set of high RFID tag tracking areas or hotspots. E are two element subsets of V signifying association or connection between the two objects or elements. In this study, E is the edge connecting the two hotspots in this study.

Given a graph G = (V, E), the number of vertices in V is the order of G and the number of edges in E is the size of G. They are denoted as | V | and | E |, respectively [209].

5.1.2 Combinatorial Optimization

Combinatorial Optimization (CO) is a technique used to solve discrete domain problems where brute force solutions are not feasible. Integer Linear Programming, Bin-Packing are a few examples of known applications of CO. As the space of all possible solutions is usually very large, brute force search methods are not applicable. Randomized search algorithms such as hill-climbing, tabu search, genetic algorithms, and simulated annealing are a few of possible alternatives [210].

5.1.3 Traveling Salesman Problem

The Travelling Salesman Problem (TSP) is finding the lowest cost tour of a given number of cities while visiting each city only once. Though its origins are unclear, it is known to have been mathematically formulated in the 1800s by the Irish mathematician W.R. Hamilton and by the British mathematician Thomas Kirkman [211]. In TSP, the distance between two cities can be the same, known as a symmetric TSP, or generally as an undirected graph. Distances can also be different each way, such as when airfares with varying fees from different airports. It is also possible that the path is non-existent in both the directions or exists in only one direction, such as one-way streets, known as a directed graph, or asymmetric TSP. In this research, a symmetric TSP is used.

Mathematically, a solution to symmetric TSP attempts to find the least total cost tour while visiting each city only once, when given a weighted graph, where the weight w_{ij} on the connection between city i and city j is non-negative. Presently, enumerating every possible tour is the only way to find the lowest cost tour for the general problem. There are mathematical models which provide solutions if the total number of cities to visit is below a certain threshold [140]. Each possible tour is a permutation of the number of cities ($1\times2\times3\times\ldots$ n) which is is **n!**. For large values of n, it is not possible to find the cost of each tour in reasonable time frame.

5.2 Simulated Annealing

The simulated annealing analogy is that of annealing metal to have desired physical properties, energy is the cost function or optimization objective function, and temperature is the control parameter. The analog of temperature in simulated annealing is the probability of a worse solution being accepted as the next state. Global optimal solutions can be accomplished as long as the cooling process is adequately slow. Metropolis et al. [212] described a Monte Carlo based method, now known as the Metropolis algorithm, as an early effort to simulate equilibriu~~m.~~. The algorithm used a Metropolis loop typical to simulated annealing to determine the way to randomly explore a new possible solution with a Metropolis criterion whether to eliminate or accept it at a constant temperature until equilibrium is achieved. In 1982, Kirkpatrik [213] applied the Metropolis algorithm to solve combinatorial optimization problems.

Kirkpatrick et al. [213] demonstrated the application of statistical mechanics techniques for combinatorial optimization. Statistical mechanics are the study of the behavior of large systems with multiple independent factors that affect the state of the system.

5.2.1 Initialization

The simulated annealing algorithm begins with a random solution followed by the process of annealing or cooling that, on average, constantly improves the solution. However, applying other heuristic techniques (local search such as greedy approach or genetic algorithm) as a precursor to the initial solution might be helpful in improving the speed in arriving at an optimal solution.

In our study, the first tour is randomly created from the set of points that are passed on from the multiobjective genetic algorithm in the previous chapter. The created tour is shuffled to randomly reorder the tour.

The error value is generated from the same error model defined for the genetic algorithm in the previous RTLS chapter. As the SA algorithm attempts to generate a single optimal solution instead of parallel evaluations as implemented in the GA, the least error value from all the six facilities is calculated and used for getting the cost or error value for SA implementation onwards. Also, the number of points or hotspots in the tour is completely dependent on the output that the GA achieved already.

5.2.2 Cost Function

The cost function is defined by the problem under study and measures the quality of the solution calculated at every iteration of the algorithm. The delta error evaluations in the SA algorithm that gives the change in cost or energy from the current to the new solution is a criterion of solution acceptance.

5.2.3 Initial temperature selection

The starting temperature is important to the SA optimization. Initial temperature, if not adequately high, impacts the search space and the final solution might be very close to the initial solution. At extremely high temperature, the solution can move to nearly any state of the search space, becoming too large, and the algorithm might seem like a random search. The simulated annealing algorithm is more effective only after the temperature eventually cools down enough so the search is not so extensively random anymore. There are various methods to compute initial temperature [214].

In this research, the initial temperature is set to a very high value, such that almost all the energy changes are accepted. In the beginning, it is desired that almost every neighbouring solution is accepted [215]. Dowsland [216] suggests starting at a very high temperature, then cooling rapidly until a certain proportion of worse solutions are accepted and then it can be cooled slowly after. Rayward Smith [217] showed the initial temperature should be high enough so that about 60% of worse solutions are accepted and then that can be used as a starting value for the initial temperature, followed by slow cooling from thereon. Since these methods closely resemble the physical annealing process of melting the material to its liquid form at extremely high temperature that doesn't change its state any further and then the beginning of slow cooling starts from there. Research shows that that there is no known perfect method for finding the one suitable temperature value for various problems so attempting to follow one of the methods or suggestions above seems promising.

5.2.4 Temperature decreasing method

In order to arrive at an optimal solution, there is a need to find a method to decrement the temperature in the system. Care must be taken when choosing a decreasing method as it can critically affect the performance of the algorithm. Theoretically, it is stated that adequate iterations at each temperature are required to ensure stability at that particular temperature. Some researchers say each temperature should be iterated exponentially to the problem size, which does not seem practical [214]. Another possibility is finding a method that balances between the two methods. The temperature parameter temp can be decremented in geometric or arithmetic way. The geometric decrement is used in the SA implementation in which temperature is updated as equation given here

$$t\text{emperature} = temperature * (1 - coolingRate)$$

Using a geometric temperature decrement is known to be superior and experiments have shown that the value for coolingRate (0 < coolingRate < 1) ranging from 0.8 and 0.99 can be used to obtain optimal solutions without sacrificing computational performance [218]. Better solutions were found at higher values of coolingRate, approximately 0.99 in the experiments conducted in the research. However, it took longer to decrease the temperature and reach the stop condition. After several trial simulations, the cooling rate used here was set at .997.

One of the last decisions in the cooling schedule is selecting the number of iterations at each temperature value. The number of iterations can either be constant or even be reduced to single iteration at each temperature with a gradual decrease in temperature, as suggested by Lundy et al. [219]. Alternatively, a dynamic number of iterations can be done, with more iterations at lower temperature values in order to exploit the best of local optimum solutions whereas fewer iterations (or explorations) at higher temperatures are acceptable [220], [221]. In the experiments conducted in this study, 10 iterations at each temperature is implemented as it minimizes the error value more than a single iteration. This becomes evident after testing for several runs.

5.2.5 Final temperature selection

The stop criteria in this study is the state of no change in the system where no more acceptance of worse solutions is taking place at an appropriately low temperature. It is shown in experiments that the probability of accepting the worse solution at the temperature value approaching zero is comparable to using zero.

5.3 Experiments and Results

To find a best path covering all the segments, a multiobjective Simulated Annealing algorithm is used. The aim is to minimize the two objectives simultaneously, specifically, the error value (time in seconds where the patient location is not known) and the quantity of readers used to track the patients. The performance of the SA optimization algorithm for mRTLS in terms of relevant parameters is presented here in the Table 9. The final temperature is the temperature at which a change in error value or deltaE (i.e., the tracking error of mRTLS) becomes almost steady after

4000 simulation runs of the SA and the near optimal solution gives the best error in secs (5,809,618 secs or untracked seconds overall). This solution is applied as input to A* legalization algorithm discussed in the next chapter.

Table 9 Multiple SA simulation runs

Simulation runs for 4000 iterations each							
mRTLS (SA) Run	**Final Temperature**	**Best Error** *(secs)*	**deltaE** *(norm.)*	**deltaE / Temperature**	**Error** *(%)*	**Non-Error** *(%)*	**Readers**
1	**30155.61336**	**5809618**	**98119.88**	**-3.25378492**	1.08%	98.92%	6
2	30155.61336	6459059	111441.02	-3.69553153	1.20%	98.80%	6
3	30155.61336	4830891	74694.91	-2.47698195	0.90%	99.10%	6

After multiple runs of the SA, the optimization implemented using mRTLS model confirms that the system on average gives a coverage of almost 99% with six mobile readers running on the upgraded trajectories.

Initial testing of the optimization algorithm using SA conducted using a single iteration at each temperature gave acceptable results. However, further examination using the temperature schedule of decrement after ten iterations showed better solutions. The Figure 28 Simulated annealing temperature schedule shows the temperature schedule performance.

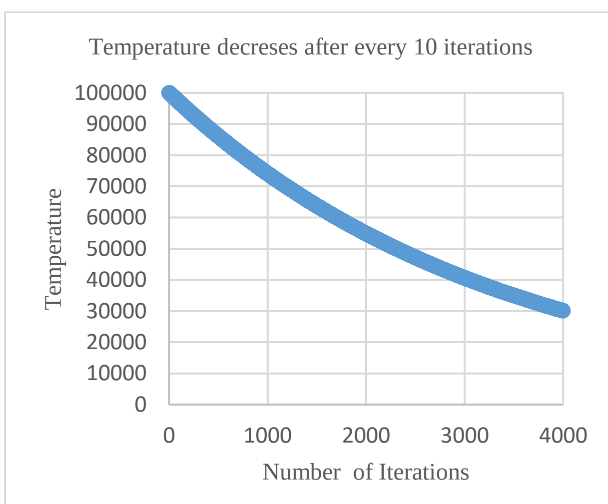

Figure 28 Simulated annealing temperature schedule

The final solution is obtained after 4000 iterations of SA and minimizes the error value in seconds to obtain the solution with the least error. The selected cooling drops quicker at the preliminary temperature but takes a gentler pace while going towards the minimum temperature suitable for the annealing process to get the best results. The Figure 29 shows best error minimization over multiple runs of SA for optimized solutions. Beyond 2000 iterations, there is no apparent improvement. The best error is the error of the best solution found so far. Figure 29 illustrates the progression of a solution which would include exploration of worse as well as better solutions. Here the cost increases with temperature.

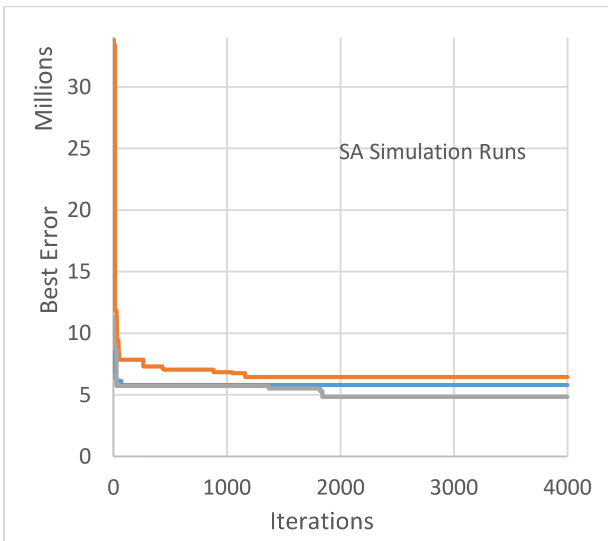

Figure 29 Simulated Annealing-based Optimization

The near optimal static solution from the multiobjective genetic algorithm is used as an initializing parameter to the simulated annealing algorithm that is implemented as a dynamic parameter variation experiment within AnyLogic. In SA after finding a solution, it is evaluated within AnyLogic using the EDIS data, followed by varying a parameter, and the new solution is probabilistically accepted or eliminated. The multiobjective SA algorithm produces an optimized path for all the readers in the layout. The solution generated further optimizes both costs by reducing the number of readers even more while attempting to minimize tracking errors.

After the first parameter variation experiment (static parameter variation experiment) that gives the best solution after GA based optimization for RTLS (Figure 30), the second parametric variation experiment is conducted for the augmented mRTLS model using the AnyLogic simulation tool.

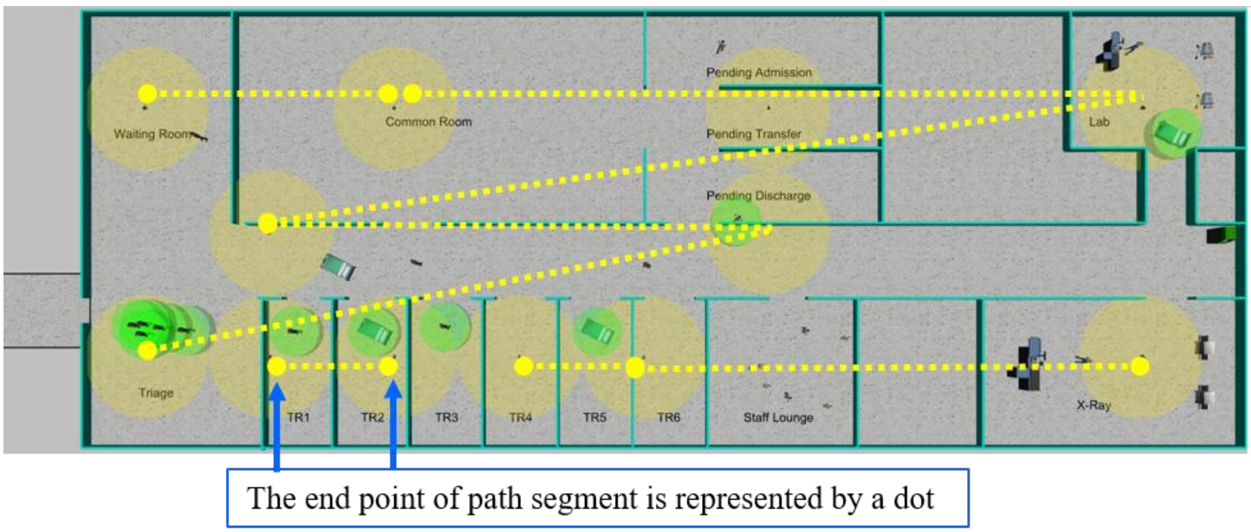

Figure 30 The parameter optimization of a static RFID reader model using a Genetic Algorithm that illustrates the high RFID read areas.

Subsequently, the SA algorithm is applied to a dynamic parameter variation experiment that provides the final optimized solution, i.e. the best RFID coverage and a minimum number of readers necessary to maintain an adequate error margin (Figure 31). After running the GA RTLS optimization algorithm, the near optimal solution string obtained indicates the number of static readers and the coverage associated with the best solution in the form of error value. In general, an increase in number of readers leads to reduced error in patient tracking. However, more readers will certainly add to the cost of the designed tracking system at different levels (purchase, maintenance etc.). In order to have a cost-effective system with an acceptable error rate using an RFID based mRTLS, fewer readers must be considered.

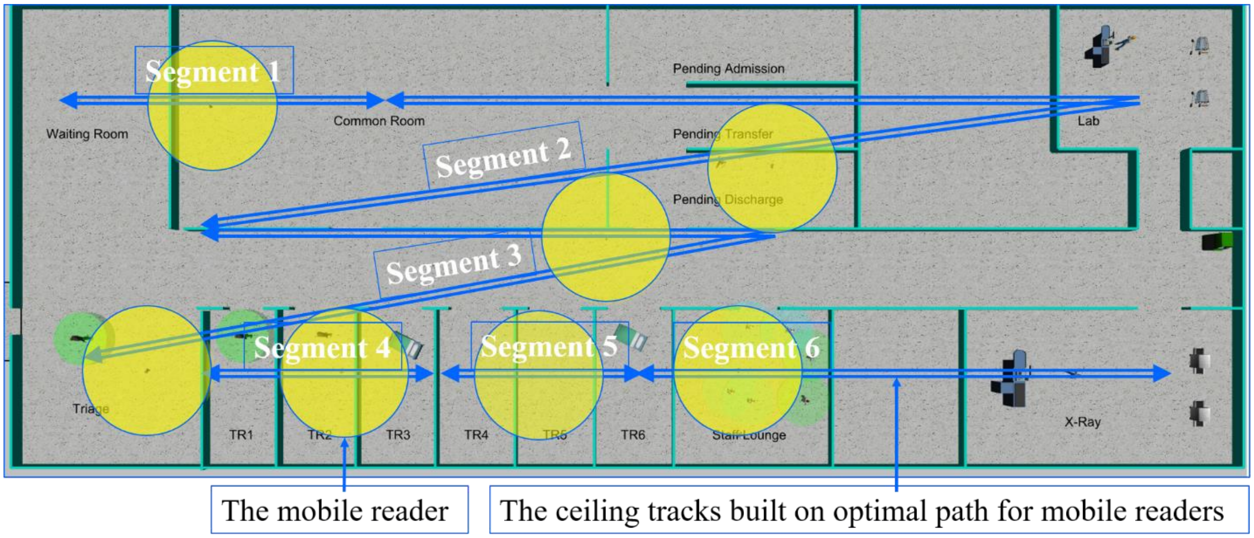

Figure 31 Dynamic parameter optimization of the mobile RFID reader model using SA that generates optimized paths which the mobile readers traverse

The optimization process started from implementing the GA based RTLS model where the tracking error gets minimized. This develops into an improved cost-effective mRTLS system with a minimal number of mobile readers. traversing on near optimal ceiling-mounted tracks, instead of a large number of static readers in the earlier model. The next step involves legalizing the tracks by implementing the A* algorithm to escape the physical barriers (walls/obstructions) discussed in detail in the next chapter. The flow of multiobjective optimization using GA and SA algorithms integration to this stage of mRTLS design is demonstrated in the flowchart shown in Figure 32. The simulated annealing algorithm definitions and flowchart details are provided in the appendix.

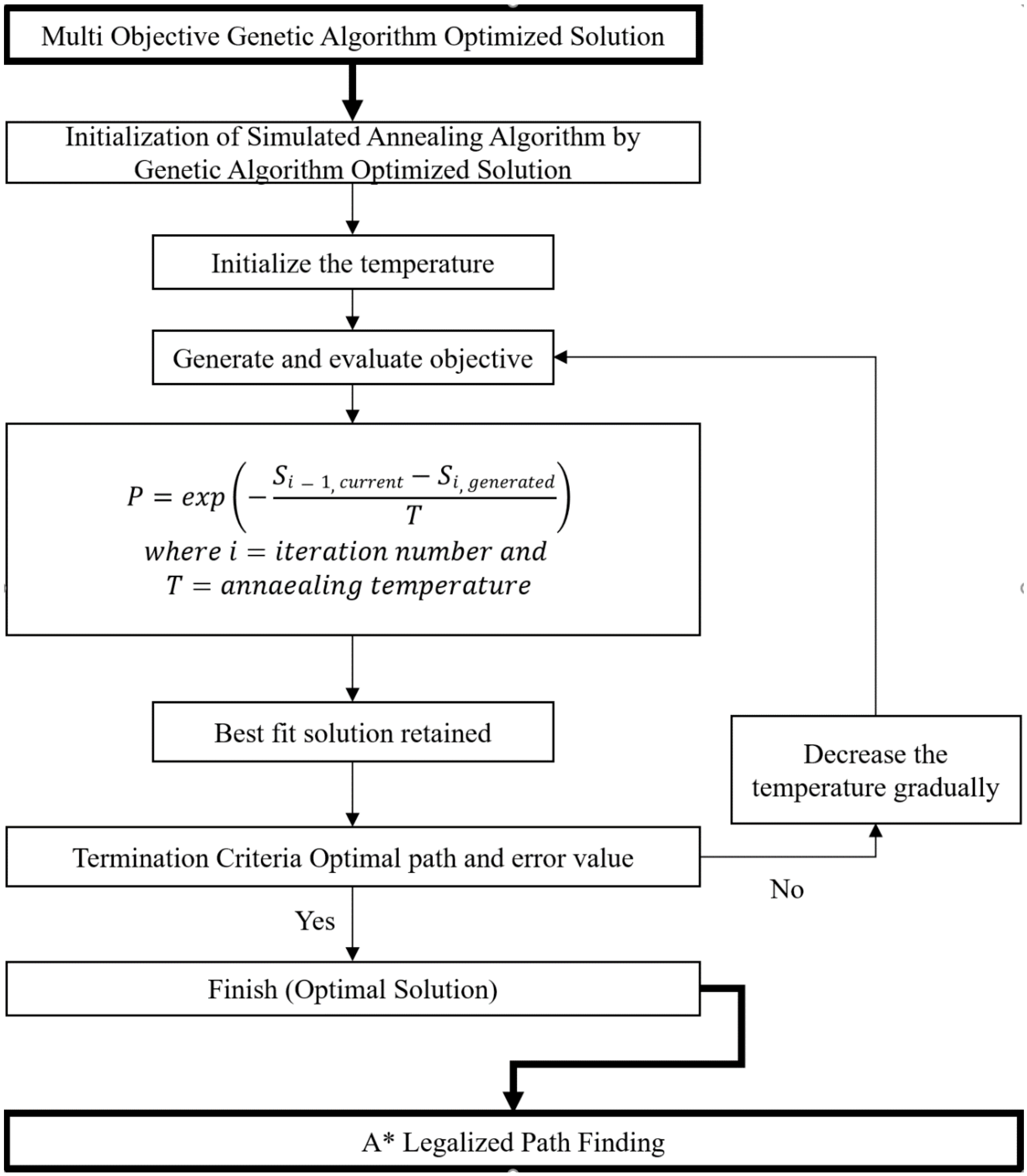

Figure 32 Overall Multiobjective Optimization using the GA and SA

The Table 10 shows the performance of RTLS optimization with fixed readers and an augmented mRTLS optimization of nearly half the number of mobile readers with almost 99.9 % coverage. However, there is a slight decrease in the coverage (.49%) as compared to earlier RTLS model using static readers, which is not surprising as the number of readers is minimized to six instead of 14 static readers.

Table 10 The optimization progress from static RTLS to mobile RTLS (mRTLS) optimization

Data	**Readers**	**Error (E)** *(seconds)*	**Non-Error (NE)** *(seconds)*	**E** *(%)*	**NE** *(%)*
EDIS		523,278,720		-	-
EDIS + (ED ABM) + Optimized RTLS	14	2954779	533,666,107	0.5%	99.4%
EDIS + (ED ABM) + Optimized mRTLS	6	5809618	530,811,268	1.08%	98.91%

The genetic algorithm gives a near optimal solution with a smaller number of fixed readers (hotspots) with minimal error values as compared to other alternative assignments of fixed readers. Simulated annealing provides an improved solution with even further minimized number of readers by replacing the fixed ones with mobile readers, but with a little higher error value.

5.4 Summary

The two multiobjective optimization algorithms are integrated within the AnyLogic simulation software to experimentally validate the proposed mRTLS reader system. The parameter variation experiments implemented on the models enables “what-if” scenario verification and visual observations. The optimization algorithms allow customization of their parameters. Within the GA population size, number of readers in an individual solution, rates and types of crossover and mutation operators are modifiable. The selectivity of the best solution per epoch, also known as elitism, is customizable. The implemented RFID ABM with mobile readers provides an option to change the reader range, velocity of the mobile RFID, their trajectories and number of readers.

The hospital data imported in the designed model can be changed and the simulated data can be used for the purpose of analysis so the output of a large number of runs of the simulation can be analyzed statistically.

As mentioned, the best solution generated by multiobjective GA is used as input for the multiobjective SA algorithm to further improve optimization of the required number of readers and the best reader paths that ensures fewer errors. The experimental results demonstrate a decrease in tag tracking error with a concomitant reduction in the number of mobile RFID readers when compared with a greater number of static readers, even with those readers placed at high traffic locations. This is attainable by the designed error model. The readers in a high traffic area can accurately track an individual or an asset but lose track of it as soon as it is out of range. In the error model developed, the reader that is moving effectively extends its range, thereby reducing the tracking error. This is believed to be primarily due to the fixed trackers only reading tags in their proximity, while a mobile reader is able to get a better estimate of tag movement largely attributable to the time constants associated with relatively slow patient movement in an ED. This can be attributed to read hotspots being found in hallways and waiting rooms. Since the mobile trackers not only cover the hot spot locations, but also the territory between these locations, more information can be obtained. The readers are moving with constant velocity in the present designed model. Perhaps, if the readers moved at different rates or had dwell times at hotspots, the error could be reduced further. This is an interesting possibility for future work.

Another influence of this perhaps unexpected result is the way in which error is defined within the system. Tags operate as state machines, in either a non-error state or an error state, depending upon when the tag was last discovered by the tracking system and its movement since that time. A tag is put into the error state upon arrival at a new location and will remain in this state until seen by a reader. Once discovered, it will transition to the non-error state, and remain that way until moving to a new location, as the error state changes only when the patient moves and not when the reader notices it or when the reader moves. Using this error model puts static readers at a disadvantage, as discussed above, due to the location of the hotspots. But it is believed that this error model more accurately reflects the ability of generating valid, useful data than others which were tested. It is also the author's opinion that this error model provides an accurate assessment of the system functionality required by a RTLS.

Examining Figure 33, it is immediately apparent there would be issues in implementing the track system in this layout. The tracks do not account for obstacles such as walls or other restricted areas. To resolve this issue, a path planning algorithm is used to legalize each individual path segment. The use of an A* path planning algorithm is discussed in depth in the next chapter.

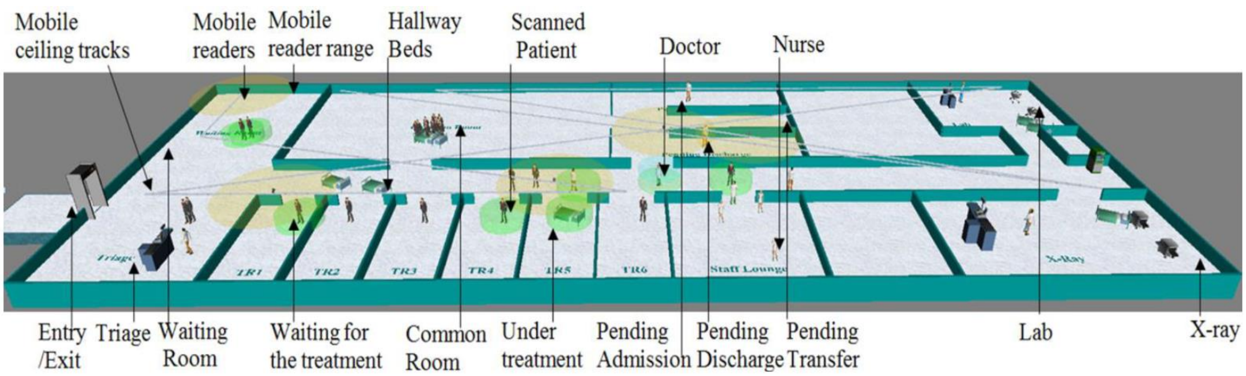

Figure 33 A screen shot of augmented RFID RTLS ABM Simulation

Similar to the use of the GA in determining hotspots, one could argue that the SA simply connected up areas of greatest tag density. While this is true, the analysis provided by the SA optimization also provides some quantitative measure of error loss due to a reduced number of readers and the paths they traverse. Again, this add some degree of credibility to a decision support system in provisioning of an mRTLS or RTLS.

Chapter 6: LEGALIZED MOBILE REAL TIME LOCATION SYSTEM

While developing our initial mobile RTLS, several shortcomings were identified, most notably, lack of legal paths on which our mobile RFID readers could travel as shown in Figure 34. Legal paths are defined as those which avoid obstacles, such as walls or restricted areas within the ED. This issue leads to difficulty in the practical application of the system. In order to resolve this shortcoming, a grid system and an A* search algorithm was used to develop legal movement paths for the readers to follow. With these paths identified, construction and installation of a track system on which the readers will travel can be accomplished.

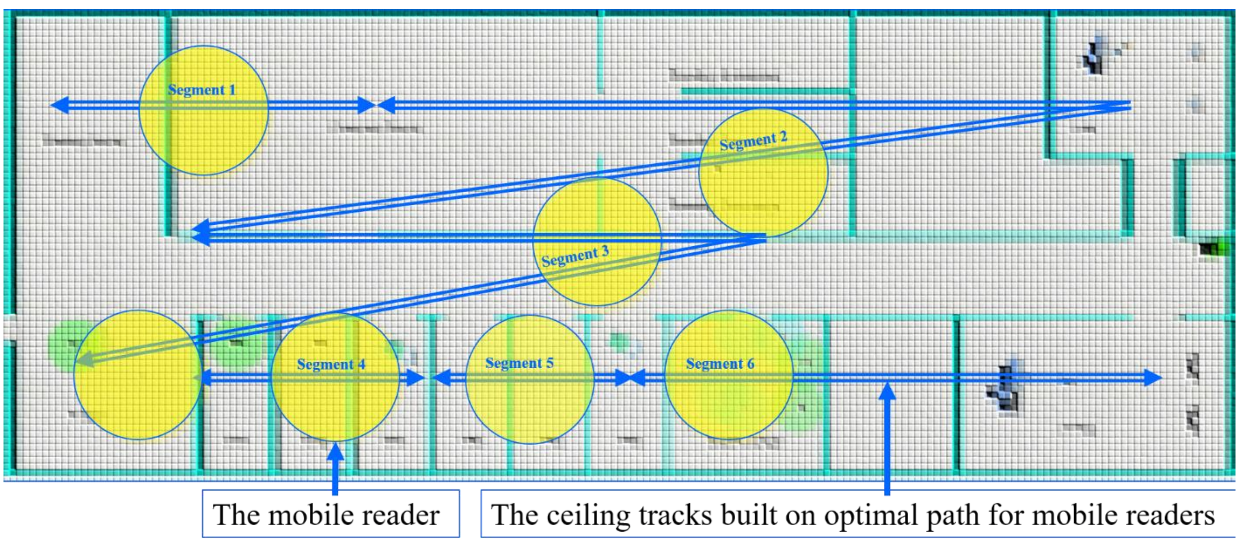

Figure 34 Initial paths, moving through walls

6.1 Legalized A* based Path Finding for mRTLS

In order to practically implement the improved global path, obstacles such as walls and inaccessible areas in EDs need to be taken into account. This process of finding a route from point A to point B within a given area is referred to as Path Planning. The generalized path planning problem can also be viewed as a graph search problem [222]–[224]. The most popular path planning algorithms are Dijkstra's that provides shortest path through interconnected nodes and A*, which improves the Dijkstra's search by adding a heuristic component to the trajectory planning from point A to point B [222]. Dijkstra's algorithm explores all directions, even those that are not so favourable, and will find the shortest route, though not in the most efficient manner. A* searches the shortest path by exploring promising directions without wasting time. This is accomplished using the known distance from the initial position and the anticipated distance to the target, also known as a heuristic, when estimating the cost if this node was included in the path. The use of heuristics in A* helps in reaching the target (goal) node faster [225], and is the difference between it and Dijkstra's algorithm. In order to implement the A* algorithm for planning legalized path for the ceiling mounted tracks for mobile readers to traverse on, there are few steps involved.

The first step in the process requires a partitioning the layout space into cells, where each cell is either blocked or not. The number of cells or grid partitions will affect the resulting path. If the number of divisions is too small, there may be paths through small gaps that may not be found. If the number of divisions is very large, the algorithm would require additional processing time, while not gaining any appreciable improvement in the solution. The use of a 10-unit cell size was chosen in this work, as it was small enough to allow for all gaps to be identified, while not being too small to be overly time consuming to calculate (The scale for the model is defined as one model unit is equal to 10 centimeters. In other words, 1 metre = 10 model units). Our ED simulation layout, overlaid with a grid that consists of both blocked white line cells and unblocked dotted line cells, is shown in Figure 35.

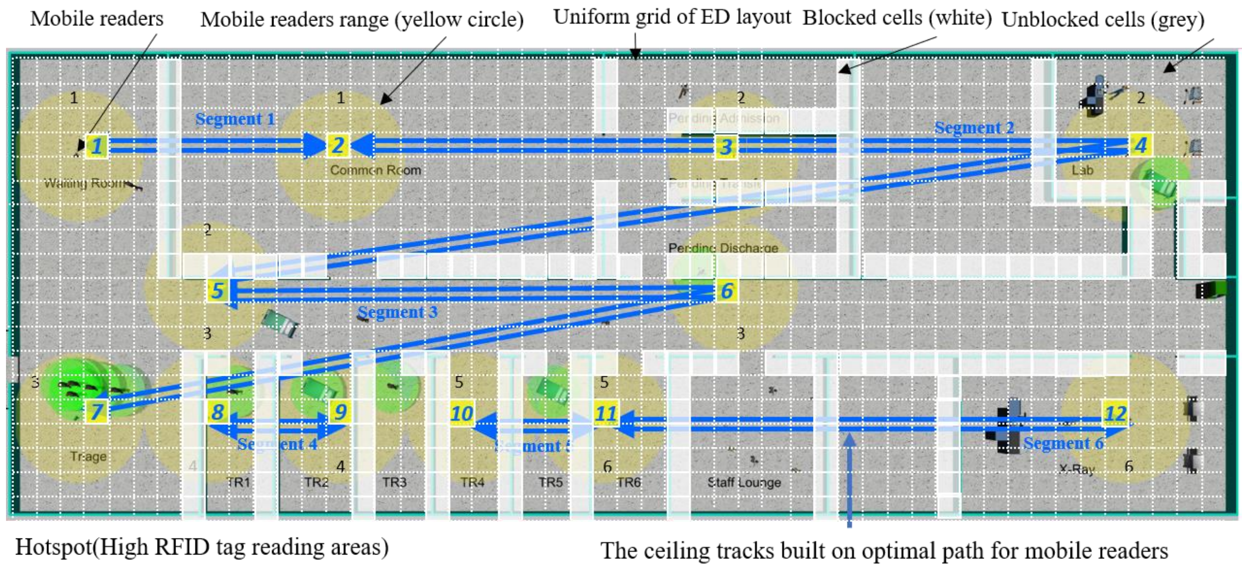

Figure 35 Grid layout showing dotted open cells, and white line blocked cells

The designed ED layout in the mRTLS simulation model is partitioned into 94 columns and 36 rows. This gives us a grid layout for the model with a width of 930 units and a height of 350 units. Each cell/tile size (10*10) in the grid is 10 units in width and 10 units in height.

$$Cell\ size\ =\ 10$$

$$Column\ count\ =\ width\ /\ cell\ size\ =\ 930\ /\ 10\ =\ 93$$

$$Row\ count\ =\ height\ /\ cell\ size\ =\ 350\ /\ 10\ =\ 35$$

Every cell is given an index value for x and y positions. The index value for the X (width) is termed as xIndex that starts from 0 to 93 for the columns starting from the left and Y (height) is termed as yIndex starting from 0 to 35 for the rows starting from the bottom. The Y (height) and X (width) are highlighted in yellow and green respectively in the Figure 36. Each cell represents a location or a point with x and y coordinates in the ED layout in this case, that is associated with an index value (i.e., xIndex and yIndex). In order to fine tune the location/position and agent animation angle relative to animation guide shape in AnyLogic software, offsets are used.

Initially, all input positions from the algorithms are mapped to a specific cell within the grid. Once it has been determined which cell a given point is within, the path planning algorithm uses the center point of the cell for all further calculations. Thus, the center of a cell is calculated as:

$$Half\ cell\ size\ =\ Cell\ size\ /\ 2\ =\ 10\ /\ 2\ =\ 5$$

$$xPosition\ =\ xIndex\ *\ 10\ +\ Half\ Cell\ Size$$

$$yPosition\ =\ yIndex\ *\ 10\ +\ Half\ cell\ Size$$

$$where\ the\ cell\ location\ is\ defined\ in\ 2D\ as\ (xPosition, yPosition)$$

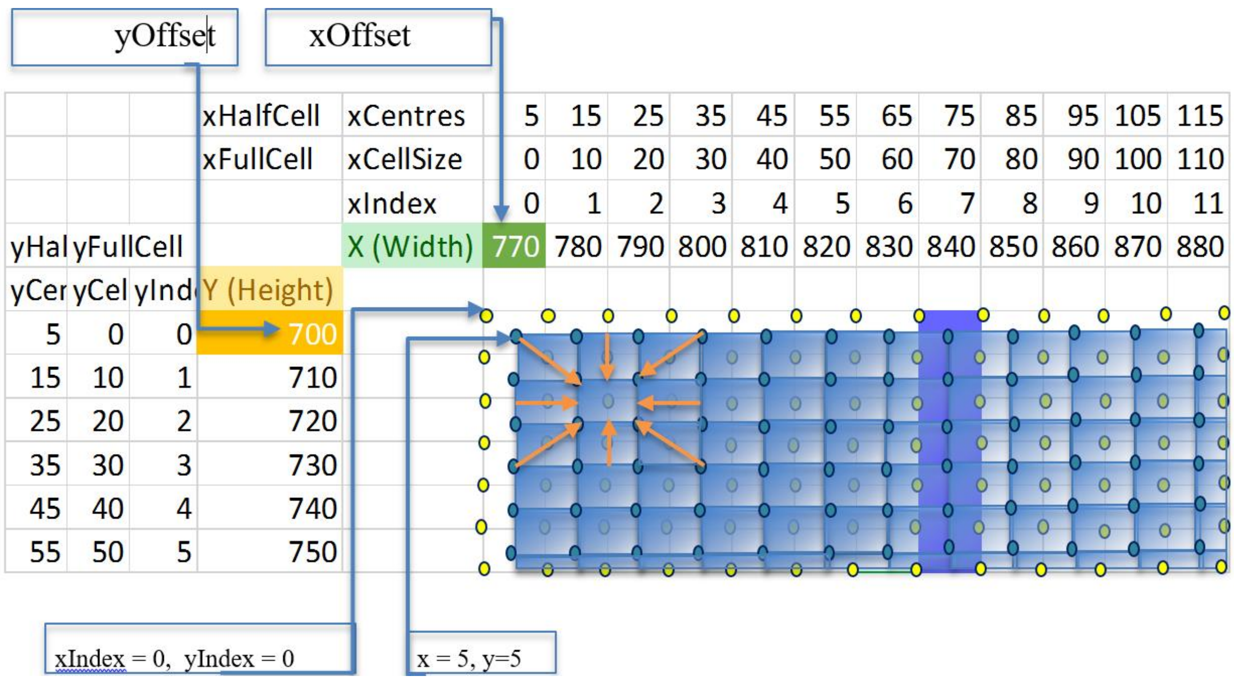

Figure 36 Relationship between cell indices, positions and center locations.

All the possible neighbouring cells around the start cell position are explored. Each cell can have eight neighbours in total - Top, Bottom, Left, Right, Top Left, Top Right, Bottom Right and Bottom Left.

As the A* algorithm begins the process at the starting node, searches through the eight adjacent neighbours, selects the best/inexpensive node. The process continues with its further exploration of the next set of neighbouring nodes of the current best node (Figure 37).

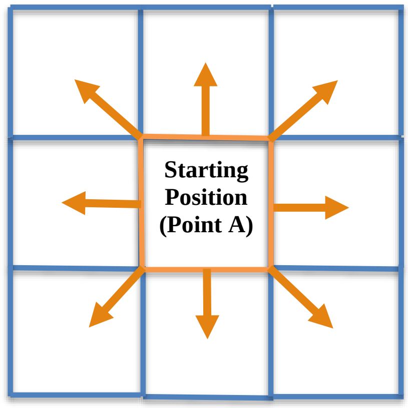

Figure 37 Possible neighbour cells

The algorithm implementation includes defining a "*neighbours*" method that stores all the eight adjacent cells in an ArrayList (datatype) and determines whether the cell is blocked (obstruction by a wall) or unblocked (permissible) in the constructed grid. The next move is estimated based on the exploration of all neighbouring eight cases as shown in Figure 38 and Figure 39.

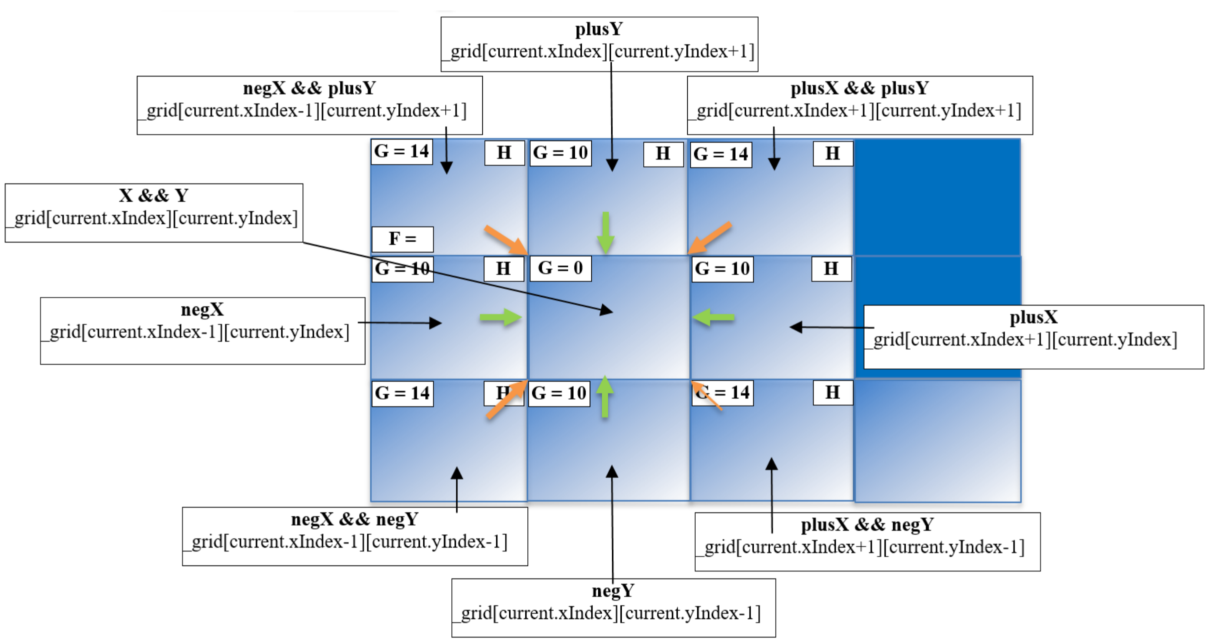

Figure 38 Illustration of array indices as used within the code

In case there is the presence of wall/obstruction in the neighbouring cell, then the search does not consider the blocked cell (blue cells in Figure 39) and keeps on exploring further neighbouring cells where the movement is allowed or legalized.

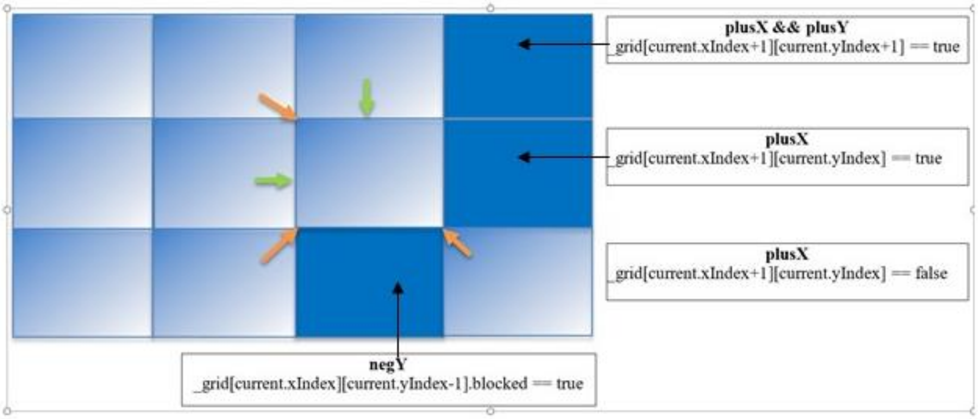

Figure 39 Blue cells are blocked neighbour cells.

6.2 Design and Description

The algorithm determines the partial path that will expand into a longer path at each iteration of main loop of the algorithm. This is done based on cost estimation towards the goal. The path is selected based on minimization of the function $f(n) = g(n) + h(n)$ when n is current node on the path, $g(n)$ is the cost incurred in forming a path from start node to the current node on the path and $h(n)$ is the heuristic, or estimated cost, of the path from the current node to the goal node [223]. Heuristics are specific to the problem under study. When applying heuristics, using a consistent, or monotonic, function allows for checking each possible node only once, while still finding the optimal path [223], [226], [227].

Movement cost (Grid) is calculated using the Euclidean distance, where moving diagonally to a neighbour incurs a cost greater than movement on the axes, as shown in Figure 40.

$$f(n) = g(n) + h(n)$$

g(n) = calculated total distance from start to current node.

h(n) = estimated cost from current cell to end cell. This is calculated using straight-line Euclidean distance from the current cell to the destination cell.

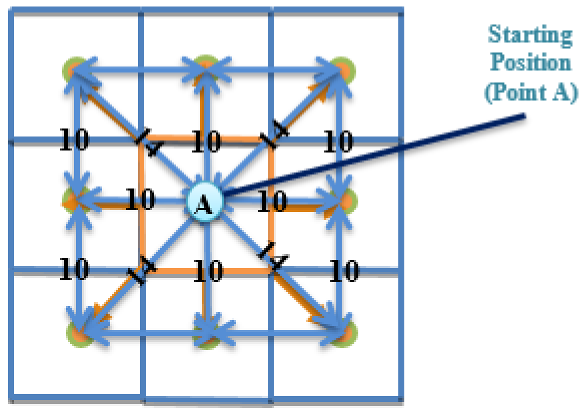

Figure 40 Cost of moving from current location at Point A to any of its neighbours.

If the estimated cost to reach the goal is always less than or equal to the actual cost to reach the goal, then the heuristic is said to be *Admissible.* This is the case with *A* in this situation, as we are using the straight-line distance from each node to the goal node when calculating the heuristic, and straight-line distance is the proven shortest distance between any two points. An admissible heuristic is necessary in order for the algorithm to find the lowest possible cost route.

A consistent or monotonic heuristic is one in which the estimate to the goal from the current node is always less than or equal to the estimated cost from any neighboring node to the goal, plus the cost of reaching that neighbor from the current node. Since we are using the straight-line distance measurement for the heuristic, and a straight-line is the proven shortest distance between 2 points, it is not possible for the estimate from a neighbouring node, plus the distance to travel from the current node to that neighbour, to be less than the proven shortest distance. To prove this, we assume there exists a path from point A, through point B, ending at point C, which is less than the straight-line distance from point A to point C. This contradicts a straight line being the shortest distance between two points. In one case, the paths could have equal distance, where point B lies exactly on the straight line from point A to point C. Therefore, our chosen heuristic is monotonic.

6.3 Implementation

The algorithm defines the path, expanding from start node, using the node with lowest cost estimate to the goal. This is done using a priority queue, which orders its nodes based on cost estimate. In case of a priority tie between two elements, then the order in which the element was placed in the queue is used, also known as FIFO, or First In, First Out. The search process in the algorithm is illustrated in Figure 41.

G , H
F

0	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1													wall				
2													wall				
3													wall				
4													wall				
5													wall				
6						14 ,120 134	10,110 120	14 ,100 114	24,104 128				wall				
7						10 ,110 120	0 100 100	10 90 100	20, 80 100	30,70 100			wall	106,40 146	110,30 140	114,20 134	0
8						14,120 134	10,110 120	14,100 114	24 ,90 114	34,80 114	44,70 114		wall	96,40 136	100,30 130	110,20 130	
9								24,110 134	28,100 128	38,90 128	48,80 128	58 ,70 128	wall	86, 50 136	96,40 136	106,30 136	
10									38,110 148	42,100 142	52,90 142	62, 80 142	72,70 142	82, 60 142	92,50 142		
11										52,110 162	56,100 156	66,90 156	76,80 156	86,70 156			
12																	

Figure 41 Shows the discovered path and the f(x) = g(x) + h(x) values for each cell.

The A* search begins with removing the node with the lowest value from the queue. The *f(n)* and *g(n)* values of the neighbouring nodes are then recalculated. The updated neighbours are then added to the queue for processing later. The algorithm continues to explore until the least *f(n)* value for the goal node is calculated or until the queue is empty. The final *f(n)* value of the goal node is the cost of the shortest path, since *h(n)* value at the goal node is zero since our heuristic is admissible. The algorithm precisely provides the shortest path length. In order to easily retrace the steps the algorithm took, each node maintains the information about its previous neighbor on the path. After the algorithm is applied, the last node or the ending node will refer to the previous node in the path, followed by each of the previous nodes in the path in the similar way till it reaches back to the starting node.

The initial process flow starts with identifying the initial location (start node) and the goal location (target node) of the mobile reader (i.e., reader agent). The start location is the first hotspot location (the best tag tracking locations from the GA output) and the initial goal location (the subsequent hotspot from GA). The next step is to create an openList and closedList to store unevaluated and evaluated nodes. The node that is estimated to be on the shortest path (i.e., heuristic value + cost) to the goal node from the start node is eliminated from the openList and stored as the current node. At this point it is repeatedly checked if the current node and the target node location the same. If not, then the process continues to find adjacent nodes to the current node and adds to the successor list. In case the successor list node costs less, then it gets added to openList until there are no more nodes remaining in the successor list. The final output is the cheapest path from the start node to the goal node avoiding all the walls/obstructions. The complete flowchart of A* algorithm implementation is shown in Figure 42.

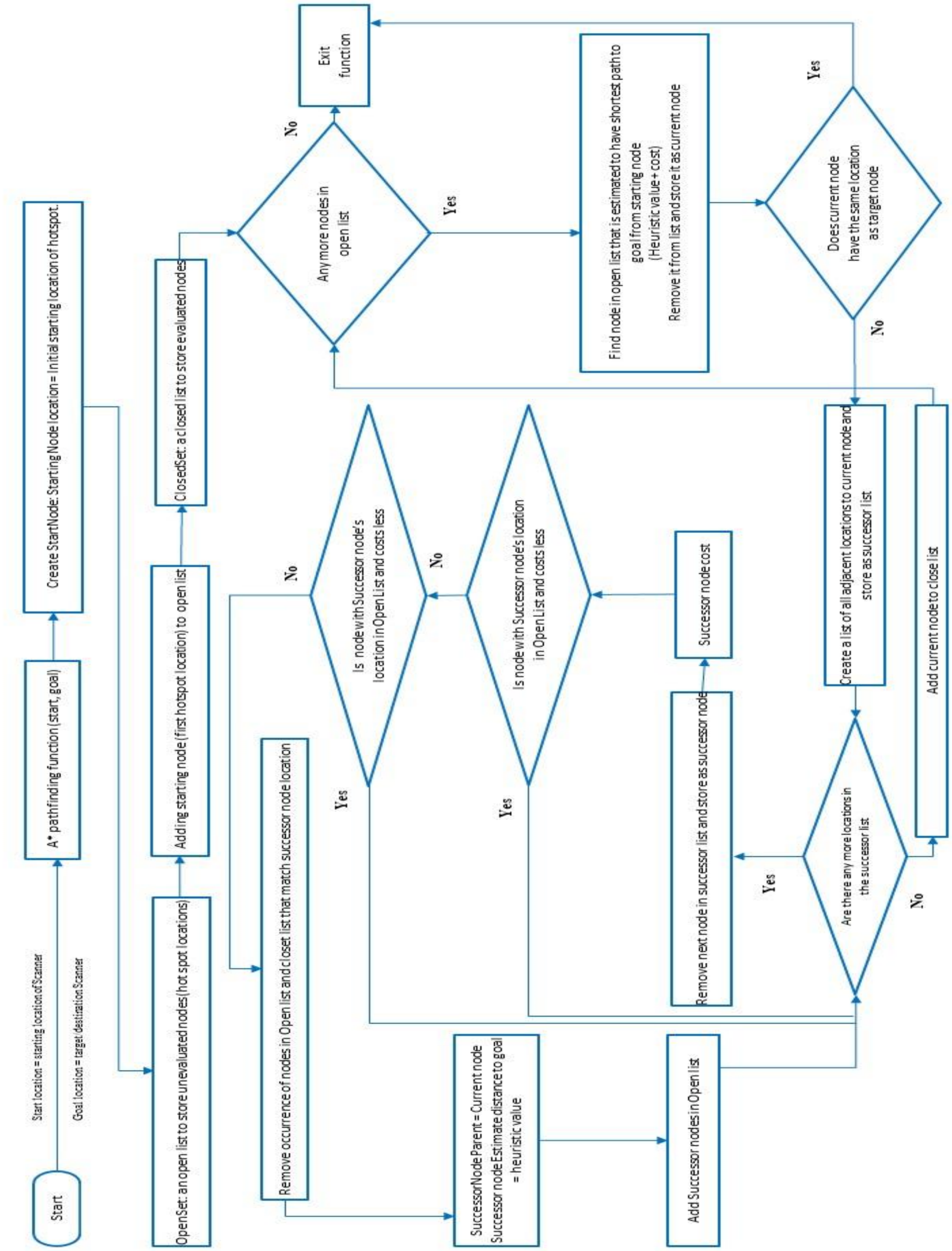

Figure 42 Flowchart of legal path finding algorithm[228]

6.4 Simulations and Results

The system is tested for different ED layouts as shown in the figures below. The legalized mRTLS is tested with three different layouts. The screenshot (Figure 43) shows the simulation run for the layout of ED in Winnipeg similar to the Victoria Hospital Emergency Department (Layout 1). The algorithms successfully determine the best legalized path evading the barriers in the layout.

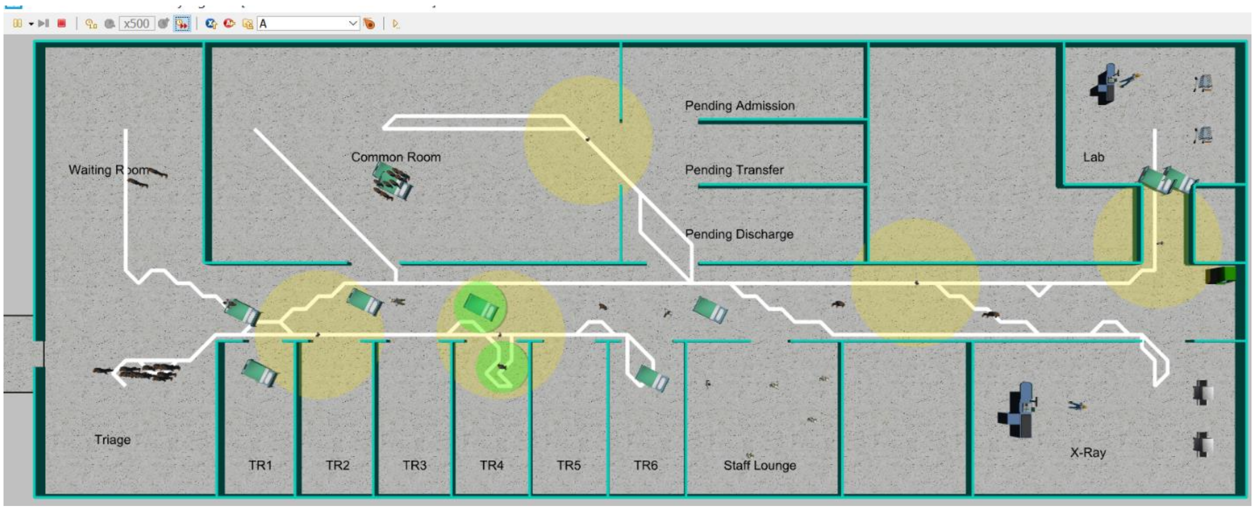

Figure 43 Legal Path that avoids the walls for Layout 1 (Victoria hospital Emergency Department)

The second ED layout is similar to Health Sciences Centre Emergency Department in Winnipeg. This layout is little more complex than the first one, as there are a greater number of walls and treatment areas included in it. The best path shows the trajectory found by the A* algorithms that is able to escape the walls completely as shown in Figure 44.

The final layout tested is the most complex one as it comprises of the utmost number of walls/ obstructions. This layout is very similar to Seven Oaks Hospital Emergency Department in Winnipeg. After applying the A* path finding algorithm, one of cost-effective and legalized path is accomplished. The screenshot of the simulation run is shown in Figure 45.

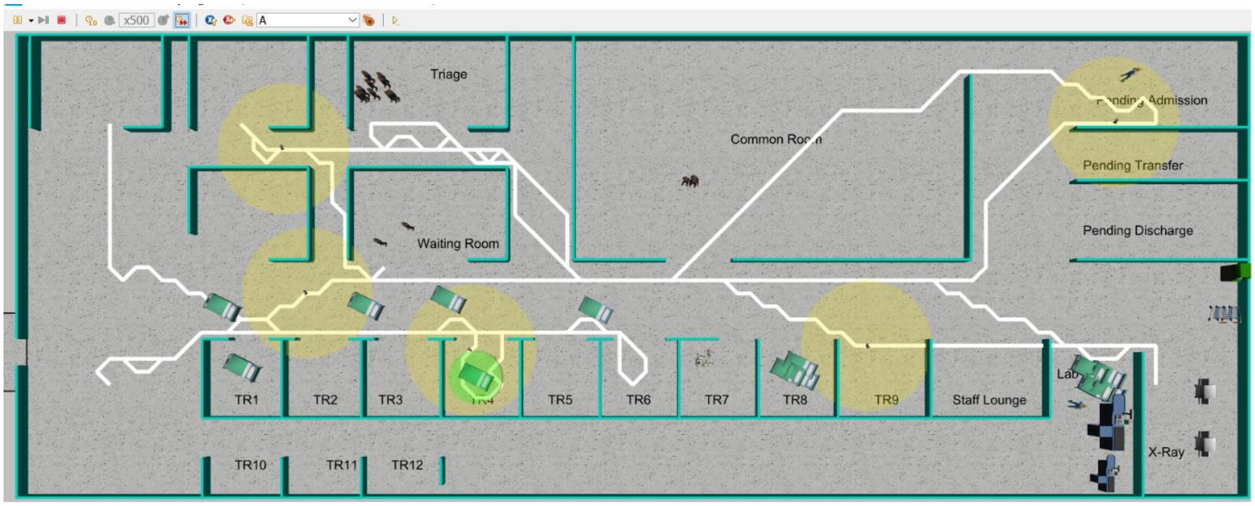

Figure 44 Legal Path that avoids the walls for Layout 2 (Health Sciences Emergency Department)

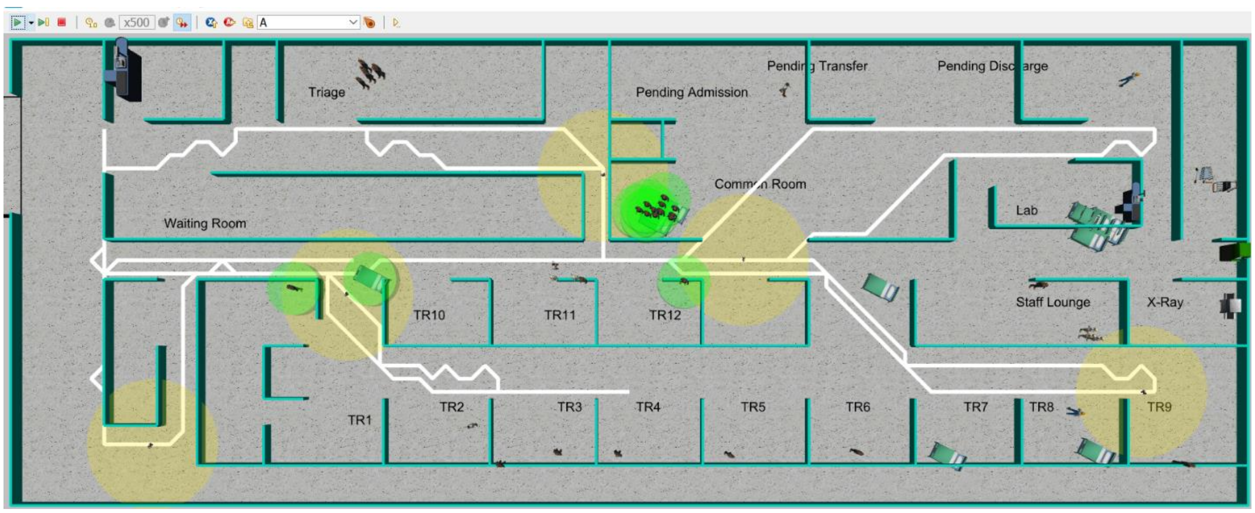

Figure 45 Legal Path that avoids the walls for Layout 3 (Seven Oaks Emergency Department)

6.5 Conclusions and Limitations

The proposed system is based on A* which is introduced to design an efficient mobile RTLS. The developed design effectively creates a practically feasible path for the moving readers. Table 11 shows the performance of mRTLS with lmRTLS. Three simulation runs using SA with GA as input together with the A* algorithm show approximately similar results. The overall coverage improves by 0.2% with the same number of mobile readers but the tracks are successfully formed escaping the walls in the ED layout. This was not expected, as adding obstacles might have added to error value.

Table 11 GA and SA with A* based optimization for legalized path finding for mRTLS

lmRTLS (GA + SA + A*)	Temperature	Best Error *(seconds)*	deltaE	deltaE/T	E (%)	NE (%)	Readers
1	**30155.613**	**4740426**	**80429.44**	**-2.667**	**0.88%**	**99.12%**	**6**
2	30065.146	4293954	77039.97	-2.562	0.80%	99.20%	6
3	30065.146	5125337	84335.45	-2.805	0.96%	99.04%	6

Table 12 gives a summary of statistics in terms of multiobjective optimization process starting from the EDIS data, then augmented RTLS to the mRTLS leading to final lmRTLS system.

Table 12 Overall optimization from EDIS to RTLS to mRTLS to Legalized mRTLS (lmRTLS)

Data	Readers	Error (E) *(seconds)*	Non-Error (NE) *(seconds)*	E *(%)*	NE *(%)*
EDIS		**523,278,720**	-	-	-
EDIS + (ED ABM)	**27**	**2341782**	534,279,104	0.4%	**99.6%**
EDIS + (ED ABM) + Optimized RTLS	**14**	**2954779**	533,666,107	0.5%	**99.4%**
EDIS + (ED ABM) + Optimized mRTLS	**6**	**5809618**	530,811,268	1.08%	**98.91%**
EDIS + (ED ABM) + Optimized lmRTLS	**6**	**4740426**	531,880,460	0.88%	**99.11%**

The coverage shows constantly improvement in the proposed RTLS system and its improved design. On the representative layout used to demonstrate results in this thesis, the initial RTLS with 14 readers (static) gives coverage of 99.4%, then applying mRTLS, the coverage of 98.91% (decreases by 0.49%) but the number of readers (mobile) is reduced to less than half (six readers). The final design lmRTLS gives improved results of 99.11% (increasing the coverage by 0.2%) with the same quantity of mobile readers (i.e., six).

The generated mobile tracks help in accomplishing the practical RTLS installation in a cost-effective manner. One noticeable limitation of the A* algorithm is that it forms a zig zag path, as path smoothing is not a part of the algorithm. Additionally, A* is limited in its ability to address problems such as moving obstacles, dealing with minimum or maximum allowable turning radii, changing maps, cooperative movement, etc. [225], [229]. It is worth mentioning that there is at least a possibility, that a non-optimal SA solution may in fact become a more optimal overall solution when constrained to legal path planning.

Chapter 7: CONCLUDING REMARKS

The first chapter briefly presented the complex problems in emergency healthcare data collection systems and their influence on patient care. The method of agent-based modeling is concisely stated with its possible use for simulating an emergency care facility in order to indicate finer details and gaps in the system. By means of agent-based modeling of an emergency department, an efficient design to deploy a radio frequency based real time location system is suggested as one of the techniques with a provision for better collection of healthcare data. The proposed innovative system of a mobile real time location system is intended to provide a cost-effective solution by minimizing the quantity of readers along with significant decrease of tracking error or uncertainty.

The second chapter further elaborates on the issues related to emergency department patient wait time relating to the underlying issues indirectly pointing towards the data collection problems in healthcare systems. Apart from examining different statistical approaches, agent-based modeling specifically relating to RFID based solutions for emergency departments are also analyzed. The current state of art solutions either focus on designing efficient deployment of static/fixed readers or on RF based concerns such as reflections and overlapping coverage issues. There is significant progress in the research field in terms of applying agent-based modeling techniques. However, the agent-based models designed for healthcare facilities focus explicitly on either patient flow, emergency department throughput or resource allocation. There is little work done to date that considers different aspects such as patient tracking and automation of data collection for healthcare.

Chapter three attempts to apply two different methods. The first method examined involves statistical analysis to identify the loopholes in the system by conducting a thorough investigation of the procured healthcare data with 19,404 patient records from the six emergency departments of the major hospitals located in Winnipeg, Manitoba. However, the quality of data made the analysis difficult to extract significant results. For example, the data did not reflect staffing.

Chapter three further investigates the method of using agent-based modeling to design an emergency department model that allows one to not only integrate the patient data but also augment the model with our novel real time location system design to automate the patient tracking. In order to make use of available data, a preprocessor program is implemented that parses the raw data file into a clean file format that can further be utilized as an input parameter for the designed ED-ABM model. The ABM provides the capability to analyze a complex system such as an emergency department by using different individual units called agents. This enables the creating of the corresponding agents with specific characteristics and behavior to get a realistic simulation of a system such as an emergency department. The ABM approach gives better insight to the patient treatment processes and the wait times associated with it. The agent-based model approach gives us the opportunity to create a proficient design and has flexibility to explore changes and test scenarios before developing an actual prototype or committing to a new policy.

The fourth chapter discusses the use of a Genetic Algorithm (GA) in finding the hotspots, or areas of high traffic for a given ED layout. As discussed, a weighted fitness function is used to allow for the combination of the 2 opposing objectives, reducing the number of readers while also maintaining an acceptable error level. Chapter 4 also demonstrated several use cases of the algorithm, include a simple case to demonstrate the expected functionality of the algorithm.

The fifth chapter explores the efficiency and practicality of the designed solution in order to further optimize the system using Simulated Annealing in order to find the best path between the previously identified hotspots. The sixth chapter extends the developed model to consider legal paths to deal with the presence of obstacles such as walls. Our design provides a cost-effective solution for automation of patient and asset data collection processes that can be used by decision makers of healthcare policies. The results showed that fewer readers are required to track the patient through the system while still keeping an acceptable untracked/error value.

In order to make the designed model more practical and realistic, the provision of walls is introduced in the emergency department layout, explained in chapter six. To achieve a legal path, an A* path planning algorithm is used, where a grid map is created to augment the designed mRTLS model with the presence of walls/obstructions where blocked cells are the walls and unblocked cells are the permissible ones. The mobile real time system can be applied to any hospital environment as discussed in chapters five and six.

With the current state of patient wait times in emergency department in Winnipeg, Manitoba and other provinces, an immediate and effective solution is needed to become more efficient. The major contribution of this dissertation is the novel design process for a mobile real time location system. The system was tested using actual data from emergency healthcare facilities. the thesis demonstrated a novel data driven ABM of an ED, optimized the location of and number of static readers for an RTLS, optimized trajectories mobile readers would traverse while maintaining an acceptable tracking error with fewer readers for an mRTLS, and finally adjusted tracks for mobile readers to be legalized along hallways and through doorways.

A weakness or criticism of the approach taken is that the argument may appear circular in that the ABM is driven by EDIS data which is used to validate the mRTLS or at least add credibility to the approach. The idea is to take advantage of available data in developing a better or more automated system that relieves healthcare workers from data entry as it pertains to the location of patients and assets. An alternative data source, if EDIS like data were not available, would be to undertake a survey using an individual portable reader housed at potential reader locations sampling patients who were provided a tag upon entering the ED. This portable reader could be relocated after a brief period (several days) to a new location thereby providing an alternative baseline for suitable reader locations. It may also be the case that simply identifying the most read areas would be suitable starting points for optimizing mobile reader deployment.

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APPENDICES

Appendix A: Additional definitions and supplementary figures

Events

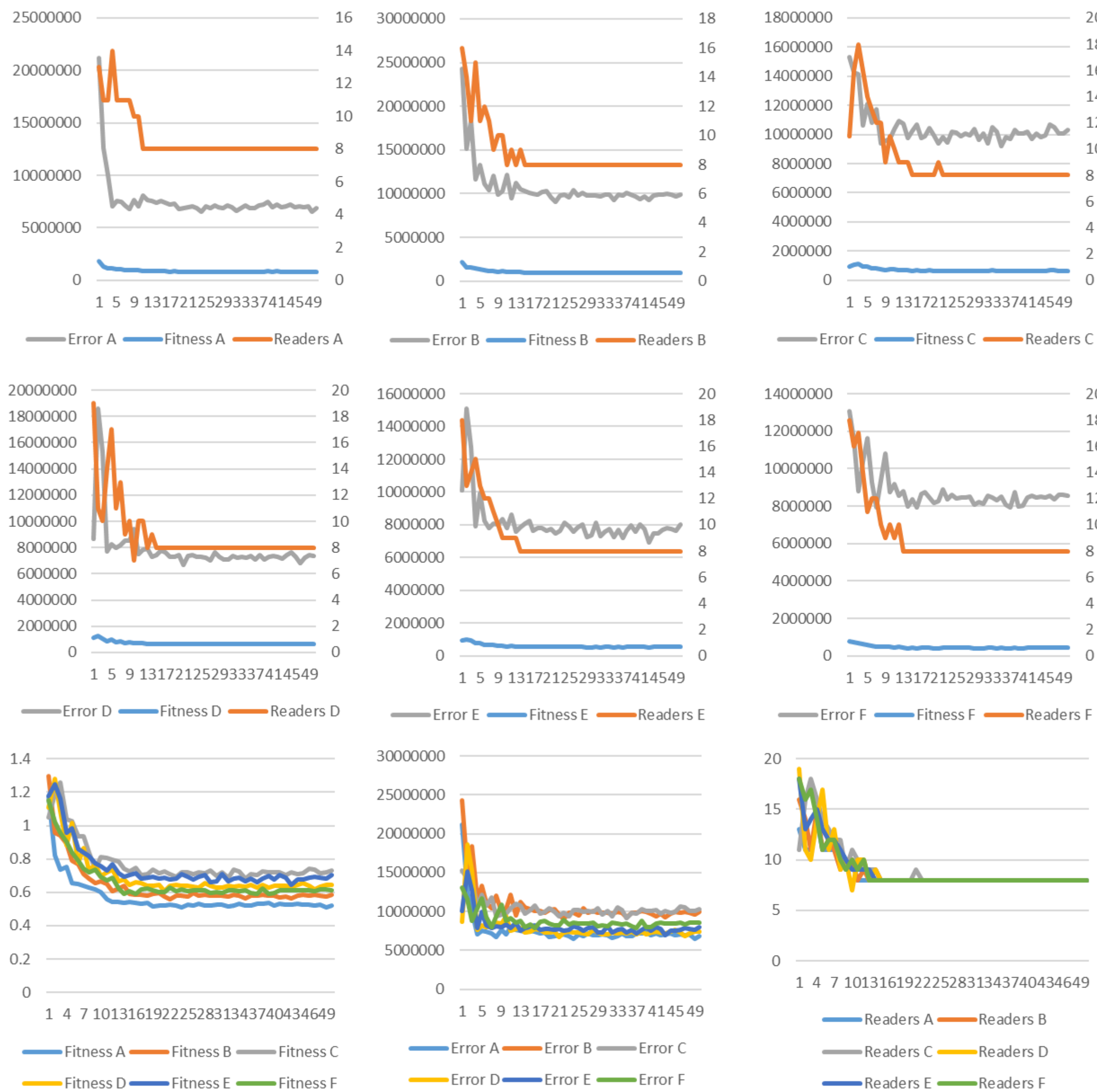
Event is a model element used to schedule an action in the designed model such as modeling delays and timeouts. Similar action can be accomplished using timed transtions in statecharts as well. However former is more efficient. The events can be triggered by timeout, by condition or by rate. To schedule concurrent and independent events dynamic model event can be used.

Statecharts

An advanced behavior can be modeled using state transition diagram or statecharts. statecharts constructs define event and time driven behavior or pervasive operations. The statechart involves states and transitions. Transitions may be activated by timeouts, messages received by a statechart, or Boolean conditions defined by the user. The transition execution changes the state leading to activation of further new transitions. Hierarchical states may contain more states and transitions.

Supplementary figures for the benchmark example for each facility

Performance of optimized RTLS for Benchmark example (left to right movement of patients in a square ED layout).



SA definitions for mRTLS

State (s): A particular tour from the GA optimized set of locations or hotspots points

Neighbouring State (s`): state generated by randomly swapping the order of two locations

Cost Function (C): determines the total cost (error) of a state (tour)

Relative Change in cost (delta (δ) or deltaError (deltaE)): the relative change in cost (error) c between s (i.e., ($S_{i-1,\ current}$)) and s` (i.e., ($S_{i,\ generated}$))

Acceptance Probability Function (P): determines the probability of moving to a more costly expensive (higher error) state

Cooling Constant (beta (β)): the rate at which the temperature T is decreased every time a new solution is found.

n = number of locations or points (approximately 12 to 14 locations are obtained by GA optimization)

T_0 = initial temperature (set to 100000)

T_k = the temperature at the k^{th} instance (when a new solution state is accepted)

$T_{k+1} = \beta T_k$, where β is (1- cooling rate), (i.e., (1 - 0.003))

$$P(\beta, T_k) = \begin{cases} e^{(\frac{-\delta}{T_k})}, & \delta > 0 \\ 1, & \delta \leq 0 \end{cases} \text{ for } T_k > 0$$

$$\text{where } \delta = deltaE = (S_{i-1,\ current}) - (S_{i,\ generated})$$

Here the S is the solution where ($S_{i,\ generated}$) represents a better (lower S) state that is only conditionally accepted. If P is the probability of acceptance, the value would be e^$\left(\frac{-((S_{i-1,\ current})-(S_{i,\ generated}))}{T}\right)$ i.e. a probability. For $\delta > 0$, at any given Temperature T, Probability P is greater for smaller values of δ or deltaError. This means that if a state s` (i.e., ($S_{i,\ generated}$)) is very slightly more in cost (error) than s (i.e., ($S_{i-1,\ current}$)), then there is a higher possibility of being accepted as compared to the one which is much more expensive than s (i.e., ($S_{i-1,\ current}$)). The flow of multiobjective optimization using GA and SA algorithms integration to this stage of mRTLS design is demonstrated in the flowchart shown in Figure 46.

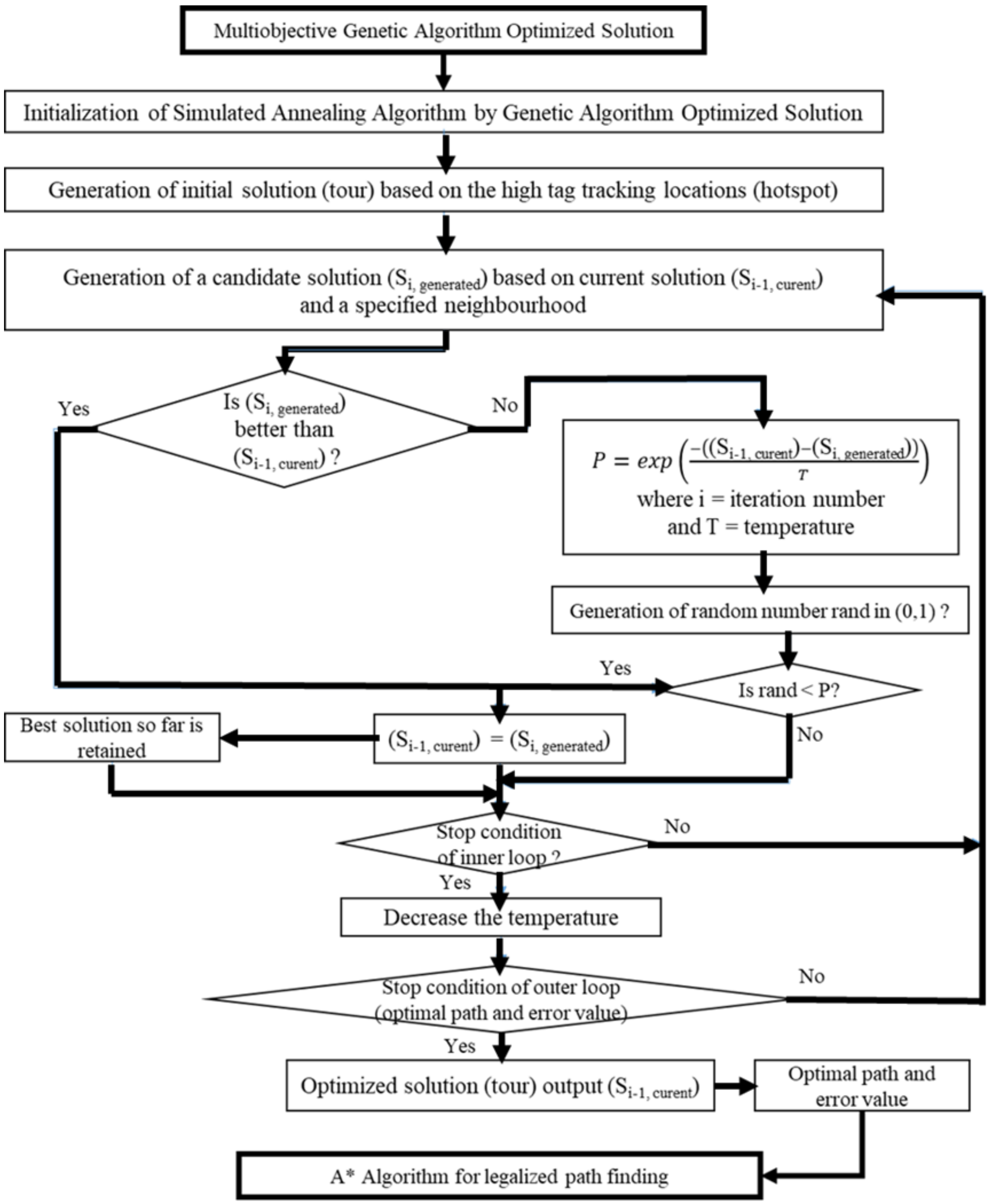


Figure 46 Overall Multiobjective Optimization using the GA and SA

Probability of acceptance decreases with decrease in temperature as the algorithm moves from exploration (accepting more worse solutions) to exploitation (accepting more good solutions) phase. At each step, the probability of acceptance continues to move towards zero until an improved solution is achieved.