EFFICIENT VEHICLE ROUTING OPTIMIZATION FOR AUTISTIC USERS.

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EFFICIENT VEHICLE ROUTING OPTIMIZATION FOR AUTISTIC USERS

ABSTRACT

In recent years, daily life without a vehicle would be impossible. As an inevitable result, the number of vehicles on the road increases day by day in various large cities around the world. The increased number of vehicles is a big concern because it causes a lot of traffic congestions, especially during peak hours. Besides, there has been a rapid rise of on-demand Ride-Hailing Services (RHSs), such as Grab, Uber, EzCab, and MyCar, etc. This allows passengers with smartphones to place trip requests and assign them to drivers according to requester's location and drivers' availability. In consequence, efficient routing algorithms are needed for the sake of enhancing the availability of car-resources. Even though there is an emerging number of RHS applications, there is a lack in their algorithms to tackle the issue of the special characteristics for the autistic users' requirements. Therefore, in this research, a routing algorithm for ride-hailing services has been proposed. The new proposed algorithm is called Autistic-Features Ant Colony (AFAC). This proposed algorithm utilizes the Ant Colony Optimization (ACO) with autistic features to enhance the efficiency and performance of the overall system and the autistic user's satisfaction in ride-hailing services. AFAC considers the road and the autistic features simultaneously to find the optimum route for the autistic user. While the road features play a vital role in finding the optimum route from nearby car-resources to the autistic user, the autistic features help to make a better selection of car-resources in terms of providing autistic users with specialized drivers who can deal with them. Simulation experiments have been conducted using the Unity game engine to analyse the effect of these features on the performance of the overall system. AFAC is designed based on client-server architecture, which includes both the server-side and the client-side parts. The communication between the client and the server is made by requesting the Hypertext Transfer Protocol (HTTP). The Simulation results were obtained by measuring the performance of three algorithms named Ant Colony, A Multiple Parameter control for Ant Colony (MPAC), and the proposed AFAC. The design and analysis of the comparison have been done using MATLAB tool. The experimental results showed that the performance of the proposed AFAC algorithm outperformed the classical Ant Colony and the recent MPAC algorithms.

Keywords: Autism, Ant Colony, Vehicle Routing Problem, Routing, Ride-Hailing Service.

OPTIMASI PENGGANTIAN KENDERAAN BERKESAN UNTUK PENGGUNA OTISTIK ABSTRAK

Kehidupan harian tanpa kenderaan adalah mustahil. Sebagai hasil yang tidak dapat dielakkan, jumlah kenderaan di jalan raya meningkat setiap hari di pelbagai bandar besar di seluruh dunia. Peningkatan bilangan kenderaan adalah amat membimbangkan kerana ia menyebabkan banyak kesesakan lalu lintas, terutamanya semasa waktu sibuk. Selain itu, terdapat peningkatan pesat Perkhidmatan Ride-Hailing (RHS) atas permintaan, seperti Grab, Uber, EzCab, dan MyCar dll. Ini membolehkan penumpang menggunakan telefon pintar untuk meletakkan permintaan perjalanan dan melampirkannya kepada pemandu berdasarkan permintaan lokasi dan ketersediaan pemandu. Akibatnya, algoritma penghalaan yang cekap diperlukan untuk dioptimumkan demi meningkatkan ketersediaan sumber-sumber kereta. Walaupun terdapat beberapa aplikasi RHS yang muncul, terdapat kekurangan algoritma ini untuk menangani isu ciri khas untuk keperluan autistik. Oleh itu, dalam kajian ini, sebuah enjin penghalaan untuk sumber-sumber kereta berdasarkan perkhidmatan perjalanan yang disampaikan telah dibentangkan. Algoritma baru telah dicadangkan bernama Autistic-Features Ant Colony (AFAC). Algoritma yang dicadangkan ini menggunakan Ant Colony Optimization (ACO) dengan bantuan mudah alih bagi autistik untuk mempertingkatkan kecekapan prestasi sistem keseluruhan dan kepuasan pengguna autistik dalam perkhidmatan ini. AFAC mempertimbangkan jalan dan ciri autistik secara serentak untuk mencari laluan yang optimum bagi pengguna autistik. Walaupun ciri jalan raya memainkan peranan penting dalam mencari laluan yang optimum daripada sumber kereta yang berhampiran dengan pengguna autistik, ciri autistik membantu untuk membuat pemilihan sumber kereta yang lebih baik dari segi memperuntukkan pengguna autistik dengan pemandu khusus yang mampu menangani pengguna autistik. Eksperimen simulasi telah dilakukan dengan menggunakan enjin permainan Unity untuk menganalisis kesan ciri-ciri ini pada sistem perforkeseluruhan sistem. AFAC direka berdasarkan kepada senibina pelayan pelanggan, yang merangkumi kedua-dua pihak pelayan dan bahagian sisi pelanggan. Komunikasi antara klien dan pelayan dibuat dengan membuat permintaan kepada Hypertext Transfer Protocol (HTTP). Hasil Simulasi dipamerkan dalam penilaian prestasi tiga teknik yang bernama

Ant Colony, A Multiple Parameter control for Ant Colony (MPAC), dan AFAC. Reka bentuk dan analisis perbandingan telah dilakukan menggunakan MATLAB. Keputusan Eksperimen menunjukkan bahawa prestasi algoritma yang dicadangkan AFAC mengatasi kaedah klasik Ant Colony dan algoritma MPAC terkini.

Kata kunci: Autisme, Ant Colony, Masalah Routing Kenderaan, Routing, Ride-Hailing Service.

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LIST OF SYMBOLS AND ABBREVIATIONS

ACO	:	Ant Colony Optimization.
AFAC	:	Autistic Features Ant Colony.
API	:	Application Programming Interface.
ASD	:	Autism Disorder Spectrum.
DARP	:	Dial-A-Ride-Problem.
DVRP	:	Dynamic Vehicle Routing Problem.
DVRSP	:	Dynamic Vehicle Routing and Scheduling Problem.
GPS	:	Global Positioning System.
HTTP	:	Hypertext Transfer Protocol.
ICT	:	Information and Communication Technology.
IDE	:	Integrated Development Environment.
MPAC	:	A Multiple Parameter control for Ant Colony.
RHS	:	Ride Hailing Service.
TSP	:	Travelling Salesman Problem.
VRP	:	Vehicle Routing Problem.
VRSP	:	Vehicle Routing and Scheduling Problem.
VRSPTW	:	Vehicle Routing and Scheduling Problem with Time Window Constraint.

LIST OF APPENDICES

CHAPTER 1: INTRODUCTION

This chapter introduces the research background, the motivation behind conducting it and its problem statement. Moreover, it includes the research questions, objectives, scope, significance and a general outline of the research.

1.1 Research Background

In recent years, daily life without a vehicle would be impossible (Zegras, Ben-Joseph, Hebbert, & Coughlin, 2008). The number of active vehicles on the road increases day by day in many large cities around the world. Increasing the number of vehicles in many large cities around the world is a big concern because it causes a lot of traffic congestion, especially during peak hours. In the metropolitan areas around the globe, congested traffic is an unavoidable condition. According to a statistical report presented by Sperling and Gordon (2008), today more than a billion motor vehicles are driven ashore. In the next two decades, vehicle ownership would double across the world.

There has been a rapid rise of on-demand Ride-Hailing Services (RHSs), a service that has been prominently occupying the market of online transportation, where apps such as Grab, Uber, EzCab, and MyCar are actively allowing passengers with smartphones to place trip requests and attach them to drivers upon the request’s location and drivers' availability. This rise in demand for RHS has led to the imbalance in the availability of cars where some areas lack service coverage and having a shortage of cars (Boldrini, Incaini, & Bruno, 2017a). For RHS companies to achieve consumers’ diverse demands, they need to focus more on finding out solutions to enhance their algorithms; the optimization of these algorithms should be built upon updating the features for the sake of allocating car-resources as a means for attaining consumer’s satisfaction (Feng, Kong, & Wang, 2017b).

In 2009, a new method for RHS has been introduced by Uber company (Bashir, Yousaf, & Verma, 2016). The method was designed to suit the online web portal and the smartphone's application. The application allows passengers to request a ride enabling them to choose their pick-up and drop-off point. The request then is sent to several drivers where one of them, in turn, accepts the request and thus comes to the pick-up point to send the passenger to his drop-off point using his private car which is not owned by Uber. The drivers are being monitored through their app that they have installed and registered before. The estimated fare is displayed on the driver's phone screen and thus the rider pays it according to his preferred method of payment. This new method of RHS has been very successful in satisfying the ever-rising need of the customers around the world where it is estimated that more than 633 cities accommodate Uber as a major efficient platform of transportation (Mahapatra & Telukoti, 2018).

Despite all these applications of RHS serving a huge market of passengers, there are certain people who are not benefited by such a service due to their disabilities. Autism is an example where their disability requires special care. The National Institute of Mental Health explains that Autism Spectrum Disorder (ASD) as a "group of developmental disorders" which comprises of several skills, symptoms, and disability level. People with Autism have unusual behaviours, social and communication challenges (Craig et al., 2018; Fernandez & Scherer, 2017; Thabtah, 2018; Yang et al., 2018). Therefore, this study is proposing a new algorithm named Autistic Features based Ant Colony (AFAC).

1.2 Research Motivation

In this section, a brief of major factors is explained which resulted in the motivation behind this research work. Recently, the tremendous demand for mobile-based ride-hailing services in almost all major cities in the world has opened new horizons and opportunities in the field of e-commerce. Many research gaps have been presented for the

RHS in order to develop algorithms that help in providing an efficient allocation of available car-resources and increase the overall efficiency of the RHS system.

This arouses researchers in providing efficient methods to enable individuals who are not able to use this advanced technology such as the people who have disabilities and elderly on which they could gain advantage from the RHSs (Shaheen, Cohen, Yelchuru, Sarkhili, & Hamilton, 2017). Moreover, many technologies are used for accessibility and advanced mobility, in which information systems and dynamic ride-sharing are used in supporting transportation services for disabled people and elder adults. However, the adoption of this dynamic and heuristic approach to be used by RHS to serve the special features of the autistic users is still a challenge.

As of recently, one of the well-established meta-heuristic algorithms is the Ant Colony Optimization (ACO). Although the majority of studies of meta-heuristic are academic applications, it is very essential to note that ACO algorithm is being used by companies in solving real world-problems (Dorigo & Stützle, 2019). Therefore, enhancing the existing algorithms to cope with autistic features and improve the efficiency of allocating car-resources is highly demanded.

1.3 Research Problem

Recently, there has been a rapid rise of on-demand Ride-Hailing Services (RHSs), such as Grab, Uber, EzCab, and MyCar, etc. This allows passengers with smartphones to place trip requests and assign them to drivers according to requester's location and drivers' availability (Feng, Kong, & Wang, 2017a). Although RHS has become important in our daily life, there is a lack of providing such services to people with special needs such as those with Autism Spectrum Disorder (ASD). However, the current RHS is not capable to provide such service to the autistic users considering their special needs and facilitating effective features for them to request a ride independently. Therefore, providing an effective service to autistic users will offer a seamless use to the RHS services. Moreover, this efficient technique is required to identify a suitable car-resource to a particular autistic user based upon their specific disabilities to ensure better user experience. Furthermore, RHS companies are suffering from a lack of available cars (car-resources) to meet user demands (Boldrini, Incaini, & Bruno, 2017b). During the daytime, the availability of cars is very unbalanced, and some areas even lacking cars and therefore are underserved. Thus, efficient algorithms are required to optimize the use of available car-resources via optimizing the routing scheme as well as evaluating optimal travel routes and calculating the best automotive resources for the autistic user.

1.4 Research Questions

The following research questions are to be addressed throughout this study:

1- What are the current techniques of dynamic vehicle routing problems in RHS and the common autistic features?

2- How to propose an algorithm to appropriately select the optimal resources for autistic users?

3- How to evaluate the proposed algorithm and measure its efficiency?

1.5 Research Objectives

1- To investigate and explore the existing methods in RHS as well as to identify the common autistic features.

2- To develop an algorithm named Autistic Features based Ant Colony (AFAC) to select the optimal car-resource for the autistic users.

3- To evaluate the performance of the proposed AFAC algorithm and compare the results with previous algorithms.

1.6 Research Scope

This research is focused on enhancing the efficiency of vehicle routing system taking into consideration different road features and autistic features simultaneously. The road features play a vital role in finding the optimum route from nearby drivers to the autistic user. These road features are the road distance, width of the road, and number of traffic lights on each road. On the other hand, autistic features help to make a better selection of car-resources in terms of providing autistic users with specialized drivers who are capable of dealing with autistic users. These autistic features are Speech-to-Text for verbal communication and Text-to-Speech for non-verbal communication.

1.7 Research Significance

An improved algorithm is proposed to enhance the efficiency of the vehicle routing system taking into consideration different road features and autistic features simultaneously. As such, this improves the accuracy and provides a chance for autistic users to use Ride-Hailing Service (RHS) with their own features. Intelligent selection of available car-resources is done by using Autistic Features based on Ant Colony (AFAC) optimization algorithm.

1.8 Organization of the Research

This research consists of five chapters organized in a rational sequence to make it easy for the reader to understand the research content and help in understanding the research objectives. These chapters are outlined as follows:

Chapter 1: Introduction

This chapter presents the research background, the motivation behind conducting this study and its problem statement. Moreover, it includes the research questions, objectives, scope of the study, significance and an outline of the research.

Chapter 2: Literature Review

This study consists of five main sections: Vehicle Routing Problem (VRP), Ant Colony Optimization (ACO), Ride-Hailing Service (RHS), Autism Spectrum Disorder (ASD), and related work, which will be discussed respectively.

Chapter 3: Research Methodology

This chapter presents the methodology of the research, discusses the research techniques which were applied during this research. In addition to this, the Autistic Features of Ant Colony Optimization (AFAC) framework will be explained and discussed along with the functionality of every component in details.

Chapter 4: Results and Discussions

This chapter explains and discusses in detail the process of experimentation in order to validate the efficiency of the proposed AFAC framework in a studied environment.

Chapter 5: Conclusion and Future Work

This chapter summarizes the study findings. The potential improvements in the proposed AFAC framework for future work are addressed.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter is divided into five main sections. They are Vehicle Routing Problem (VRP), Ant Colony Optimization (ACO), Ride-Hailing Service (RHS), Autism Spectrum Disorder (ASD), and related work, which will be discussed respectively.

2.2 Vehicle Routing Problem (VRP)

A vehicle routing problem (VRP) is considered as a well-known NP-Hard problem which has attracted many researchers (Soysal & Çimen, 2017; Zeddini, Temani, Yassine, & Ghedira, 2008). There are many examples of VRPs such as delivery services, school bus routing, ride-hailing services (A. E. Rizzoli, Montemanni, Lucibello, & Gambardella, 2007).

VRP is a collection of routes and designing an optimal delivery, which is disseminated to various customers areas or cities, subject to side constraints (Laporte, 1992). Vehicle routing problem is considered a greater achievement in operational research, which facilitates people after more than fifty years of research (Bochtis & Sørensen, 2009). This is an optimal planning solution for vehicles, which is applied in many applications of practical life. Simply it is said that VRP is a problem, which used to determine a route that provides least-cost from one point to the geographically dispersed riders (such as warehouses, stores, cities, and schools), (Bochtis & Sørensen, 2009; Mohammed et al., 2017; Mostafa & Ahmad, 2017).

A classic VRP problem provided the situations of real-life from the field of distribution. Theoretically, the VRP extracted from two main problems of the optimization: The Traveling Salesman Problem (TSP), and the arc routing problem.

Considering the arc routing as the counterpart to node routing in which it focuses on service and resource constraints, where constraints occur on the arcs rather than the nodes. The optimization aim, in this case, is to reach a minimum cost of the total routing. On the other hand, the purpose of TSP is to provide a solution to the problems of a salesman who intends to visit different cities and need to have a possible shorter route; this is called a minimization problem (Shmoys, Lenstra, Kan, & Lawler, 1985). Additionally, VRP is considered as a generalization of TSP with some clear differences. The two problems vary only in the type of constraints that must be satisfied by each one of them (Namany & Kissani, 2017). Several methods are established to solve it, some of them are exact algorithms, and others aim to provide a solution through heuristics (Ha, Bostel, Langevin, & Rousseau, 2014; ZIROUR, 2008). Heuristics can be referred to as estimated techniques utilized to discover outstanding solutions within a reasonable time, in quite extensive search spaces. However, these are different compared to the actual methods used in discovering an optimal solution (Uran, 2005).

With the addition of bases, the VRP is extended to TSP, through which the vehicles that travel should start and then return to. Some variations exist in this simple concept as to the situations and problems of real-life. This straightforward one depot VRP problem has no capacity limitations and is named as a Single Depot Vehicle Routing problem (SDVRP), (Karakatič & Podgorelec, 2015; Laporte, 1992).

2.2.1 Definition of VRP

In this section, a precise definition of VRP is divided into two subsections which are theoretical and mathematical definitions. The theoretical section gives a brief meaning of VRP while the mathematical section explains the equation of VRP.

2.2.1.1 Theoretical definition

Vehicle routing problem classical definition asserts that for a κ number of vehicles located in a depot D, the vehicle then distributes products to m number of customers. The VRP solution goal is to find routes, which are cost-efficient and aim to deliver a product to m number of customers using κ vehicles. Consequently, the objective here is to keep the overall cost minimum for different trips. Though there are some constraints, which should be satisfied while making the delivery of items, among the most important constraints are the following:

- The start and finish of the routes must be a depot.
- Apart from the depot, only one visit is made to each customer (stations).

Additionally, the transportation cost in VRP is stated in different ways. It could be a time window, distance, or number of vehicles which are used for the completion of routes (Laporte, 1992; Namany & Kissani, 2017).

2.2.1.2 Mathematical definition

In a mathematical form, VRP process is defined as follows:

$G = (V, \varepsilon, C), where\ V = \{v_0 \dots., v_n\}$ is the set of vertices; $\varepsilon \{ \left(v_{i,v_j}\right) \mid \left(v_{i,}v_j\right) \epsilon \mathcal{V}^2 , \mathrm{I} \neq \mathrm{j} \}$

is the arc set; and $\mathrm{C} \left(c_{ij}\right)_{\left(v_{i,v_j}\right)\in\varepsilon}$ (is a cost matrix defined over ε, representing travel cost, distance, or travel time).

Usually, vertex v_0 is called the depot, on the other hand remaining vertices in $\mathcal{V}$ shows the requests (or customers) which should be served. The process of VRP consists of searching a combination of routes for identical vehicles $\mathcal{K}$ which are based at depot, each point of the route is visited once only, and choosing the route which minimizes the overall cost of routes (Pillac, Gendreau, Guéret, & Medaglia, 2013).

2.2.2 Types of VRP

There are various classifications of vehicle routing problem according to different contexts. The details of VRP classifications are explained in (Cao & Yang, 2017).

2.2.2.1 Capacitated Vehicle Routing Problem (CVRP)

There are many proposed types of VRP. The most basic type of VRP is the Capacitated Vehicle Routing Problem (CVRP) (Borgulya, 2008; Pereira, Tavares, Machado, & Costa, 2002). This routing problem was first presented by Dantzig and Ramser (1959), but then it was originally suggested for modelling network problems with the deterministic variable (Mohammed, Ahmad, & Mostafa, 2012). The function of CVRP is to provide an optimal route for the vehicle which aim to serve some specific customers (Adewumi & Adeleke, 2016; Ha et al., 2014). One of the main conditions for the VRP is to load each provided vehicle according to its capacity; this problem is known as CVRP. If total time (cost or distance) of the vehicle bounded by the prescribed time, this problem is said to be Distance Constrained Vehicle Routing Problem (DCVRP) (Shao, Guan, Ran, He, & Bi, 2017).

2.2.2.2 Vehicle Routing Problem with Backhauls (VRPB)

Vehicle Routing Problem with Backhauls (VRPB) deals with delivery or pick up to make all the deliveries first and then pickups are made. Alternatively, it is said that VRPB problem is the extension of VRP which involve both the pickup and delivery points (Gajpal & Abad, 2008; Goetschalckx & Jacobs-Blecha, 1989).

2.2.2.3 Vehicle Routing and Scheduling Problem (VRSP)

Vehicle Routing and Scheduling Problem (VRSP) is one of the very specific vehicles routing problem, where researchers added some additional constraints to VRP for the optimization and handling of the scheduling process of existing fleet in addition to computing and optimum routes. One of the VRSP subcategories is called Vehicle Routing and Scheduling Problem with Time Window Constraint (VRSPTW) in which allowable time windows, other time-based constraints, delivery time constraints, and delivery deadlines should be handled. Additionally, the VRSPTW is evolved as one of the significant areas which continue to progress in handling generalization and realistic complications of the basic route model (M. M. Solomon, 1987; Xiao & Konak, 2016).

2.2.2.4 Vehicle Routing Problem with Time Window (VRPTW)

The Vehicle Routing Problem with Time Window (VRPTW) aims to provide its services within the provided period. The VRPTW process aims to generalize the classical vehicle routing problems with the addition of time constraints window (Li & Lim, 2003; Michelini, 2018).

2.2.3 Dynamic Vehicle Routing Problem (DVRP)

Dynamic Vehicle Routing Problem (DVRP) also named as online Vehicle Routing Problem, which is risen recently because of the advancement in information technology and communication which allow data to be collected and managed instantaneously. In this process, some of the given orders are identified in advance, i.e., before starting of the working day, but new orders arrive as the day progress, and this system has to incorporate the new orders as well. The availability of the communication system between the driver and the dispatcher (where the tours are calculated) is present. The dispatcher communicates with drivers periodically and additional visits also given to them. In this procedure, the driver has information regarding the next assigned customer to him/her (Montemanni, Gambardella, Rizzoli, & Donati, 2005).

2.2.4 Dial-A-Ride Problem (DARP)

Dial-A-Ride Problem (DARP) reports the problem of delivering transportation services from door to door with high customer satisfaction (Ho, Nagavarapu, Pandi, & Dauwels, 2018). DARP is an extension of the delivery and pick-up problem within the class of VRP (Archetti, Speranza, & Vigo, 2014).

Alternatively, it is said that DARP is the alternative of VRP, which aims to dispatch a fleet of vehicles in which customers are transported among their suggested pickup and desired drop-off locations in the given period. Overall, this process focuses on transportation with a minimum cost for the vehicle and avoids the longest route. This also provides safety and comfort to the passenger. Accordingly, DARPs get motivation from the applications of real-life. Initially, the application aims to provide non-profit DARP services for the disabled and elderly people, in which cost minimization is a basic objective. The operational limitation of the process includes the waiting time and ride, vehicle capacity, delivery/pickup timeframes, and layout of equipment in the vehicle (Karabuk, 2009; Qu & Bard, 2014). Each of these applications provides different features related to reality, which bring their limitations, objectives and further yields insights (S. C. Ho et al., 2018).

In DARP any available taxi or cab can be dynamically scheduled, and various road conditions are taken into consideration. The modern RHS has introduced a new type of Dynamic Vehicle Routing and Scheduling Problem (DVRSP), which is mostly related to DARP. In both VRP problems, the main aim is to provide pick-up and drop-off services. The routing and scheduling problem occur in RHS, where private car owners act as car-resources, which can be assigned to any nearby user for pick-up and drop-off services.

The DVRSP scenario for RHS addresses the case where the fleet of vehicles are arbitrarily located on the map, continuously moving, and can become available or unavailable at any point of time.

2.3 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is a process in which scientists work on the bees, ants, termites and other social insects behaviour pattern for the stimulation of process (Sankar & Krishnamoorthy, 2010). In ACO, the artificial agents who are the population individuals build stochastically and incrementally the solution to a given problem. The agents develop a solution to the problem using a graph-based representation. The moves of the agents explain which solution mechanism should be added to provide a solution for the construction (Dorigo & Birattari, 2011).

ACO is an algorithm based on meta-heuristic which aim to provide solutions to combinatorial optimization problems by using artificial ants (Blum & Dorigo, 2004). ACO analyses real ants' behaviour, which is constructed on our knowledge of the distance to other locations and memory of the past actions. Naturally, a single ant cannot communicate effectively or hunt the food, but they work in a group and can resolve problems of complex nature and accumulate food for their colony. The communication among ants is made possible through a chemical substance called pheromone.

A single ant secretes enough quantity of pheromone so that the route can be followed by other ants. The movement of ants is done randomly, but when a pheromone trail is available, then ants decide either to follow it or not. If an ant goes on the provided trail, the new ant secretes the pheromone to attach with the provided trail, and as the pheromone trail increase then it provides a path to the next ant to follow. Therefore, when more ants travel on the provided path they would attract more ants, and they will work in a sequence (A. E. Rizzoli et al., 2007).

Moreover, the ants that use the shorter route to reach at food source reach back their home sooner and hence, mark their path twice before returning of other ants. This helps other ants to select the same path before leaving their nest. As the time goes, more of the ants complete their route through the shorter way, in this way the secretion of pheromone is quicker on their shorter paths, hence, it is less likely that longer paths are followed. The pheromone evaporates, and it makes the less followed route less likely to be detected and not used for the next time. However, the use of random paths by an individual ant gives direction to the colony of ants to discover different routes and provide effective navigation for the obstacles, which hinder in their routes. The ant's selection of trail is a process of pseudo-random proportional and is the main component of ant colony optimization’s simulation algorithm (Dorigo & Gambardella, 1997).

The ACO algorithm is utilized to resolve various computational problems, and it is minimized to search for feasible routes of the optimization graph, which consists of nodes. It discovers a suitable path by the use of graphs (Singh, 2017). As shown in the optimization graph in Figure 2.1, an ideal solution to the optimization problem can be facilitated using feasible routes. From the possible paths, the algorithms of ACO explore the paths which give minimum cost and provide the optimum solution of the problem (Sameh Abd El-Haleem, 2012). Additionally, for the ACO algorithm, the same is done using artificial ants who search for food by using the method of optimization problems. Each ant provides a solution by making a local decision which is initiated by the heuristic information and the pheromone information (Yin, Du, Liu, Sun, & Zhong, 2018).

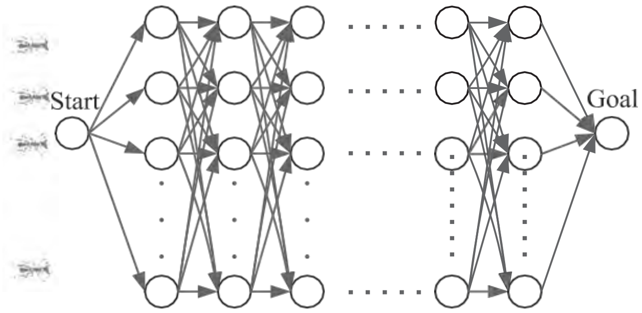


Figure 2. 1 Feasible Paths in the Optimization Graph

2.3.1 Evolution of Ant Colony Optimization

In the real world, the movement of ants is done randomly, and when an ant finds food, they made their return by following the pheromone trails. When other ants see these paths, they do not move randomly and follow the previous path and reinforce the same path for returning home if they find the food. Concerning time, the trail of pheromone keeps on evaporating, and thus the attractive strength of the path reduces. If ants follow the same path for a longer time, it takes more time to evaporate the pheromones. The shorter paths are followed more frequently, and thus the density of pheromone on that path is higher than the longer paths. The evaporation of pheromone has its advantage to avoid the convergence of the optimal solution. If there is no pheromone evaporation, this will mislead the following ants, and the first path is more attractive for the other ants. Therefore, when a strong path is made by the ant colony, and the source of food is available, other ants follow the same path, provide positive feedback from the ants and all the other to follow the same path. In operations and computer science research, the ACO algorithm works on the probabilistic technique to solve the computational problems which help to follow the shortest path through graphs (Y. Wang & Zhang, 2011).

The algorithm of ACO scheme is shown in Figure 2.2, after pheromone trails initialization, construct Ant Solution manages an ant's colony which asynchronously and concurrently move to the adjacent states by moving along with neighbour nodes to construct the problem. Nodes are moving in a stochastic way utilizing a local decision policy through the use of pheromone trails and heuristic information. Such information considered as local information which is independent of previous iterations quality. (Sousa, Lopes, & Alencar, 2011). In such behaviour, the ants incrementally create a solution to resolve the problem.

```
Procedure Ant colony optimization
    Set Initialize parameters, pheromone trails
    While (termination condition not met)
        Do Construct Ant Solution
           Update Pheromone Trails
           Daemon Actions
    End
End
```

Figure 2. 2 Ant Colony Optimization

Once an ant builds a solution, or when the process of solution is underway, the ant assesses the given solution that is used to update the procedure of pheromone trails to make a decision on how much pheromone should be deposited. The process of updating pheromones is that the existing trails of the pheromone are modified; the pheromone is either increased by the ants or decreased because of the evaporation process. The secretion of new pheromone helps to strengthen the existing trail, which makes the prior connection strong and can be used by many ants in the future. The Daemon action procedure helps to apply centralized actions, which couldn’t be developed by single ants. Daemon actions help to activate the locally developed optimization procedure or collect the information globally which help to decide whether the optimized procedure is useful or not, for the secretion of further pheromone (Sagayam & Akilandeswari, 2012). The algorithm of ACO aims to find a feasible path through the behaviour of ants searching for a path to the source of food from their colony. Therefore, this research work uses the

ACO algorithm to optimize the routing scheme for RHS which is discussed in detail in section 2.4.

2.3.2 Application of ACO in VRPs

Considering flexibility and freedom in meta-heuristic based problems is one of the features of the ACO algorithm which can be applied in different VRP scenarios (Psaraftis, Wen, & Kontovas, 2016), such as DVRP and DARP which have been discussed in more detail in section 2.2.3 and 2.2.4 of this chapter. Moreover, ACO algorithm was applied to solve SDVRP (Bullnheimer, Hartl, & Strauss, 1999) where the algorithm system of hybrid ant was presented, and then improvements were made by the use of exact information (for capacity utilization and savings).

The simulation of artificial ants develops vehicle routes and chooses the next city by using a probabilistic transition rule like TSP. If the probability 'P' for the movement from a particular city j to the city i is higher, then the probability of the next city to be chosen is high. The vehicle routing problem was solved through the development of multiple ant colony (Bell & McMullen, 2004). This method for solving the VRP problem uses unique pheromones that are deposited by the specialized ant groups. The intention of this segregation is done to differentiate paths, which are generally used during the first route of the vehicle than that of the second time of their movement. This technique is helpful when there is an increase in the problem or the required vehicles.

The ACO algorithm has been studied and applied in many VRPs scenarios such as DVRP, CVRP, VRPTW and TDVRP (A. Rizzoli, Oliverio, Montemanni, & Gambardella, 2004). Two case studies have been presented for VRP with time frames. They presented the ACO's application to the overall industry size problems for a chain of supermarkets in Switzerland and pick-up and delivery problem for the industry in Italy. Through the ACO application, the vehicle route performance is improved, and hence it proves that this is a strategic planning process in practical world applications. Based on savings algorithm, a heuristic desirability function is used (Paessens, 1988).

Besides ACO based approach, many other heuristic approaches have been proposed, such as a genetic algorithm that is based on heuristic approach for solving the machine load problem of a flexible manufacturing system (FMS) (Tiwari & Vidyarthi, 2000). Genetic algorithms applications aim to solve the problem of multi-depot vehicle routing which aim to optimize the vehicle routing problem where multiple customers, multiple products and multiple depots are considered (Lau, Chan, Tsui, & Pang, 2010). The finding of a route with a minimum cost of the vehicle is now introduced through the use of a new hybrid genetic algorithm (Liu, Jiang, & Geng, 2014). An optimization approach is based on a Discrete Particle Swarm (Gong et al., 2012; Kuo, Zulvia, & Suryadi, 2012), the mimetic algorithm (Khebbache-Hadji, Prins, Yalaoui, & Reghioui, 2013; Yao et al., 2017; Žalik & Žalik, 2018; Zeng, Yu, Chen, & Liu, 2018) and local search (Meng, Li, Dai, & Dou, 2018; Zhang, Wei, & Lim, 2015).

The functionality of ACO is well understood by the use of an example. The ACO application is considered by the travelling salesman problem. In TSP, distances and a set of locations are given. The major issue is to search for a closed tour which has a minimum length in which one city is visited once only (Dorigo, 2007; Srivastava, Citulsky, Tilbury, Abdelbar, & Amagasa, 2016).

For applying ACO to TSP, the graph associates the cities with the number of vehicles. This graph is said to be a “construction graph”. As through the TSP, it is easy to move from one city to another, the construction graph is completely connected, and vertices numbers are the same as the number of cities. The length of the edges is set among the vertices according to the proportion of distances among the cities shown by these vertices, and an association is made through heuristic values and pheromone strength with the graph’s edges. The strength of the pheromone changed at run-time and highlight the collective ant's colony experience, while values of heuristics are dependent on the problem values, which in the TSP case is developed to converse the length of the edges.

For ants to construct a solution, they do the following: The starting point of an ant is selected from a random city. Then, at every construction step, the movement is made through the edges of the graph. The paths are memorized by each ant, and in subsequent steps, the movement is made at the edges, which do not follow the vertices on which ants have already visited. The solution is constructed by the ants by visiting it through vertices of the graph. At each step of construction, an ant focuses on visiting those vertices which are not yet visited by them. The rule of probability is biased by heuristic information and pheromone values: the higher the heuristic and pheromone values linked on the edges; most likely the ant chooses it. After the completion of the ant’s tour, an updated pheromone level is present on the edges. Initially, the values of pheromone are decreased by some percentage. An additional pheromone is received by each edge according to the quality of the pheromone solution it already has. This process is applied repeatedly until the termination of the procedure (Chiong, 2009; De Rango & Socievole, 2011; Dorigo, 2007; Srivastava et al., 2016).

2.4 Ride-Hailing Service (RHS)

Nowadays, Ride-Hailing Services (RHSs) have been emerged to be part of the urban transportation (Hu, Kong, Sun, Dong, & Zong, 2018). The definition and overview of RHS are explained in more details below to better understand about RHS.

2.4.1 Definition of RHS

RHS is a transportation system where the arrangement of rides is made through the mobile application, and it connects the driver who is using his own vehicle and passenger who needs a ride (Taylor et al., 2015). RHS such as Grab, Uber, EzCab, and MyCar, etc.

help drivers to offer ride services for the riders to request and get the rides. Commonly, the services are utilized through mobile phone applications and information systems to match drivers with passengers (Sun & Edara, 2015). On the other hand, passengers would pay the fee based on mileage meter using their credit cards, and RHS firms would keep a percentage of each fare and pay the remaining amount to their drivers (Rogers, 2015).

2.4.2 Background of RHS

Most of the challenges in transportation are related to the optimization at a certain cost function. Such issues of optimization are mostly NP-hard and usually ensures an exponential rise in time used in computing, coupled with a rise in the size of the model. Furthermore, and in recent times, the RHS context of the car-passenger matching, has become quite critical. More so, due to the introduction of the provision of RHSs by numerous companies, it turned to be more essential to look for an optimum solution for the challenge of matching, in a lessened time of computation. Thus, metaheuristics can be utilized for the aforementioned purpose. Interestingly, metaheuristics have become famous and attracted researchers attention recently (Ropke & Pisinger, 2006). They are mostly used in certain problems, with the sole aim of discovering an optimal solution that could be used globally (Szwarc & Boryczka, 2019; Toutouh, Nesmachnow, & Alba, 2013).

The RHS involves three parties: Service Provider (SP), drivers and riders. Riders are usually those peoples who want to hail a ride by using their smartphone. Drivers on the other hand offer ride using their own cars. The service provider company receives a request for a ride from riders and then their requests are matched through the application with available drivers. The principle of ride-matching is based on the location of both the driver and the rider. The principle of matching between rider and driver is started when SP receives a request from the rider and then sends the same to the driver. The request made by the rider also includes the pick-up and drop off locations. The service provider then chooses the closest and available drivers to the pickup location of the rider. For this purpose, drivers need to report their location and availability continuously to the SP. After a match between a rider and driver, the SP allows the rider and driver to make a contact with each other by sending the information of one party to the other, i.e., their name, phone number, etc. If both parties make the acceptance, then the rider continuously tracks the driver's location. The start of the ride is notified to the SP when the driver picks up the rider. The SP continuously locates the driver during the ride. At the end of the ride, the SP is notified by the driver that he is available for the next ride (Khazbak, Fan, Zhu, & Cao, 2018).

Due to the ever-increasing need for effective systems of transportation in mega-cities, in addition to using smartphones ubiquitously, user-centric urban RHSs, some of which are Grab, Lyft, Didi, Careem, Uber, among others, are becoming more recognized. Furthermore, coupled with the provision of reliable transportation mediums with reduced travel-times, these services prove to have revealed greater possibilities with regards to being able to cater for the growing challenges of congestion and pollution (Syed, Gaponova, & Bogenberger, 2019).

A related issue with RHS is regarding providing of service to elderly persons, and disabled people. For instance, Uber implemented a service tagged as UberWAV, which allows disabled passengers to request vehicles that are accessible to a wheelchair. In such manner, UberASSIST makes the provision of regular vehicles with specialized driver training, and this is currently available in thirteen cities in the U.S. Nevertheless, such services are not available in some markets, in fact, in markets where they are available, there are frequent reports of complaints by passengers due to the lack of UberASSIST drivers and UberWAV vehicles (Shaheen et al., 2017). However, other firms such as Lyft is trying to dive into partnering with the public transport agents, in offering passengers that have special needs with customized vehicles (Young & Farber, 2019b).

Another growing concern is that RHS drivers may not receive the necessary training to assist disabled passengers. Since the training is not required by RHS companies, it has led to instances of mistreatment and abuse (Young & Farber, 2019a). The Autism Spectrum Disorder (ASD) is one of the categories that need special dealing to provide the service by RHS driver. This study considers the RHS with ASD in order to simplify the RHS for autistic users.

2.5 Autism Spectrum Disorder (ASD)

This section gives more details for the autism disorder including features and types of ASD.

2.5.1 Definition of ASD

ASD is a neurodevelopmental condition that affects development at an early stage and persists into adulthood (Craig et al., 2018). ASD is a diagnosis that identifies individuals with a range of disorders involving impairment of communication and social interaction, and repetitive patterns of behaviour and interests (American Psychiatric Association, 2013; Turkington & Anan, 2007). Although they are not part of the formal diagnostic criteria, intellectual impairments, motor deficits, and sensory impairments are often co-morbidly diagnosed. Interventions that are individualized and correctly implemented can help to build up communication and social skills, and decrease maladaptive behaviours of an individual's having an autism spectrum disorder (National Research Council, 2001).

2.5.2 Features of ASD

ASD is characterized by various challenges related to social skills, speech and nonverbal communication, and repetitive behaviours (Diagnostic, 2013; Thabtah, 2018;

Yang et al., 2018). It includes problems in mutual social communication, social communication, communication through non-verbal behaviour and social relationships development. Repetitive and limited behaviour include both verbal and stereotypic behaviour. From the prognosis and phenotype of ASD perspectives, the major important characteristics are communication skills (Özyurt & Eliküçük, 2018).

Currently, research attentions have been focused on ASD in childhood natural development (ALZGHOUL et al., 2019). ASD is one of the most complex developmental disorders. It has been observed in recent years a noticeable increment in the prevalence of ASD. As asserted by the Centre for Disease Control and Prevention, the prevalence of ASD is about 1 in 59 children aged 8 years old are diagnosed with ASD (Baio et al., 2018).

There are two major characteristics of ASD category; a) There is a constant insufficiency in different situations of social interaction, b) The repetitive and limited behaviour, as most of the symptoms appear in early childhood on which they cause difficulty in daily life.

Communication disorders may exist individually or collectively with other diagnoses such as autism spectrum disorder. The challenges related to communication are one of the main indicators during the diagnostics of the ASD (American Psychiatric Association, 2013). For individuals working in the field of autism intervention, facilitating social communication is considered one of the first steps to a successful learning intervention. Developing communication skills lays the building blocks for all other learning to occur. Once a child or adult can communicate their wants and needs, understanding the communication of other people, many barriers to learning are removed. As autism spectrum disorder is qualified as a “spectrum disorder,” the levels of impairment in communication can vary substantially among individuals with such a diagnosis (Stauffer, 2015).

2.5.3 Technologies for Autistic People

Technologies designed for persons with autism usually fall into one of two groups (Frauenberger, Good, & Pares, 2016). The first group is known as Assistive Technology (AT), and its motive is to provide support to autistic persons, hence helping to reduce the difficulties they experience in their lives (Frauenberger, 2015). On the other hand, the 2nd group deals with technologies that are viewed as channels of delivery for intervention in learning, coupled with the assurances of engaging groups that are difficult to reach, via innovative ways (Ramdoss et al., 2012). Some instances of the 1st group comprised of the transporters, an emotion-recognition intervention (Golan et al., 2010), as well as a vSked scheduling system that is collaborative and interactive (Hirano et al., 2010).

2.5.3.1 Information and Communication Technology (ICT) for People with Disabilities

As ICT keeps evolving, the area of "inclusive ICT"- which refers to the removal of barriers in accessing Information and Communication Technologies by disabled persons, has as well gained increased attention. Additionally, an emerging number of mainstreams, daily ICT, some of which are mobile devices, amongst desktop computers, progressively extend facilitating functions for the access of information and communication, for disabled persons. Also, features such as screen magnification, voice recognition and text-to-speech, input and touch gesture, colour scheme and contrast changeability, of which in previous times required standalone hardware and software that were specialized and embedded with ICT devices off the shelf. Furthermore, disabled persons are being enabled by digital technologies in receiving content and information in their most preferable and perceivable formats (Raja, 2016). Hence, disabled persons now have a more extensive chance of finding and interacting with clients, as well as selling their services and goods without being obstructed by infrastructural and physical obstacles.

Persons with Autism generically learn via visual displays, which might make them experience some difficulties in undergoing verbal instructions (Gustlin & Delacruz, 2011). This is so due to the reason being that they have challenges in generalizing issues or making summarized connections. Additionally, persons with autism find it difficult to filter inessential information and hence might encounter issues with fine motor control.

2.5.3.2 Mobile Technology for People with Autism

Diverse forms of technology are being utilized by mobile technology such as smartphones, tablets/iPad, iPhone, which to a great extent enhance the lives of autistic persons. Other features such as mobile broadband access, geolocation, weight of the devices, alongside their minimum size, can easily enable portability, hence widening the areas where technology can be accessed.

The "touch screens" found on mobile devices, can help people with fine-motor control issues to access them more easily, as to when compared to their counterparts who do not make use of mobile devices, which mostly entails the use of a cursor or a mouse (Duncan & Tan, 2012).). Therefore, ASD-diagnosed persons, would in easier ways make use of the screen and large coloured buttons that can allow user selection. Additionally, the user interface is eye-catching and easy to use, especially for persons who have weak fine-motor skills. It also makes provision for practical communication solutions for persons with autism, in associating with their families, among others in their community (Yee, 2012).). Thus, algorithms, sensors, and technologies, which can sense or express emotions, hence influencing the bad behaviour of the users, in this case, ASD-diagnosed persons, have been developed continuously (Boucenna et al., 2014).

2.5.4 Types of ASD

Mainly, ASD is divided into three types: Asperger's Syndrome, Autistic Disorder, and Pervasive Development Disorder. Each spectrum type is explained by its different degrees of symptoms.

2.5.4.1 Autistic Disorder

This spectrum type is also called "classic" autism. Generally, this type explains the thinking of people when they listen to the word "autism". The Autism Support of West Shore explains that these spectrum disorder types characterized as "significant language delays, social and communication challenges, and unusual behaviours and interests". Moreover, these people are typically affected by disabilities related to their intellect too. This is a common and severe autism type (Freitag, 2007).

People with the autistic disorder could also have a problem when other people touch them, perform repetitive or restricted behaviours, an overload of experience sensory, and also have communicating issues. The same type of symptoms is also there with other autism types, but this type explains that those are severe symptoms.

2.5.4.2 Asperger's Syndrome

This is an autism spectrum disorder with a milder effect. These people may also come across with similar symptoms as other types feel, but in this category, those are milder. Generally, these people have unusual interests and behaviours, additional to social challenges. The symptoms in the Asperger's are not as severe as experienced in other types of those they have problems with their intellectual disability and language (Minan, 2014; M. Solomon, Goodlin-Jones, & Anders, 2004).

2.5.4.3 Pervasive Developmental Disorder

This type of autism spectrum disorder is called “atypical autism”. Pervasive development disorder is only for those people who have some problem with any other types discussed previously, but not both collectively. Those affected with PDD-NOS (Pervasive Developmental Disorder-Not Otherwise Specified) could feel symptoms of milder or fewer types. Generally, people with PDD-NOS only has to suffer from communication and social issues (Volkmar, Reichow, & McPartland, 2012). These people perform their function at the highest performing autistic types and could not have any fitting with any of the other two types. In this work, the communication features in a particular voice and text among ASD types have been applied based on the previous studies.

2.5.5 Communication Impairments

Persons that have autism spectrum disorder show a wide range of abilities and skill development, and these remain true for their ability to communicate with others. Communication impairments in persons with autism spectrum disorder range are incapable of developing speech to functional development, but the idiosyncratic use of speech and language (Tager-Flusberg, Paul, & Lord, 2005).

Around 50% of persons with autism are incapable to make a speech for their daily requirement of communications (American Psychiatric Association, 2013; National Research Council, 2001; Tager-Flusberg et al., 2005). For these individuals when speech is developed, there are often impairments in aspects of speech such as the ability to initiate or sustain communication, articulation difficulties and trouble with both spoken and written language comprehension (Brown, 1978).

2.6 Related Work

A Recursive Ant Colony Optimization for estimation of parameters (RACO) of a function was proposed by Gupta, Arora, Singh, and Gupta (2012) for a combinatorial problem where RACO employs the ant colony algorithm recursively instituting an additional term ‘depth’, which determines to what extent of recursion is the accuracy of results for RACO method where it rises with depth which leads to a highly accurate solution. However, in RACO, the ants are not located in every city, so it could affect the overall performance. A study by Ochiai and Kanoh (2014), introduced a hybrid meta-heuristic that linked the ant colony algorithm with Dijkstra’s algorithm, which concludes that the suggested methodology can be utilized to find a better solution than the classical methods. However, this approach uses simple distance and basic optimization technique which causes poor selection of cars. The authors in (Dong, Zhao, Qu, Chi, & Cui, 2014) developed a Multi-Hop Routing Optimization Method built on an improved ant colony algorithm for the vehicle to roadside network for the performance of the path selection in Vehicle Ad-hoc Network (VANET) where they adopted a novel bionic intelligence swarm algorithm known as ACO on which they have changed its parameters, they showed that the algorithm can search for an optimal path very fast which enhances the efficiency of the system. On the other hand, Multiple Parameter control for Ant Colony (MPAC) has been suggested to consider multiple parameters using ACO to enhance the efficiency of vehicle routing performance.

However, in their scheme, there were only 30 artificial ants in the colony. This could be resulted in reducing the performance of the route selection. A New Multi-Parameter Vehicle Navigation Scheme (Combined A* Ants Algorithm) for vehicle navigation was proposed by Salehinejad, Nezamabadi-pour, Saryazdi, and Farrahi-Moghaddam (2015) where they make use of Combined A* Ants Algorithm to find an optimal improved multi-parameter path between two selected junctions based on city traveller parameters.

However, the scheme uses simple distance and basic optimization technique which causes poor selection of cars. Psaraftis et al. (2016) introduced a Dynamic Vehicle Routing based on Three Decades and Counting for a Dynamic Vehicle Routing Problems (DVRP) where a taxonomy of DVRP has been conducted. Authors in (A. Jovanović, Nikolić, & Teodorović, 2017) developed an area-wide urban traffic control based on a Bee Colony Optimization Approach for an area-wide urban traffic control problem where the area-wide urban traffic control system uses Bee Colony Optimization (BCO) algorithm and the findings show that the proposed BCO technique outperformed the Simulated Annealing (SA). However, this needs to be allocated to the BCO implementation for real-time area-wide urban traffic control. Authors Young, M., & Farber, S. (2019a) highlighted that Ride-hailing technology is forming the new age of mobility which focused on who benefits from ride-hailing and more importantly, who is most at risk from being excluded. They considered seven potentially neglected population segments and postulate on the potential benefits and barriers of ride-hailing services for them. They concluded that even the RH companies that do provide wheelchair-accessible vehicles do not provide a sufficient number of them to meet current demand. Furthermore, Interfaces of the RH application are not usually adapted to visual impairments, and vehicles are often inadequately suited to accommodate disabled passengers. Additionally, RH still needs to provide a solution to improve the mobility of those with disabilities. Finally, this study did not have sufficient data to fully grasp the magnitude of the effects of RH. Table 2.1 illustrates a summary of the most related work. The criteria were based upon several factors namely are the relevant, related, most recent, and short path studies. Relied on the ones which its findings are novel, non-conventional and focusing on delivering the best efficiency. It is worth noting that all these references have been selected and included in this study based on ACO, vehicle routing, selection of the car and Ride Hailing Service.

Table 2.1 Summary of Related Work

No.	Title	Year	Author	Problem	Methodology	Findings	Limitations
1	Recursive Ant Colony Optimization for Estimation of Parameters of a Function.	2012	Deepak K. Gupta, Yogesh Arora and Upendra K. Singh Jai P. Gupta	A combinatorial problem.	RACO employs ACO recursively introducing an additional term 'depth', which decides the extent of recursion.	RACO results showed high accuracy which increases with depth and hence produces highly accurate solutions.	The ants are not located at every city for the implementation of RACO, so it could affect the overall performance.
2	Multi-Hop Routing Optimization Method Based on Improved Ant Algorithm for Vehicle to Roadside Network.	2014	Hao Dong, Xiaohui Zhao, Liangdong Qu, Xuefen Chi, Xinyu Cui	Route selection performance in Vehicle Ad-hoc Network (VANET).	Used a novel bionic swarm intelligence algorithm known as ant colony algorithm.	By doing some changes in ACO parameters, the optimal route can be found in shorter time which increases system efficiency.	The number of artificial ants in the colony was only 30. This could be resulted in reducing the performance of the route selection.
3	Hybrid Ant Colony Optimization for Real-World Delivery Problems Based on Real-Time and Predicted Traffic in Wide Area Road Network.	2014	Ochiai, Junichi Kanoh, Hitoshi	Real-world delivery problems for home delivery based on real-time and the expected traffic.	Used a hybrid meta-heuristic that comprises ant colony optimization and Dijkstra's algorithm.	It proposed a method which introduces a better solution than existing techniques.	It uses simple distance and basic optimization technique which causes poor selection of the cars.

4	Combined A* Ants Algorithm: A new Multi-Parameter Vehicle Navigation Scheme.	2015	Hojjat Salehinejad, Hossein Nezamabadi-pour	Vehicle Navigation.	Combined A*Ants Algorithm.	It looks for the best optimum multi-parameter direction between two preferred intersections based on city traveller parameters.	It uses simple distance and basic optimization technique which causes poor selection of cars.
5	Dynamic Vehicle Routing Problems: Three Decades and Counting.	2016	Harilaos N. Psaraftis, Min Wen, and Christos A. Kontovas	Dynamic Vehicle Routing Problems (DVRP)	A taxonomy of DVRP	A taxonomy of DVRP has been conducted.	N/A
6	Area-wide urban traffic control: A Bee Colony Optimization Approach.	2017	Aleksandar Jovanovic´, Miloš Nikolic´, Dušan Teodorovic	The problem of area-wide urban traffic control.	The area-wide urban traffic control system is developed based on the Bee Colony Optimization (BCO) technique.	The proposed BCO technique surpassed the Simulated Annealing (SA).	To achieve a real-time area-wide urban traffic control, it should be allocated to the implementation of the BCO.

7	Ride-Hailing Platforms Are Shaping the Future of Mobility, But for Whom?	2019a	Mischa Young and Steven Farber.	who is likely to benefit from ride-hailing and more importantly, who is most at risk from being excluded from it?	It considered seven potentially neglected population segments and postulate on the potential benefits and barriers of ride-hailing services for them.	Interfaces of the RH application are not usually adapted to visual impairments, and vehicles are often inadequately suited to accommodate disabled passengers. RH needs to provide a solution to improve the mobility of those with disabilities.	This study did not have sufficient data to fully grasp the magnitude of the effects of RH.

Recently, simple distance-based selection of the car-resources is used, or basic optimization technique as shown in Table 2.2. Most of these techniques cause the poor selection of car-resources. Hence, in this research, the efficient algorithm is suggested to enhance the routing scheme and select the best automotive resources for the autistic user based on autistic user's features and road features.

Table 2.2 Resource Selection for Vehicle Routing

Author	Year	Algorithm	Area
Ochiai, Junichi Kanoh, Hitoshi	2014	Hybrid ant colony optimization	Real-world delivery problems based on real-time and expected traffic in wide-area road network.
Hao Dong, Xiaohui Zhao, Liangdong Qu, Xuefen Chi, Xinyu Cui	2014	A novel bionic swarm intelligence algorithm	Multi-Hop Routing Optimization Method Based on Improved Ant Algorithm for Vehicle to Roadside Network.
Combined A*-Ants Algorithm: A new Multi-Parameter Vehicle Navigation Scheme.	2015	Hojjat Salehinejad, Hossein Nezamabadi-pour	A New Multi-Parameter Vehicle Navigation Scheme.
Gang Wang, HaiCheng Eric Chu, Yuxuan Zhang, Huiling Chen, Weitong Hu, Ying Li, XuJun Peng	2015	FAAS and FAACS are two ACO-based algorithms originated from Ant System and Ant Colony System.	MPAC optimization is applied to the feature selection problem.
Aleksandar Jovanovic´, Miloš Nikolic´, Dušan Teodorovic	2017	BCO	Area-wide urban traffic control: A Bee Colony Optimization.

2.7 Chapter Summary

This chapter is divided into five main sections. They are Vehicle Routing Problem (VRP), Ant Colony Optimization (ACO), Ride-Hailing Service (RHS), Autism Spectrum Disorder (ASD), and related work which is related to this research and have been already discussed. The ACO is a heuristic-based searching and optimizing algorithm. Therefore, this research work uses the ACO algorithm to optimize the routing scheme for RHS. The ASD is one of the categories that need special dealing to provide the service by RHS driver. This study considers the RHS with ASD to simplify the RHS for autistic users. Various existing methods in RHS for vehicle routing problems were studied in detail to identify and analyse the prospect methods for solving the underlying research problem. Since scenarios for vehicle routing problem are changing, the focus was kept on it to get a clear insight of the research problem. Existing software uses a simple distance-based selection of cars or basic optimization techniques, as shown in Table 2.2. which causes poor selection of cars.

CHAPTER 3: METHODOLOGY

3.1 Introduction

This chapter examines the research methodology and discusses techniques applied in this research. additionally, the Autistic Features of Ant Colony Optimization (AFAC) framework is explained and discussed along with the functionality of every component in details.

3.2 Research Framework

This part presents the adopted study framework. It is divided into four stages to achieve the research objectives. In the first stage, a thorough literature review is performed to determine and describe the problem in proper research terms. The various existing methods in RHS for vehicle routing problems were studied in detail in section 2.4 of chapter 2 in order to understand and analyse the prospect methods for resolving the underlying study problem. Moreover, the features of the autistic users were explained in section 2.5.2 of chapter 2 to adapt the framework. The remaining stages of this study are presented in the following subsections. Figure 3.1 on the next page summarizes the framework adopted in this dissertation.

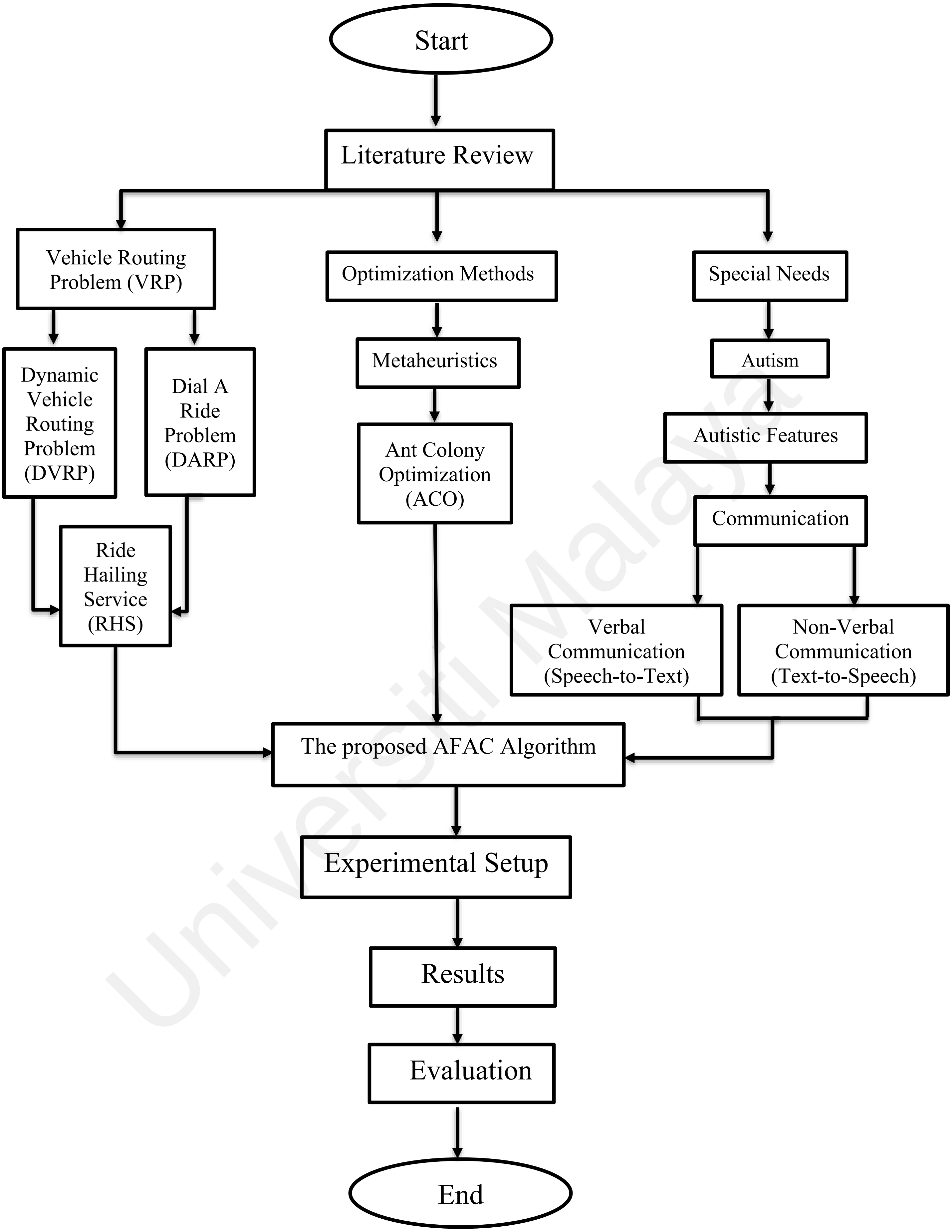


Figure 3. 1 Research Framework

3.2.1 Research Approach

In this stage, after conducting an extensive literature review, the researcher observed the usage of a meta-heuristic approach to solving the dynamic vehicle routing problem for ride-hailing services. A routing engine for car-resources in ride-hailing services has been presented employing Ant Colony Optimization (ACO) with autistic features to enhance the efficiency in terms of system performance and autistic service. The ACO algorithm is used in this research to optimize the routing scheme for RHS. The ACO is a heuristic-based searching and optimization algorithm. This optimization algorithm is designated as Ant Colony because it mimics the natural behaviour of how ants behave in their colonies as explained previously in chapter 2. The features of ACO make it a perfect candidate for the proposed AFAC framework.

3.2.2 System Design of the Proposed AFAC Algorithm

The third stage of this research work is the system design process which considered as one of the critical stages in this study. In this stage, the proposed AFAC is based on client-server technology, which comprises both the server-side part and the client-side part. All data processed in this technique is completed by the server. Built on client-server design, the AFAC system is created in a way that does not only reduce the processing burden on the autistic rider but also makes all data centralized. The application of the optimization process and its implementation on the server and client are discussed in this chapter. The framework of AFAC is highly dependent on the road features and the autistic user features which increase the overall efficiency of the system. Autistic user features help to make a better selection of car-resources in terms of allocating autistic users with specialized drivers who are capable of dealing with autistic users.

3.2.3 Evaluation of the Proposed AFAC Algorithm

The last stage of this research work is to evaluate the proposed AFAC framework as well as to compare it with other existing algorithms. In this case, a complete simulation environment has been developed using the Unity game engine environment. This simulation environment is kept flexible to allow run-time changes in different autistic users features, number of cars, road traffic conditions, and road connections, etc. Moreover, the simulation presents the performance evaluation of three algorithms named Ant Colony Optimization (ACO), Multiple Parameter control for Ant Colony (MPAC), and the proposed AFAC. ACO is managing the route distance, while the MPAC algorithm manages the road parameters during the selection process of the car. Evaluation results and findings are discussed in detail in chapter 4.

3.3 AFAC Overview

The AFAC framework is designed to be used in smartphones which is based on autistic users for the recognition of the autistic type of communication, which includes both verbal and non-verbal methods to share information location to the server through mobile. In today's modern world, each mobile is connected through location-based information system such as Global Positioning System (GPS) in which the autistic users are tracked through the internet by a smartphone. Since there is a time limitation for this research, the AFAC application is only supported on Android-based smartphones.

The AFAC system is based on client-server technology, which comprises both the server side part and the client-side part. All data processing in this technique is handled by the server. For example, AFAC system handles the complex system of car-resources and autistic users by managing their database. On the other hand, the application on the client-side makes different tasks which use minimal data sharing procedure for the performance of various RHS operations. Moreover, the communication system is recognized by two different options which are either verbal communication system utilizing speech-to-text feature or non-verbal system of communication utilizing text-to-speech feature. Additionally, a comprehensive AFAC system architecture is shown in Figure 3.2 which provides information based on the location from the server through the internet. The two distinctive parts of the application for client-side and server-side are provided in the architecture. Communications among server and clients are made by requesting the Hypertext Transfer Protocol (HTTP) service.

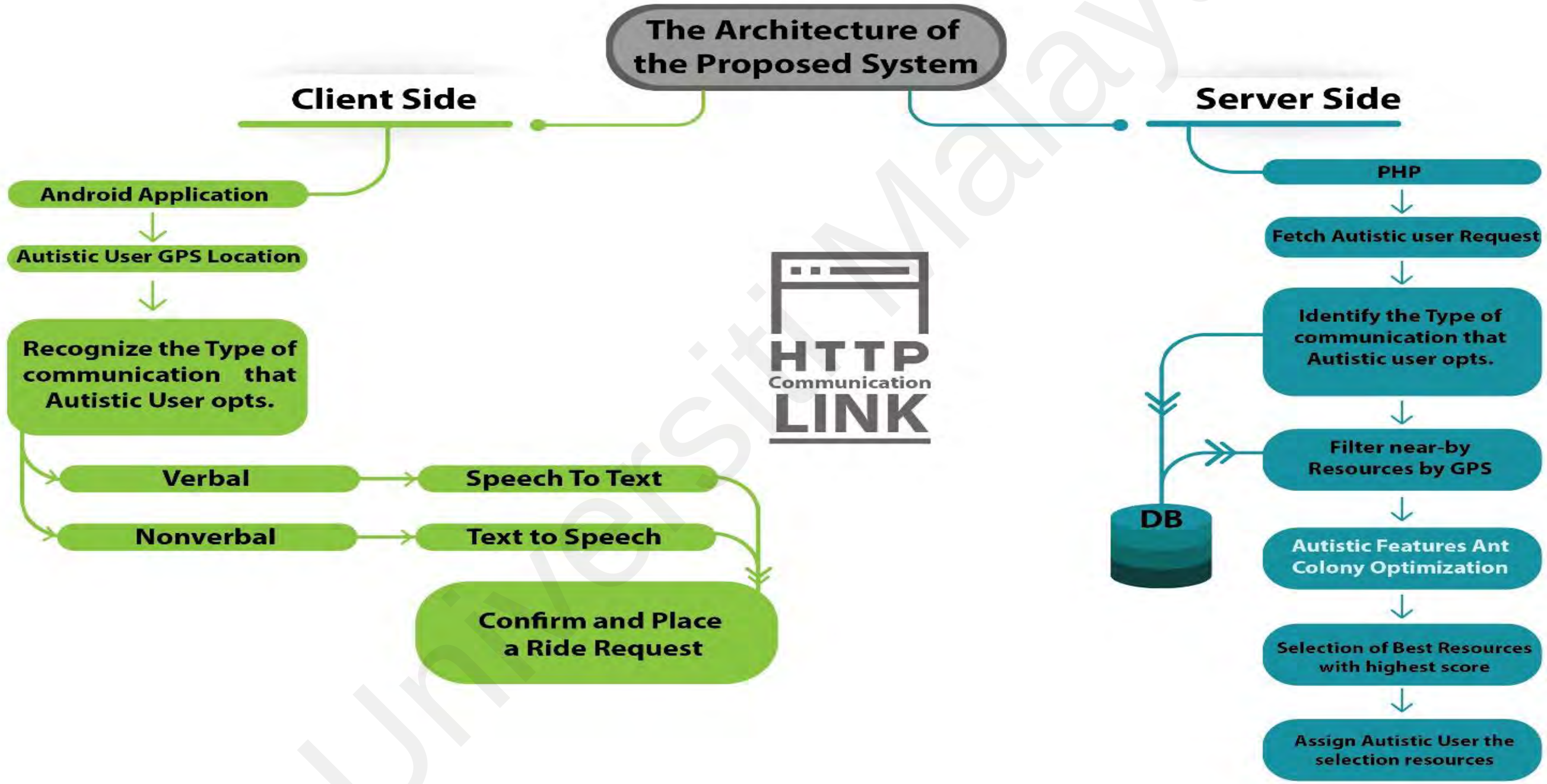


Figure 3. 2 The architecture of the proposed system

When an autistic user requests a ride, the application then gets the location of the pickup point, then the request is forwarded towards the server. Furthermore, the server filters the cars which are under the radius of 2km from the location of the autistic user by making a comparison between driver location and the autistic user's location in terms of latitude and longitude. If the system is unable to find any driver within 2 kilometers radius, then the AFAC framework doubles the radius to 4 kilometers and the process continues until it locates the nearest driver. The AFAC framework gets traffic data and compares both the driver and autistic user's location, i.e., road distance, traffic load, the width of road and number of traffic lights from web APIs and at the end, the proposed AFAC optimization algorithm selects the best available driver for the request of the autistic user. The client-side application module and the server-side application module are discussed thoroughly below.

3.3.1 Client-Side Application

The application on the client-side was developed using Android Studio 3.0 by employing Java language. An Integrated Development Environment (IDE) is used for the Android application to make the development promptly and straightaway. The studio developed in Android perform multitasks, which are supported by the Google Android SDK and is famous among the developed IDE which is useful for mobile applications in Android. An Android studio provides millions of characteristics which allow for rapid project development and give features that are useful to test different programs in the virtual environment whenever it is needed. A high-level flow diagram is provided as in Figure 3.3 which gives an understanding of the control flow structure of the application on the client-side and a discussion will be made in the next section.

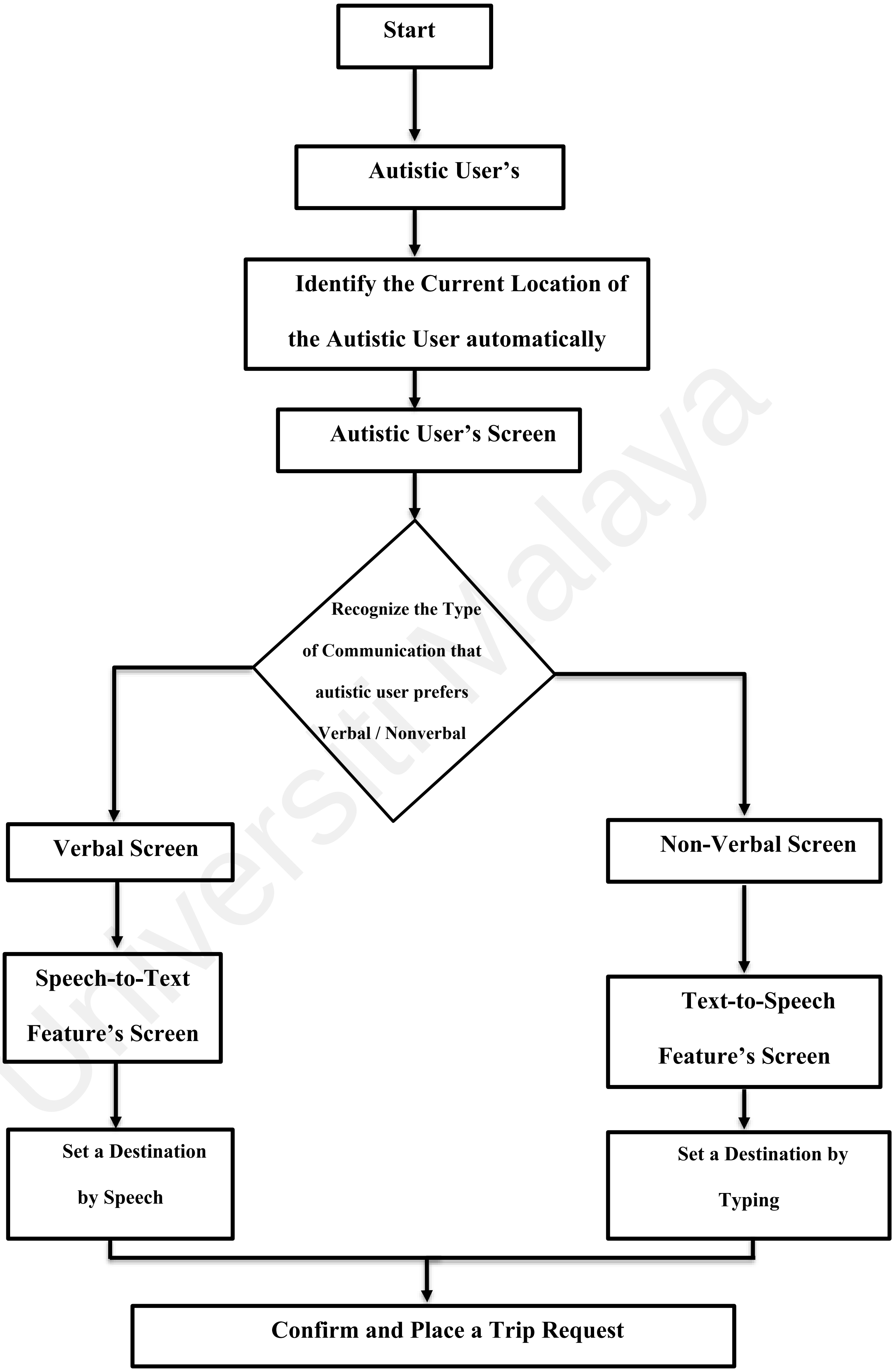


Figure 3. 3 High-level flow diagram of client-side application

As demonstrated in the high-level flow diagram above, the application starts by requesting the autistic user for login. The client-side application objectives are to send the location to the server-side through the GPS location system and to provide a platform for the autistic user to make an interaction with the AFAC framework. This research assumes that autistic users have been registered by a third party or by themselves as shown in Figure 3.4 below. Once the autistic user is logged in, the application identifies his/her current location and waits for an action from the autistic user as shown in Figure 3.5 to choose VERBAL (speech-to-text) or NONVERBAL (text-to-speech) features. Regarding the GPS location tracking, the client-side of the system serves as an active transmitter while the server-side acts as a passive transmitter, which explains that the GPS location is updated by the server when a new car-resource enters in the GPS location information from the client-side.

Figure 3. 4 Autistic User's Login Screen

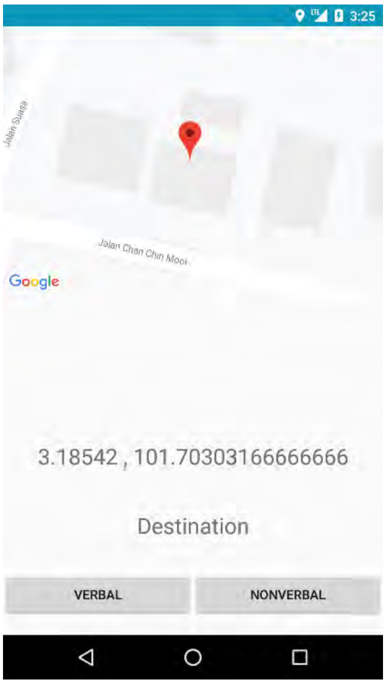


Figure 3. 5 GPS Location (Latitude and Longitude) with Autistic Features

The Android mobile application is responsible for handling the ride-hailing requests from the autistic users. The mobile application helps to locate autistic users through GPS. However, the algorithm is only active when it receives a request for ride-hailing that can save the energy of autistic user's mobile handset and ensures the privacy of autistic users. Autistic users can make a trip request through this proposed application by pressing any button on the autistic user's screen.

Furthermore, the type of communication which autistic user opts is offered through speech-to-text feature as shown in Figure 3.6 or non-verbal communication using text-to-speech feature (see Figure 3.7).

Figure 3. 6 Verbal Screen Speech Speech-to to-Text

You are going to!

Figure 3. 7 Non-verbal Screen Text-to-Speech

If the autistic user opts the verbal communication, then he/she needs to speak to the app regarding their destination (see Figure 3.8).

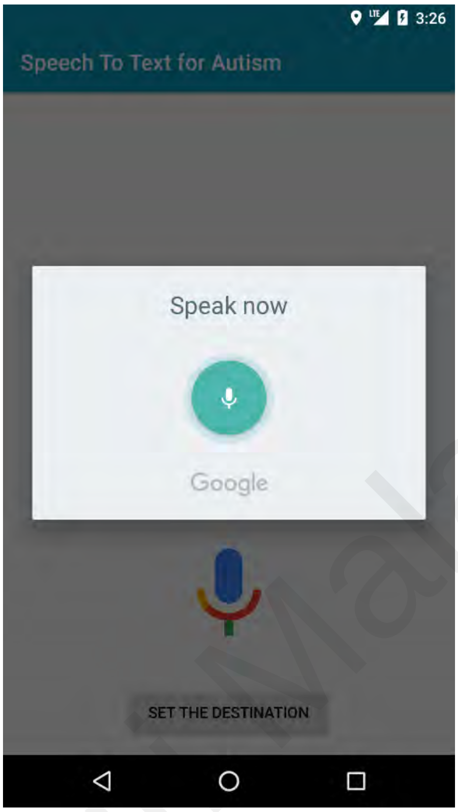


Figure 3. 8 Verbal Screen Speech Speech-to to-Text when the mic icon is touched

On the other hand, if the autistic user selects non-verbal communication, then he or she is required to type the destination, and the application will voice out the destination that autistic user has set. This helps to avoid any wrong location that is entered. After confirming the destination by the autistic user, the application sends the request to the server to allocate an appropriate driver for this autistic user. The request includes the current position of the autistic user and the communication type which the user has opted. The preferred communication option by the application is identified according to the type of autism; the user is associated with either verbal or non-verbal communication.

3.3.2 Server-Side Application

The server-side application works as the main storage hub of the AFAC framework for ride-hailing services. The server-side application manages all the requests made by the autistic users and keeps updating the available car-location. As outlined previously in Figure 3.2, all users' requests are handled and managed by the server-side application of data management. This research study focuses on the AFAC algorithm employed in the server-side application. Different from the client-side application, the server-side application performance is computationally efficient and perform very complex calculations. The communication on the client-side application is managed by the PHP programming language. On the server-side, PHP is principally based on a scripting language for web development, though, the programming language used is general-purpose.

3.3.2.1 Autistic User Request Handler

One of the server-side module's main feature is to keep an updated location of available cars in each area. It is possible that enough number of cars available in one area of the same autistic user, while on the other hand, there is no available car in another region. The GPS location of each car is continuously located by the server-side of the software and sends the updated location to the database. After receiving a request from the autistic user, the server selects top 50 available cars, which based on Naive Euclidean distance approach with a cut-off point for a 10km distance. Euclidean relies on computing the aerial distance between the geo-location of user and driver. The initial filtering speeds up further process through the AFAC algorithm. The filtered cars are judged through road features as well as the autistic user features with the core algorithm making the route. In case there are no cars available within the 10km radius, the autistic user will be notified of the lack of availability of the car in the requested area.

3.3.2.2 Database

Necessary information related to car-resources and autistic users and their history is stored in the database unit. The road information is fetched from the current implementation of the database schema through an external web Application Programming Interface (API), as the database works as a temporary buffer to maintain these characteristics for a limited time; this approach is applied because of the vast amount of data related to road conditions. The proposed database schema for the server setup can be expanded to store road conditions permanently. This stored data of the road features, statistics, and history are very useful. Yet, road statistics predictions are beyond the scope of this proposed AFAC framework. The car-resources, autistic user data and profiles are maintained to analyse the status and progress of each ride. MySQL database management system is used for the proposed algorithm to maintain and store the driver and autistic user stats as well as their stats against each ride. Besides handling the driver and autistic user's history, the database unit is responsible for storing records of features from both car-resources and autistic users.

These features of the ride-hailing service are then passed to AFAC during the process of scheduling to find the optimum car-resources for the autistic user which they have chosen. The necessary components of the proposed AFAC algorithm are used by the database unit which selects the central location through ride-hailing information. All the available features such as traffic load, number of traffic lights, road risk, road distance, and width of the road are stored in the database. The autistic user's information features include either non-verbal or verbal communication and are kept in the database. The central database is directly linked to the AFAC which is the core component of the proposed ride-hailing system and is explained thoroughly in the subsequent sections.

3.4 Optimization Framework for AFAC

The heart of the presented ride-hailing framework is the AFAC optimization framework. The optimal path is found by making the decisions on selecting the ideal car-resources for each autistic user which is performed in this module. When any ride-hailing request is made, then the developed AFAC system considers multiple features. These features include autistic user’s features as well as considering road features. The framework of AFAC is very flexible, therefore, any feature can be removed, added, or altered without the need of reinitializing or retraining the whole setup.

3.4.1 Ant Colony Optimization Algorithm for AFAC

AFAC relies on the Ant Colony Optimization algorithm to determine the meta-heuristic-based solution in a realistic time frame. The ACO algorithm proves to perform effectively in road conditions and suited for the graphical-based mathematical problem already explained in Chapter 2 of this research. These ACO features make it a perfect candidate for the proposed AFAC framework. This proposed AFAC framework augments different characteristics on top of ACO algorithm, such as road conditions like traffic. Autistic user features help to make a better selection of car-resources in terms of allocating autistic users with specialized drivers who can deal with autistic users. For example, if the autistic user opts to communicate verbally, the driver will avoid texting with the autistic user. The complete flow process of AFAC is described thoroughly in the next section.

3.4.2 Process Flow for AFAC

The process of AFAC is triggered when the server receives an autistic user request of the ride-hailing service. Requests are made by the autistic user using the client-side application through smartphone by opting either verbal or non-verbal communication system. The client-side application sends the coordination update of GPS to the server-side along with other important features to identify the communication type which autistic user opts. The received request then is sent to the central database to verify and fetch the autistic user option. All the car-resources are then filtered by the server within a 10km radius around the requested autistic user’s location. Assuming that all the car-resources have been already stored. At the same time requests for traffic data in the same region. The simulation process is described as follows:

- It starts from requesting a car and goes until finding a proper featured car.
- Keeps on moving until we reach the autistic user.
- Gets current node.
- For each path check the pheromone.
- Check for maximum pheromone.

Road information features are forwarded to the pre-processing unit which then augments the road map graph with traffic data and thus generating a map that shows roads’ conditions surrounding autistic user’s location before it is again forwarded to the Ant Colony Optimization algorithm. During data processing, road features are multiplied by weight matrix which is dependent on the importance and influence of that features for the sake of selecting the best possible optimum route and car-resource. Ant Colony Optimization in AFAC framework considers the following information:

1. Autistic User Location Information:

The position once the autistic user requests a trip.

2. Autistic User Features:

Autistic features help to make a better selection of car-resources in terms of allocating autistic users with specialized drivers who can deal with autistic users.

These autistic features are speech-to-text for verbal communication and text-to-speech for non-verbal communication.

3. List of Available Cars

As explained in section 3.3.2 above, once the request from the autistic user is received, the server selects top 50 available cars based on Naive Euclidean distance approach with a cut-off point for a distance of 10km. Euclidean relies on simply computing the aerial distance between the geo-location of the user and the driver. The initial filtering speeds up further process through the AFAC algorithm.

The process of ACO starts releasing 400 ants on the augmented roadmap from the autistic user location. The process keeps using 400 ants, yet, the number could be changed simply by modifying the number of ants of the AFAC algorithm. In the roadmap, each road has specific weights, which are explained by the road features as it includes constant road features (such as road distance, number of traffic lights in each route, width of the road, etc.), and dynamic road features such as traffic data which are obtained from the external APIs. The starting point for all the 400 ants is from the autistic user location, and then they randomly move across the gird. The speed of ant and their time to cover each road are affected by the road width. Therefore, the nearest car-resource is found by the ants based on the different features of the road. The programming is made in a way that the ants move across the map for less than 10km distance or a maximum time of 1 second. These characteristics are adjusted and have the flexibility of alteration by updating the corresponding features in the AFAC configuration setup.

When an ant reaches at a car-resource on the given map, it deposits the pheromone on the path it followed to reach the car-resource. The deposited pheromone by the ants depends on the autistic user's features. If the feature for autistic user and driver matches, then the deposited pheromone amount is high, whereas if there is no match made between the two, then the amount of pheromone is decreased. The road path where the level of pheromone is high has more chance to be followed by the following ants. As when more and more ants follow the more optimized path, they provide the best possible matching features. At each iteration the level of pheromone on the road is updated, to better mimic the natural behaviour of the ant colony, pheromones are vaporized over time. This behaviour helps in self-correcting any wrongly selected car-resource at the beginning the ACO optimization process, which is very common in any ant colony optimization process. This process of ant colony runs for a certain time (in the current implementation it has a time of 1-Second) until the achievement of equilibrium. After finishing the simulation run-time, the listed car-resources are sorted in the increasing order of their pheromone level and the number of ants following them.

At the AFAC's final stages, the features of autistic users are applied to the nearest 5 car-resources based on the level of pheromone. A certain weight is assigned to each car which depends on the features of autistic users. Any unwanted car-resources are filtered out from the autistic matrix for the final list. For instance, if the autistic user selects the feature of verbal communication, then the cars with only a non-verbal communication feature get low weight and therefore have lower chances of being selected at the final stage even if the distance of that autistic user is close to the car-resource.

After completing the last phase of the filtering procedure, the highest score of the car-resource is assigned to the autistic user. Then, all the relevant details of the car-resources and autistic user information are sent to the client-side application of both the requesting autistic user and the selected car-resource respectively.

The AFAC algorithm treats the selected car as busy and does not consider it in the next query until the previous ride ended. The AFAC overall process is illustrated in Figure 3.9 below.

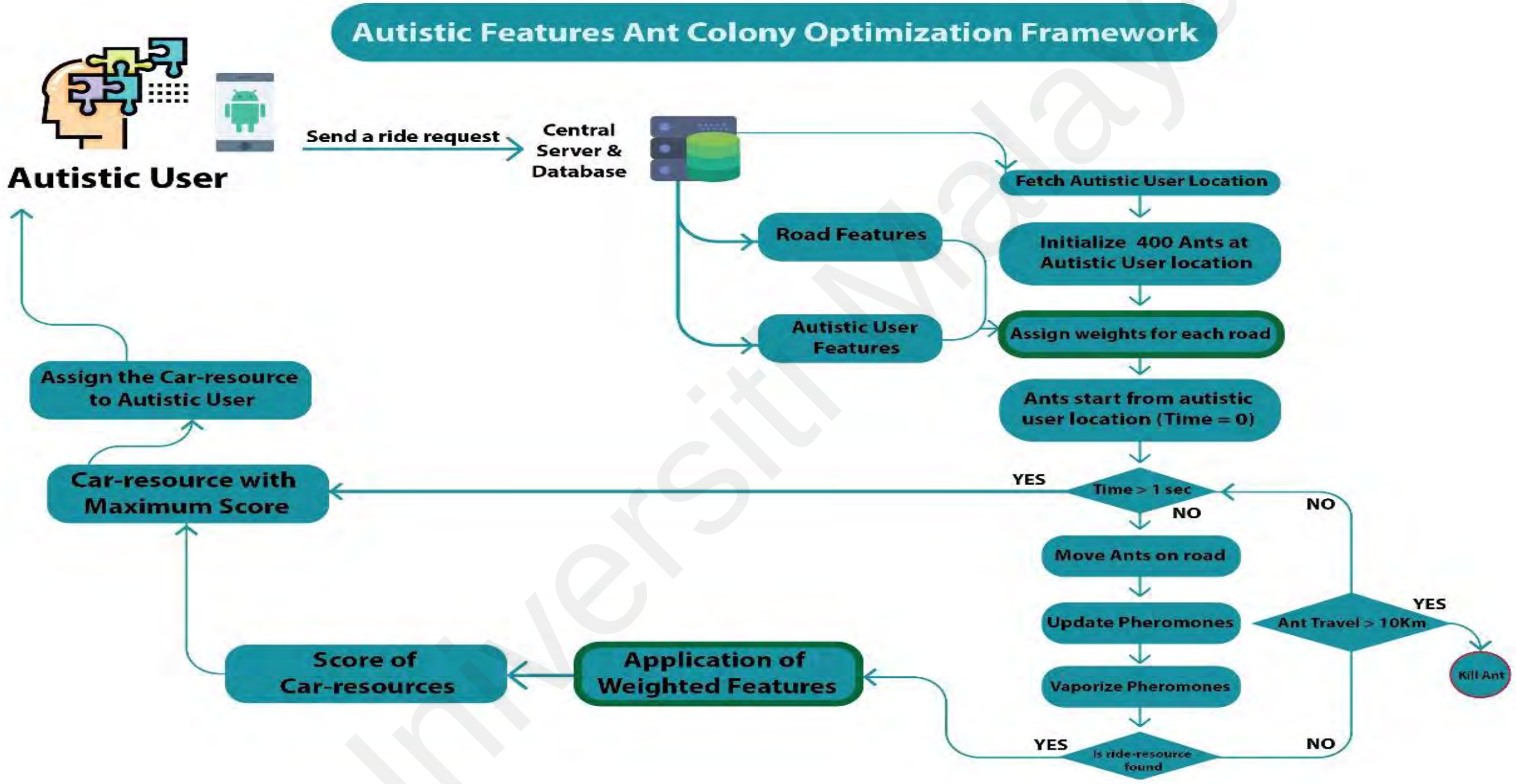


Figure 3. 9 A flow diagram of Ant Colony Optimization based framework algorithm for AFAC

3.5 Simulation Setup

This section explains the process of the simulation environment that was developed using the Unity game platform. It includes the simulation tool, simulation parameters, and performance metrics described as follows.

3.5.1 Simulation Tool

The simulation environment was created using Unity game engine version 2017.2.1fa (64-bit)-Personal Edition. Unity is a game platform which provides users with a tool to build games in 3D and 2D, where API main scripting is made in C# for the Unity editor as plugins and games with drag-and-drop feature. The simulation environment for AFAC algorithm is made in the 3D mode so that the different features of the application are understood in a better way during the process of experimentation when considering different levels of pheromones secreted by each ant. To obtain visually simulated results, users, cars, and a 3D model of ants and roads have been used.

3.5.2 Simulation Parameters

As explained in section 3.3.2 of this chapter, the server selects top 50 available cars, which based on Naive Euclidean distance approach with a cut-off point for a distance of 10km. Euclidean relies on simply computing the aerial distance between the geo-location of user and driver. The initial filtering speeds up further process through the AFAC algorithm. The filtered cars are judged through road features as well as the autistic user features with the core algorithm of making the routing process. Table 3.1 shows the simulation parameters.

Table 3.1 Simulation Parameters

Parameter	Value
Available Cars	50
Ants	400
No. of Traffic Lights	Random
Road Width	Random
Road Distance	10 (km)

Since the increased number of ants helps to obtain more constructed results which enhance the probability of providing an improved solution (M. Jovanović & Husak, 2019), the starting point for all the 400 ants is from the autistic user location, and then they randomly move across the gird. The speed of ants and their time to cover each road are affected by the road width. Therefore, the nearest car-resource is found by the ants based on different features of the road. The programming is made in a way that the ants move across the map for less than 10 km distance or a maximum time of 1 second.

3.5.2.1 Road Features of the AFAC Algorithm

A random road generation mechanism was implemented in the simulation to allow random creation of road network with a simple click of a button, the road features such as traffic load, number of traffic lights, road length and road width are also kept completely random to simulate the real-world scenarios more closely. This process provides room to do several experiments in different scenarios without requiring any modification in software again and again. The road features play a vital role in finding the optimum route from nearby drivers to the autistic user by determining the contribution of the corresponding road feature in computing. In the roadmap, each road has specific weights, which are explained by the road features.

3.5.2.2 Autistic Features of the AFAC Algorithm

A certain weight is assigned to each car which depends on the features of autistic users. Autistic features help to make a better selection of car-resources in terms of allocating autistic users with specialized drivers who are capable to deal with autistic users. These autistic features are speech-to-text for verbal communication and text-to-speech for non-verbal communication.

Any unwanted car-resources are filters out from the autistic matrix for the final list. For instance, if the autistic user selects the feature of verbal communication, then the cars with only a non-verbal communication feature get low weight and therefore have lower chances of being selected at the final stage even if the distance of that autistic user is close to the car-resource.

3.5.3 Performance Metrics

To assess the developed AFAC algorithm, performance metrics have been assessed based on the baseline work (A. Jovanović et al., 2017; Salehinejad et al., 2015; G. Wang et al., 2015).

3.5.3.1 Distance

A car-resource cr_i is only considered as a potential ride-hailing candidate for an autistic requesting user au_i only if the maximum road distance D_{max} between the autistic user location p_{aui} and the car-resources instantaneous position p_{crn} is less than max distance threshold. The D_{max} can be adjusted to maximize overall system performance.

$$D\ (p_{aui} -\ p_{crn}) < D_{max})\ \Rightarrow \begin{cases} \text{True: Select Car} - \text{Resource} \\ \text{False: Discard Ride Autistic User} \end{cases}$$

Where $D\ (p_{aui} - p_{crn}) = \sum_{x=0}^{k} D(E_x)$. $D(E_x)$ is the distance between the autistic user and car-resource. x = $0 \Rightarrow\ Autistic\ User\ Position.\ x = k\ \Rightarrow\ Vehicle\ Position.$

3.5.3.2 Traffic

This metric indicates the traffic density (Padula et al., 2013) which is used in this work to select the best route to avoid traffic between the autistic user and the car.

The traffic (Tr) is calculated as follows:

$$Tr\ =\ R * T_L$$

where $R\ =\ D(E_x)$ and T_L is the range of the traffic load which is 0 - 5, where the 0 means no traffic and 5 means very heavy traffic.

3.5.3.3 Round Trip Time

The response time can be represented by round-trip time (RTT) which is the time for requesting trip by the autistic user until gets the car.

3.6 Chapter Summary

The research methodology is presented in this chapter, study techniques are discussed, and study strategies applied in this research are explained. In addition to this, the Autistic Features of Ant Colony Optimization (AFAC) framework has been explained and the functionality of every component is discussed. The system developed based on the AFAC uses client-server architecture of a server part and a client part. All data processing in this technique is completed by the server. AFAC relies on the ACO technique to determine the meta-heuristic-based solution in a reasonable time frame. The framework of AFAC highly depends on the road features and the autistic user's features which increase the overall efficiency of the system. Autistic user features help to make a better selection of car-resources in terms of allocating autistic users with specialized drivers who are capable to deal with autistic users.

CHAPTER 4: RESULTS AND DISCUSSIONS

4.1 Introduction

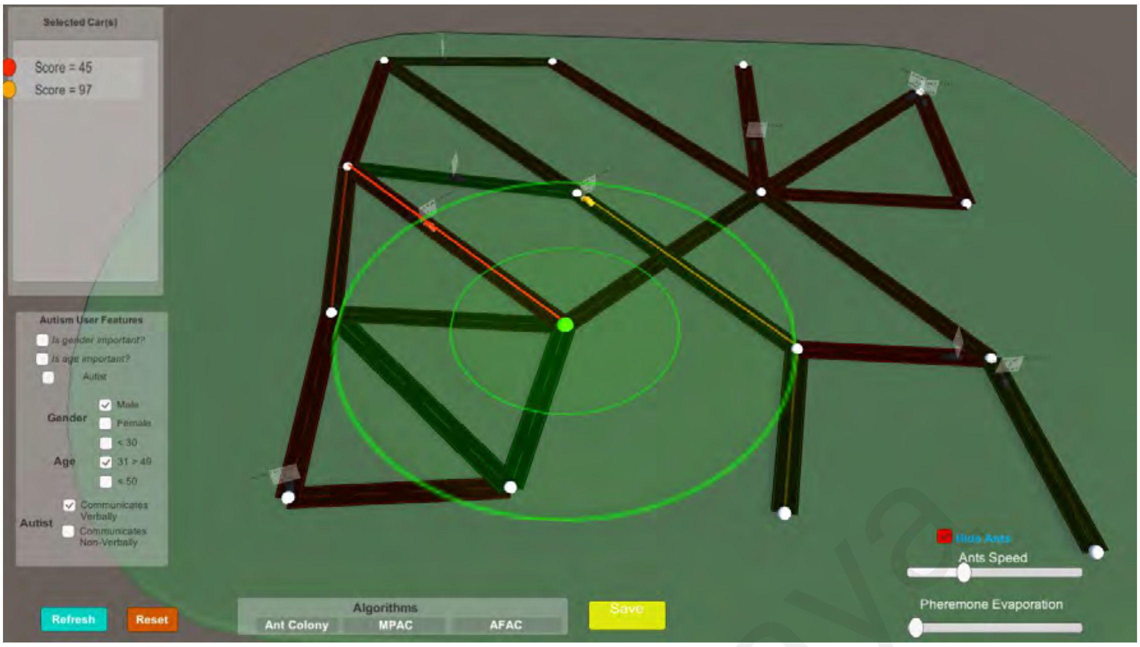
In this chapter, the process of experimentation to verify the effectiveness of the proposed AFAC framework is discussed thoroughly.

4.2 Experimental Settings

The Unity game platform is used to set the environment to perform the experiments as presented in section 3.5.1 of the previous chapter. The developed AFAC algorithm is compared with three different algorithms. The first algorithm was applied by using the classical Ant Colony Optimization (ACO) approach which is suggested for vehicle navigation in many previous studies. A Multiple Parameter control for Ant Colony (MPAC) optimization is considered to select features and is used as a second algorithm. The results of the experimentation prove that the second algorithm provides an acceptable selection as compared to other algorithms, but it selects the long routes. Though, empirical results showed increase in performance using the AFAC algorithm in many situations to keep balance among the efficiency as well as maintaining the autistic user option. In some instances, it has been observed that the classical ant colony based navigation and scheduling algorithm chooses the same resources as the AFAC and MPAC.

4.3 Experimental Results

In Figure 4.1, the car-resource was chosen by the ACO algorithm. It firstly selects all the existing cars within the specified radius. In this technique, all the cars behave as the ant nest and release ant to find the user location. After that, all the ants are released to find the best car-resources. In this simulation, there are two possible ways to reach a selected car within the radius. In this example, it can be seen clearly in Figure 4.1 that this approach doesn’t always give the best and most optimum car.



Selected Car(s)

● Score = 45
● Score = 97

Autism User Features

☐ *Is gender important?*
☐ *Is age important?*
☐ Autist

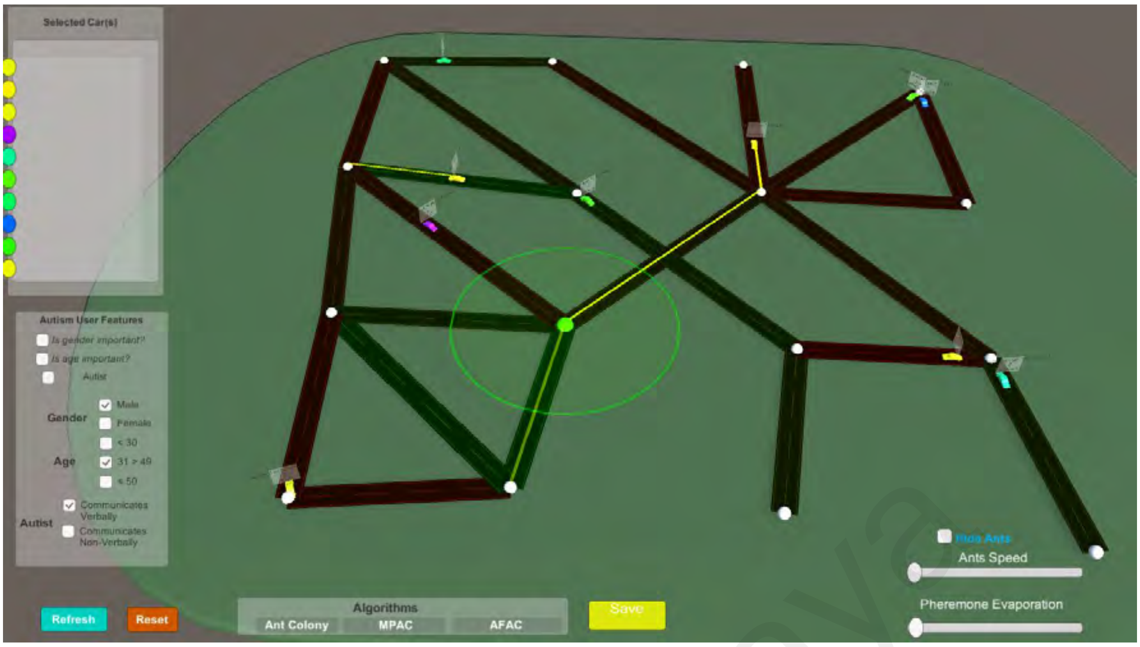
Gender ☑ Male ☐ Female

Age ☐ < 30 ☑ 31 > 49 ☐ < 50

Autist ☑ Communicates Verbally ☐ Communicates Non-Verbally

Figure 4. 1 A screenshot of the simulation result for selecting a car-resource by using Ant Colony Optimization Algorithm

In Figure 4.2, the output of the MPAC algorithm has been shown. In MPAC, the ants are released from the user location to find the best car-resources, unlike the classical Ant Colony algorithm where car behaves like an ant nest. As can be seen in this example, although there are many optimal cars around the user, this algorithm has chosen the car which is not optimal in terms of distance as well as traffic conditions.



Autism User Features

☐ Is gender important?

☐ Is age important?

☐ Autist

Gender ☑ Male ☐ Female

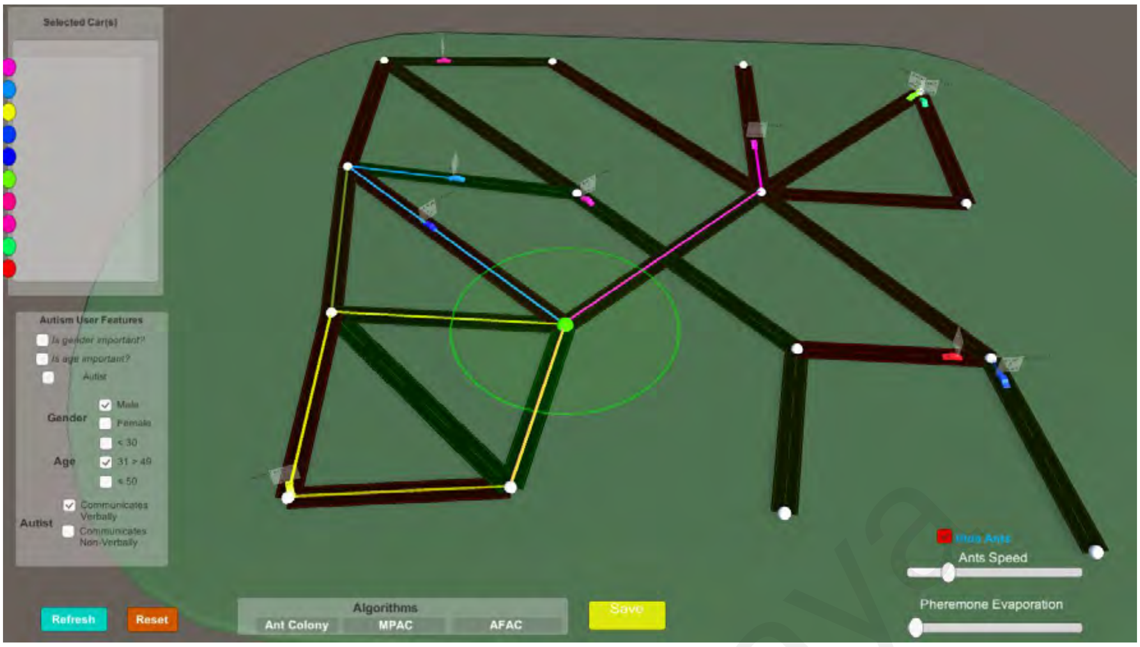
Age ☐ < 30 ☑ 31 > 49 ☐ ≤ 50

Autist ☑ Communicates Verbally ☐ Communicates Non-Verbally

☐ Hide Ants

Figure 4. 2 A screenshot of the simulation result for selecting a car-resource by using MPAC algorithm

In Figure 4.3, the output of the AFAC algorithm has been shown. In this scenario, 400 ants are released from the autistic user location to find the best car-resources. The number of ants has been increased to accelerate the process of finding optimal cars. As it can be seen in Figure 4.3, many car-resources have been highlighted to select the best optimum car with respect to distance and traffic conditions.



Autism User Features

☐ Is gender important?

☐ Is age important?

☐ Autist

Gender ☑ Male ☐ Female

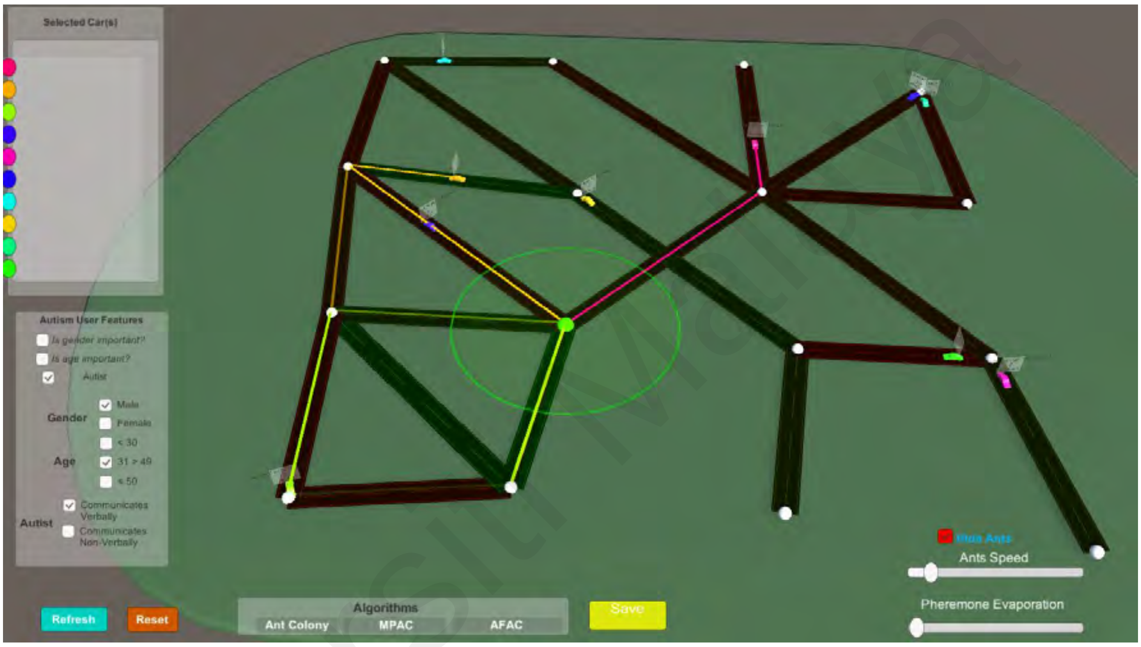
Age ☐ < 30 ☑ 31 > 49 ☐ ≤ 50

Autist ☑ Communicates Verbally ☐ Communicates Non-Verbally

☑ Hide Ants

Figure 4. 3 A screenshot of the simulation result for selecting a car-resource by using AFAC algorithm

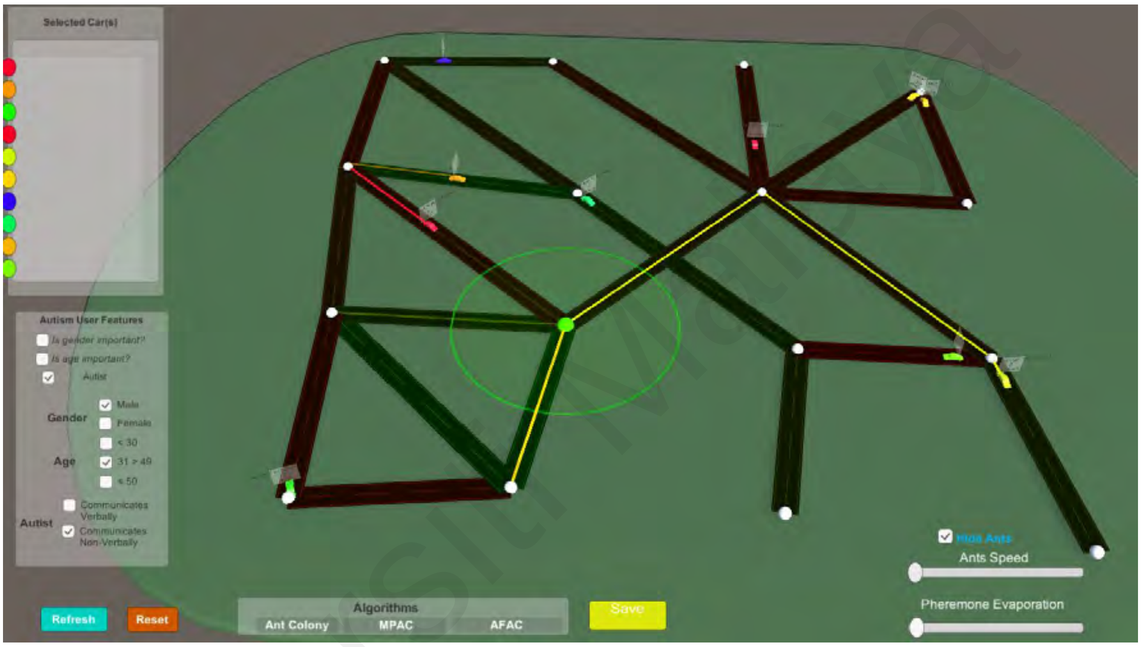
In Figure 4.4, the scenario shows the autistic feature that has been set to test the verbal communication by AFAC algorithm to find the optimum car. In this scenario, the AFAC is aware of the suitable driver who has been identified to serve the autistic user. The AFAC is capable to adopt this type of communication easily and can recognize the request of the autistic user. In this case, the specialized driver would avoid communicating with the autistic user by texting.



Autism User Features
☐ Is gender important?
☐ Is age important?
☑ Autist
Gender ☑ Male ☐ Female
Age ☐ < 30 ☑ 31 > 49 ☐ ≤ 50
Autist ☑ Communicates Verbally ☐ Communicates Non-Verbally
☑ Hide Ants

Figure 4. 4 A screenshot of the simulation result for selecting a car-resource by using AFAC algorithm considering a verbal communication feature

Figure 4.5 shows the autistic feature with non-verbal communication. AFAC can find the optimum car-resource and select the best driver who has been aware of this type of communication. In this case, the specialized driver would avoid communicating with the autistic user by calling. Although there are nearer cars that can be observed in this scenario, the AFAC can select the best choice that can satisfy the autistic users. In this scenario, AFAC finds the yellow car as the optimum car for this autistic user.



Autism User Features
☐ Is gender important?
☐ Is age important?
☑ Autist
Gender ☑ Male ☐ Female
Age ☐ < 30 ☑ 31 > 49 ☐ < 50
Autist ☐ Communicates Verbally ☑ Communicates Non-Verbally
☑ Hide Ants

Figure 4. 5 A screenshot of the simulation result for selecting a car-resource by using AFAC algorithm considering a nonverbal communication feature

4.4 Comparison of Simulation Results

To evaluate our proposed framework, the results are compared to the three algorithms in different simulation scenarios in terms of distance and traffic. Those algorithms are Ant Colony, MPAC, and the proposed AFAC.

For an accurate comparison, the same parameters have been used for all three algorithms with different scenarios. These parameters have been addressed in section 3.5.2 in previous chapter. Design and analysis of the comparison have been done using MATLAB. The figures show the average performance of each of the algorithms. Besides, it provides insight for each of them when performing in the long run.

Figure 4.6 demonstrates the optimization results in terms of the distance between autistic users and the car. It can be shown that the maximum total distance of the overall route is 108 km using MPAC algorithm at autistic user 20. This implies that the worst-case based on distance evaluation has been occurred using MPAC algorithm. The Ant Colony and AFAC outperform the MPAC in terms of distance for most of the scenarios. For autistic users 4,9,13 and 15, the other algorithms are better because this algorithm does not consider autistic features. The AFAC algorithm has the best performance which indicates that the autistic users can acquire the shortest distance using AFAC. It can be seen in the graph that AFAC has outperformed compared with the classic Ant Colony and the recent MPAC algorithms for most scenarios.

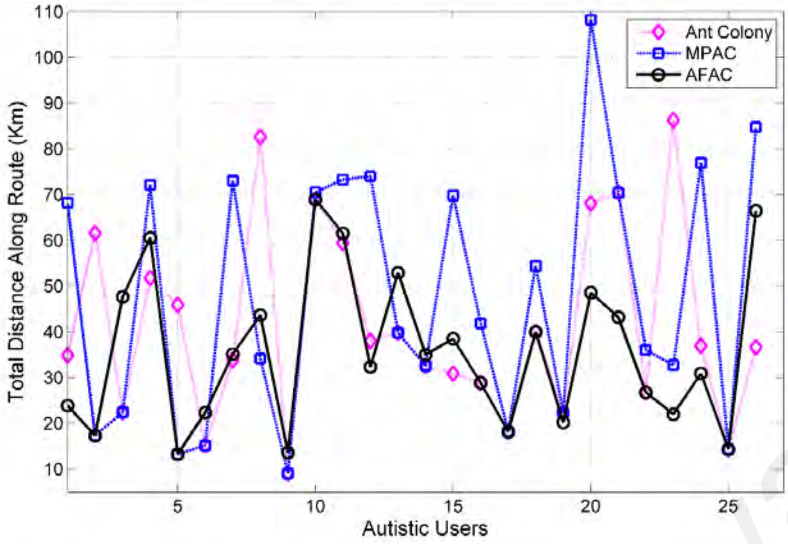


Figure 4. 6 Total Distance along Route Versus Autistic Users Using the Three Different Algorithms

Figure 4.7 shows each algorithm performance with respect to selecting the optimal route for the autistic user. It is observed that the worst traffic route is above 250 at autistic user 7 for different user scenarios using ACO. However, the ACO algorithm outperforms the MPAC algorithm in other users except users 7 and 23 as depicted in Figure 4.7. The proposed AFAC algorithm demonstrates the optimal selection in all 26 users for all different scenarios in terms of the best traffic routes.

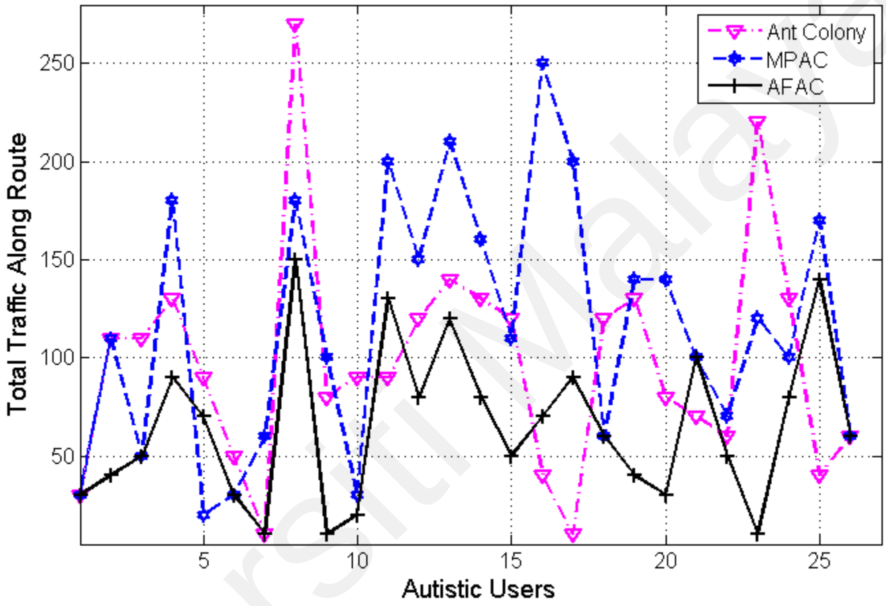


Figure 4. 7 Total Traffic along Route Versus Autistic Users Using the Three Different Algorithms

As shown in Figure 4.8, the overall performance of the developed AFAC in comparison to ACO and MPAC. The results demonstrate the effect of distance and traffic in various scenarios performed by these algorithms. It can be observed that the suggested AFAC algorithm outperforms other algorithms with respect to distance and traffic for most autistic users at all scenarios. Figure 4.8 demonstrates the performance of the proposed AFAC in comparison with the classic Ant Colony and the recent MPAC algorithms. It can be noted that the distance metric at user 20, the AFAC algorithm outperforms the MPAC and the Ant Colony algorithms by 20 and 60km, respectively. For traffic route, the AFAC algorithm outperforms the MPAC and Ant Colony by 50 and 110 traffic route units, respectively.

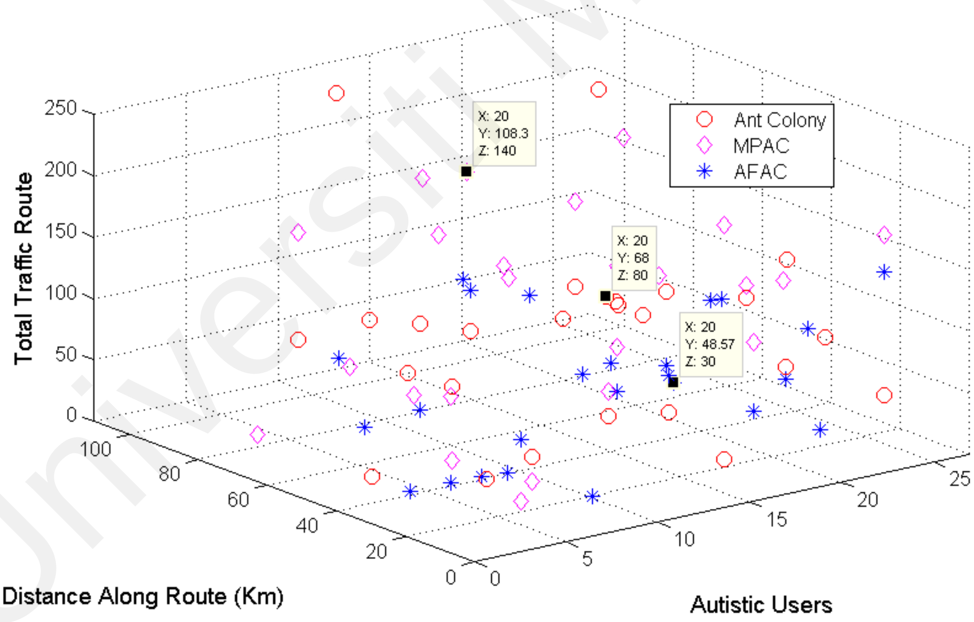


Figure 4. 8 Total traffic route and distance for all scenarios

Figure 4.9 shows the scatter plot that presents the correlation between the response time and the distance. In this figure, the x-axis represents the distance between autistic users and the car, while the y-axis represents the response time (RTT). In general, the RTT varies in the range of 0.3 – 15 minutes for all algorithms and scenarios. On the other hand, the distance varies between 9.059 – 108.2 km for all algorithms and scenarios. As shown, the proposed AFAC algorithm outperforms the classic ACO and the MPAC algorithms in most of the scenarios. For instance, when the distance was between 40-60 km, the proposed AFAC showed better performance, unlike other algorithms. Since the proposed AFAC algorithm was designed to fetch suitable and specialized drivers for autistic users, in some scenarios the RTT of AFAC algorithm was more than RTT of other algorithms. Moreover, as seen in the results, the AFAC algorithm not only performs better for autistic users but also for non-autistic users.

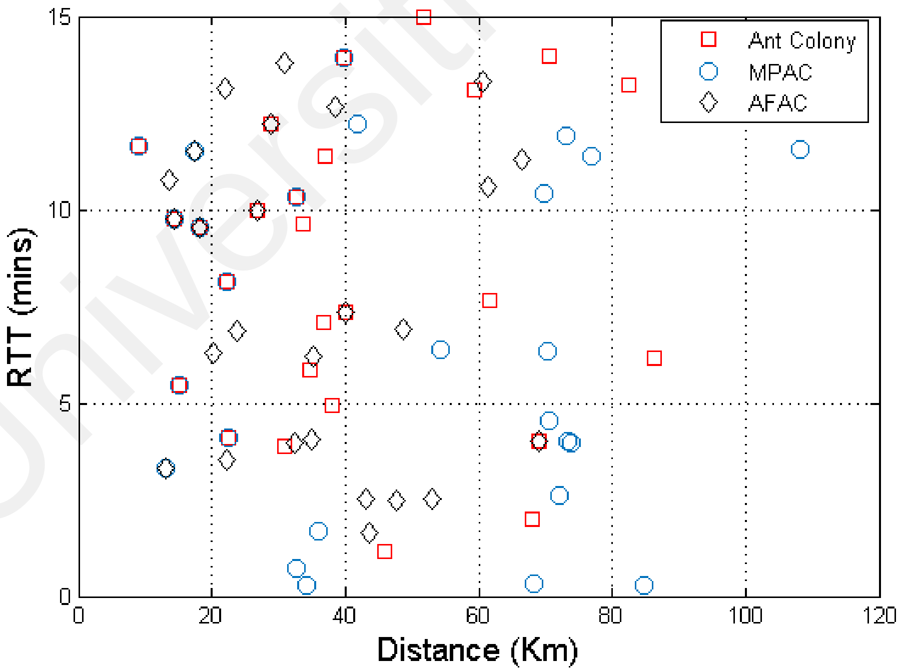


Figure 4. 9 RTT Verses Versus Distance for the three different techniques algorithms.

Figure 4.10 shows the scatter plot that presents the correlation between the response time and the traffic along the route. In this graph, the x-axis represents the traffic between the autistic user and the car, while the y-axis represents the response time (RTT). The RTT varies in the range of 0.3 and 15 mins for the traffic 10 – 250 route units for all algorithms and scenarios. In general, the correlation between RTT and the traffic is not monotonic. In some scenarios, the RTT is low for high traffic value. This is due to the effect of the road conditions and the autistic features which have been simultaneously used in the proposed AFAC algorithm to allocate the suitable driver for the autistic user.

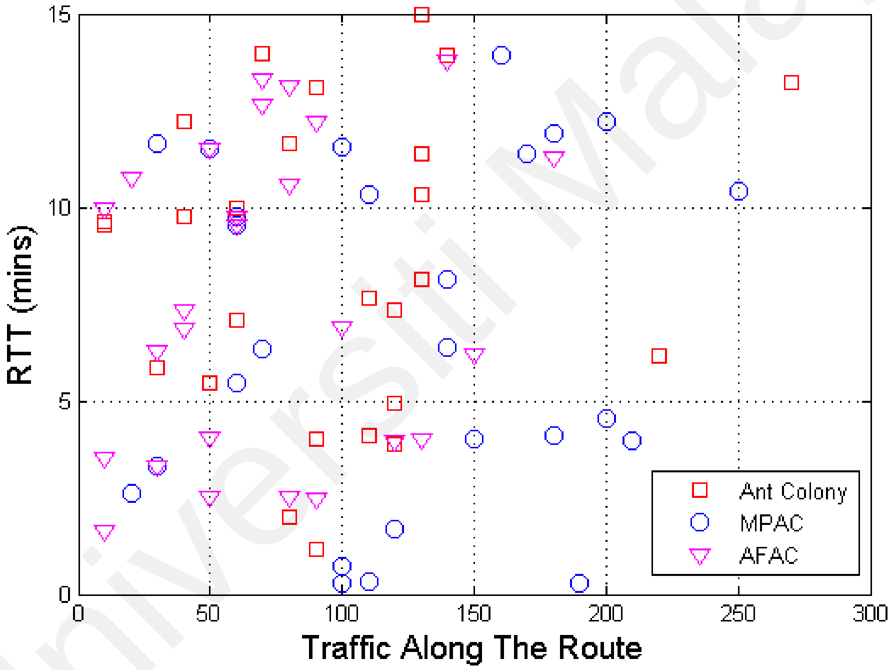


Figure 4. 10 RTT Versus Traffic for the three different algorithms

4.5 Chapter Summary

In this chapter, the findings of the proposed AFAC algorithm compared to the classic ACO and the recent MPAC algorithms are discussed. The simulation has been performed in various scenarios to show the impact of the proposed AFAC algorithm in optimizing the path and the dynamic selection of drivers for different kinds of autistic users according to the required features. The results demonstrate that the AFAC performance outperformed the classical method of ACO and the recent MPAC algorithm in most of the different tested scenarios.

CHAPTER 5: CONCLUSION AND FUTURE WORK

5.1 Introduction

This chapter summarizes the research development and findings for the developed AFAC algorithm. The potential procedures for the AFAC algorithm are presented. Finally, future trends and challenges are presented for future work.

5.2 Conclusion

This work aims to analyse and optimize the vehicle routing approach by using a meta-heuristic algorithm called Ant Colony. The proposed routing algorithm is particularly adopted towards the emerging ride-hailing services such as Grab and Uber. The proposed optimized algorithm is called AFAC which is an abbreviation of "Autistic Features Ant Colony". The AFAC is optimized for the ride-hailing service which includes specific features to select available car-resources and improve the ride experience for the autistic rider. The autistic user has two available communication options; verbal communication using Speech-to-Text feature and non-verbal communication using Text-to-Speech feature. The AFAC algorithm is fully functional and can be integrated with any existing system without much effort. Based on client-server architecture, the AFAC algorithm was developed to reduce the processing burden on the driver and rider and make all data centralized. The application of the optimization process and its implementation on the server and client were discussed in Chapter 3 of this study. The procedures of AFAC are highly dependent on the features of road and the autistic user's features which increase the overall system efficiency.

Finally, the efficiency and performance of the AFAC algorithm were evaluated by a simulation tool called Unity game engine. The simulation experiments are flexible which make them dynamically configured based on the location of the autistic user, number of vehicles, and road conditions. The characteristics of the road are observed closely by the

AFAC algorithm and the route is changed according to the road's real-time conditions. The AFAC algorithm was compared with the existing algorithms and evaluated to show the impact of the selection of the driver with existing algorithms. In most of the cases, the AFAC algorithm performed better than the previous algorithms while in some cases it provides similar results because the proposed AFAC algorithm was designed to fetch suitable and specialized drivers for autistic users as shown in the graphs (Figure 4.6, Figure 4.7, Figure 4.8, Figure 4.9 and Figure 4.10). The AFAC algorithm has a wide range of applications for RHS and other similar location-based services. Any existing framework can be incorporated with the AFAC algorithm as a third-party API or as a standalone application itself. Simulation discussion and experimental results are provided in chapter 4.

5.3 Future Work

For the sake of improvements to the developed AFAC algorithm in this research, the following issues are suggested for further investigation. The developed optimization of the AFAC algorithm for autistic users is focused on optimizing the path and the dynamic selection of drivers for different kinds of autistic users according to the required features. However, in this work, the focus is only on two features of autism which are verbal by Speech-to-Text and non-verbal using Text-to-Speech features. Thus, it would be a great benefit if a similar study will be conducted for more features that autistic users have such as communication by gestures, signs, and pictures.

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