Final Year Project Proposal

Project Title

Route and Delivery Package Optimization

Submitted by

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Coordinator

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List of Abbreviations and Acronyms

GL	Group Leader
GM	Group Members
NP-Hard	Non-Deterministic Polynomial
VRP	Vehicle Routing Problem
VRPTW	Vehicle Routing Problem with Time Windows
VRO	Vehicle Routing Optimization
GIS	Geographic Information System
SDSS	Spatial Decision Support System
LSVRP	Large Scale Vehicle Routing Problem
LS	Local Search
HH	Hyper Heuristics
GA	Genetic Algorithm
GP	Genetic Programming
GLS	Guided Local Search
KGLS	Knowledge-Guided Local Search
SMOTE	Synthetic Minority Oversampling Technique
ERD	Entity Relationship Diagram

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Final Year Project Proposal

Section – 1

1.1 Project Identification

Project Title: **Route and Delivery Package Optimization System**				
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What technology is core to your product? *(Please mark ☑ where applicable)*

[ ] 3D/4D Printing
[x] Big Data, Artificial Intelligence
[ ] Cloud
[ ] Robotics
[ ] The Internet of Things
[ ] Augmented Reality / Virtual Reality
[ ] Blockchain
[ ] Neurotech
[ ] Shared economy
[ ] Wearables, Implantables
[ ] Others (specify): ______________________

What is the target market(s) for the products? *(Please mark ☑ where applicable)*

[ ] Automotive, aviation, marine
[ ] Defence, security, safety
[ ] Environment, water management
[ ] Food, livestock, agribusiness
[x] Infrastructure, housing & transport
[ ] Oil, gas, energy
[ ] Business, marketing, finance
[ ] Education and training
[ ] Entertainment, tourism, sport/recreation
[ ] Healthcare
[ ] Mining equipment technology & services
[ ] Textiles, clothing, footwear
[ ] Others (specify): ______________________

Other Organizations Involved in the Project: *(Please identify all affiliated organizations collaborating in the project, and describe their role/contribution to the project.)*

Academic Organizations:

#	*Organization Name*	*Role / Contribution*
1.	Iqra University	Resources and Supervision
2.		

Industrial Organizations:

#	*Organization Name*	*Role / Contribution*
1.	None	None
2.		

Funding Organizations:

#	*Organization Name*	*Role / Contribution*
1.	None	None
2.		

Key Words:

Route Planning, Route Optimization

Research and Development Theme:

To optimize delivery time

Project Status: (Please mark ☑)

[x] New [ ] Modification to previous Project

[ ] Extension of existing project

Project Duration: 12 Months

Proposed Budget: Less than PKR 100,000/-

The Problem:

It is observed by the people who order food online that the time taken by the delivery company often exceeds the expected time. The main causes behind this are often longer or incorrect routes, bad road conditions or sometimes due to the inexperience riders. These significant delays often bother people a lot. The problems can be solved by using some efficient route planning techniques such as the one we are discussed ahead.

Synopsis:

The idea discussed below solves the problem of route planning by formulating an algorithm that would optimize the route by suggesting the routes that are the best suitable in some given circumstances. We are going to formulate an algorithm that will solve the problem in a multidimensional manner i.e. it will not only tell the shortest path that would get the job done in less time but would also take care of other factors that can make a simple path a longer one in certain circumstances, such as road closure or work in progress etc.

Section – 2

2.1 Problem Statement

The delivery industry is growing massively as the new newly "online" trend has started due to the Covid. Most of the businesses have now shifted to "online" platforms. This increased the demand for the packages to be delivered. Therefore, finding an optimized route for delivering the packages has become more critical and harder than ever for delivery businesses. An optimized route can create a valuable effect on cost and time taken by a package to be delivered or collected, thus minimizing the operational cost for the delivery company. Initially, route planning is not a very difficult task for a small business and, in some cases, can even be done manually. Still, it becomes harder as the volume of orders increases or the business grows. Companies also risk inflating their operational costs, often in the form of too many vehicles in their fleet and/or wasted fuel and wages due to longer than necessary routes. Delivery businesses face these types of problems every day. An effective route optimization solution will help delivery businesses minimize wages, driving time, and fuel consumption by finding the most efficient route for the entire fleet in a matter of minutes. Thus, we will formulate an algorithm that would optimize the route for a delivery company in a multi-dimensional environment, hence minimizing the operational costs incurred by the company and the time taken to deliver a certain number of parcels.

2.2 Motivation, Challenges and Goal

It is observed by the people who order food online that the time taken by the delivery company often exceeds the expected time. The main causes behind this are often longer or incorrect routes, bad road conditions or sometimes due to the inexperience riders. These significant delays often bother people a lot.

The major challenging part here is the data collection. To carry out experiments on our formulated algorithm, we need some real-time data. Get this real-time data is very difficult as no company will be willing to provide its data due to data security reasons.

Our ultimate goal is to minimize the delivery time by minimizing the operational costs incurred in terms of travel time and fuel costs due to longer or ineffective routes or even due to an inexperience rider.

Section – 3

3.1 Literature Review

Route optimization finds the best route to reduce travel cost, fuel consumption and the time taken to deliver or collect some packages. Due to its non-deterministic polynomial time (NP-Hard) complexity, it requires a lot of effort in terms of computing time to find the best route under a given set of circumstances.

A lot of work has been carried out by a number of scientists around the world but the problem still remains a critical subject in the field of optimization, especially when it comes to multidimensional optimization.

This section reviews the major approaches and methodologies used earlier to solve this problem.

Heuristic Algorithms:

There are two major categories of the heuristic algorithms being widely used for the purpose of solving route optimization i.e. Local Search and the Evolutionary Search.

Local Search

Starting from an initial solution, Local search moves from a current solution to another solution in the neighborhood. This is an iterative process in which the solution starts from a candidate node and exchanges nodes or local routes to gradually move towards a better solution. This iterative process sometimes gets trapped in the local optimum solution; therefore to overcome this many other intelligent strategies have been formulated to improve overall solution quality. These include simulated annealing [3], iterated local search [4], large neighborhood search [5], variable neighborhood search [6], and tabu search [7]. Many experiments on small and large sized VRPs (i.e. for 25 - 100 customers), using Local Search Heuristics [3, 5, 6], are found to have performed well.

Evolutionary Search

In an Evolutionary Search the whole solution space is divided into many small solutions, and then the evolutionary algorithm concurrently optimizes many solutions eventually reaching high quality solutions. It has four major steps involved:

- Representation
- Selection
- Combination
- Mutation

A few most effective evolutionary algorithms for VRP optimization are provided by Repoussis et al. [8] and Vidal et al. [9]. Mester and Bräysy [10] used the standard evolutionary optimization framework to guide exploration in the VRPTW solution space with solution initialization and evolution. Gehring and Homberger [11] parallelized the genetic algorithm and were the first to solve VRPTW instances up to 1000 customers.

The only work on the voronoi diagram was done by Milthers [34], who split the VRPTW into sub problems and then solved them with large neighborhood search heuristics. The Voronoi diagram was found to be effective in guiding the search process. However, this study only scoped the decomposition of the problem in the solution construction stage. It can be further improved.

Integration of VRO and GIS

A few effective approaches for VRP have been integrated with GIS-based SDSS to cater some real world applications. Spatial data management, processing, and visualization tools are used to collect customer orders, georeference related data, activate the solving process, and display routes for VROs, as in GIS software such as ArcGIS and TransCAD. Along with Local search, Weigel and Cao [2] first introduced implementation of a tabu search heuristics approach in a GIS environment to deal with VRO for an American retailer. Mendoza et al. [1] integrated a customized routing module, which improved solution quality with commercial solutions such as SAP/R3 and ArcGIS to cope with VROs in public utilities. Experiments on a real-world case in Bogotá, Colombia with 323–601 customers verified the effectiveness of evolutionary optimization and GIS software.

Santos et al. [12], developed a web-based user-friendly SDSSs embedded with VRO to cater a trash collection task in Coimbra, Portugal. TU et al. [13] used historical traffic information to present a cloud GIS-based spatial decision support framework with variable neighborhood search heuristics for dynamic vehicle routing. All this shows the dominance of VRO in real-life transportation applications. However, they also indicated that current spatial intelligence should be improved to cater the ever increasing number of customers in the different transportation sectors.

The classical variant of the VRP has limited capacity on their vehicles. The goal of the VRP is to find the optimal routes which visit all customers at once, respecting the capacity of each vehicle, with routes starting and ending at the depot. The classical optimization task is to minimize the overall distance. For the full model, consider the work of [14].

Some mathematical formulations based methods will thoroughly search for the values of the variables to find the mathematical proven optimal. But the problem was proven to be NP-hard [15], and finding the best routes is a hard task. For instances with more than 200 customers, the problem is usually referred to as Large-Scale VRP (LSVRP) [16]–[19]. This larger size requires extra care regarding the amount of search effort given. Therefore, such a heuristic method is needed that finds good solutions in faster time instead of an optimal solution.

Heuristics are usually based on simple moves which can be searched fast and repeatedly. These are known as neighborhoods, perturbation heuristics, and local search, and they can be classified as intra-route and inter-route. Examples of such moves are the classics 2-Opt [20], Cross Exchange [21], among others.

Most effective and efficient methods for solving the VRP use a Local Search (LS) based approach [22]. LS heuristics quality is defined by the neighborhoods utilized, ranging from the classic and simple moves to more elaborated ones. In start, the LS explores new solutions by making small moves, being robust across different problems and instances, as well as being able to find high-level solutions [23].

Works from [29] and [30] applied LS in combination with other techniques, such as Genetic Algorithm and Set Partitioning, respectively, to lead the solution or set of solutions towards better solutions. However, when it comes to large scale, as shown in [19], they lose their ability to efficiently solve the problem within a few minutes, reaching to several hours. This can be explained by applying LS to these scales, the large number of neighboring solutions makes it too costly for the full search in each neighborhood. To overcome this, some LS-based methods apply some kind of heuristic pruning, reducing the number of solutions searched.

A recent case of success [31] can find solutions for up to 30000 customers within minutes of execution time, by considering move-specific pruning techniques. More methods apply limits to the search space, usually by grouping the customers or by some sort of threshold as reviewed in [17]. However, limiting the search space is not a trivial task, since if poorly done can avoid good solutions from being found.

Hyper-heuristics (HHs) reduce the level of domain knowledge to create a good heuristic. HHs have been applied to automate heuristic sequencing, planning systems, parameter control and heuristic learning methods [32], with several cases of success. When learning heuristics, factors such as the types of components to be considered, the techniques used and which parameters should this algorithm use, need to be considered. One popular approach for building HHs are the EC techniques, such as Genetic Algorithm (GA) and Genetic Programming (GP). GA has been applied for several search problems including searching for optimal heuristic sequencing, such as [24] for the bin-packing problem. GP is more used for creating a heuristic rule which builds a solution [25], rather than improving it, such as in [26] for the Dynamic Job-Shop Scheduling. More on Hyper-heuristics can be found in the review of [32] and the book of [33].

For large-scale problems (focusing on the VRP), however, HHs have not been well explored. One example of HH being applied to an LSVRP with Time Windows [18], where the large problem size is handled before the solution is fed to the HH. The approach solves the problem and search space with a column generation technique.

Guided Local Search (GLS) is a deterministic algorithm that attempts to escape the local optimum that LS algorithms inevitably fall into [27]. GLS has a set of features that can be selected to penalize the current solution, moving it away from the pitfall. This is done by using different objective functions to guide the solution, rather than changing the solution itself [31], [27].

Knowledge-Guided Local Search (KGLS) is presented in [31] where the authors apply the Guided Local Search (GLS) with a newly introduced operator and penalization functions. This was later adapted to large-scale in [19]. The KGLS operates by sequential applications of a Local Search algorithm. These phases remove the undesired edges in order to find new solutions which can potentially lead to a better overall solution. These penalization functions were based on a study by the same authors [28] in which they investigate similarities across different VRP solutions, according to several metrics. One of the most effective metrics was the width of the routes.

Section – 4

4.1 Research Approach

A brief outline of the research pattern can be understood by the flow diagram given below:

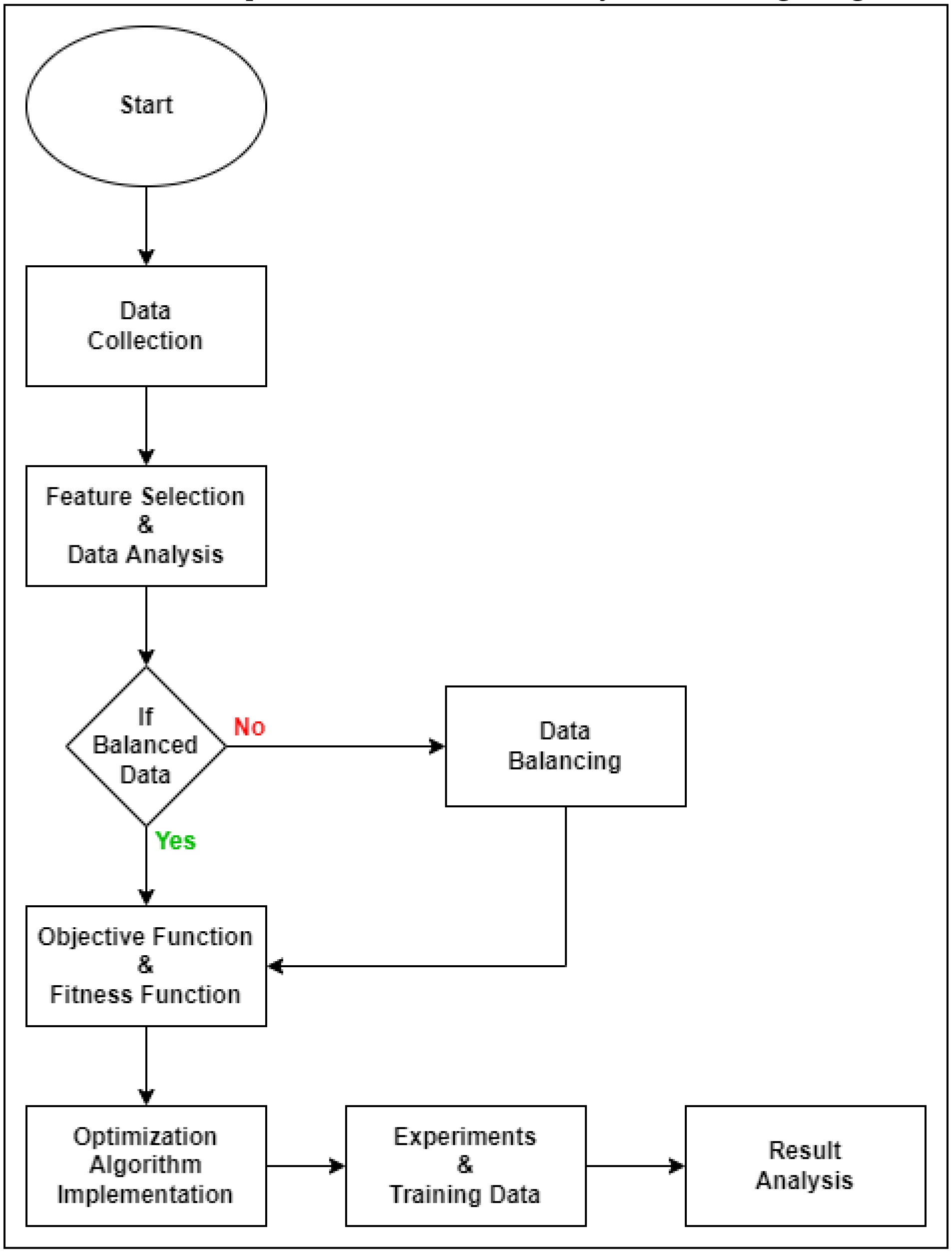

Figure 1 Flow Chart for Research Design

Each step is individually explained below:

Data Collection

For the data collection step, we first need to formulate the type of data required to carry out the research. A tentative template for the data required is as below:

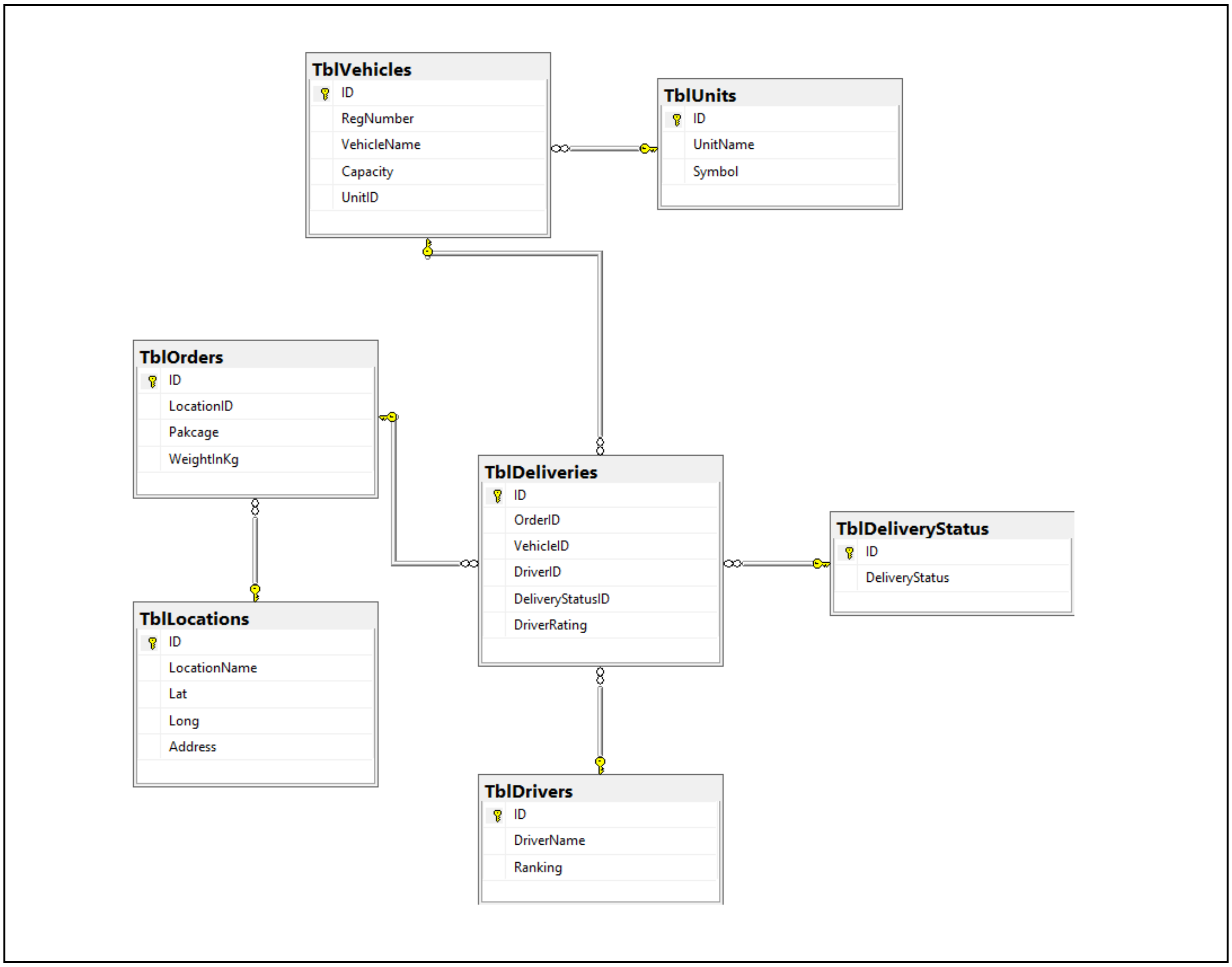

Figure 2 ERD of the data required for the system

The required data should contain several locations and information regarding drivers, vehicles, orders and their deliveries.

For the process of data collection, a small application is developed that contains forms for the above given ERD. The data regarding drivers, vehicles, orders and deliveries will be filled manually and randomly. While, for the location related data, a physical region of Tariq Road is selected. To get the exact coordinates of some real time locations, location data at several places on Tariq road will be gathered by physically visiting the places and noting down the coordinates of the location.

Another kind of data that will be required to carry out the research is the data related to several routes between the gathered nodes and the real time road conditions. For this purpose, the routing data will be collected using API services such as provided by Google Maps or Mapbox while for the road conditions data; we might need to use the dummy data as no free APIs were found that could return the real time road conditions.

Feature Selection and Data Analysis

In this step the data gathered in the above step will be examined. The variation in features of data will be studied so that we will be able to select the features that have significant impact on route planning and delivery timing.

If, for any feature the data is imbalanced, it will be balanced first using various balancing techniques. Major data balancing methods involve techniques such as cluster based oversampling and SMOTE that creates minority class samples synthetically.

Next, we will extract features on the basis of the gathered data e.g. if we are able to get the number of schools and their timings, on a particular road, we will be able to predict the traffic congestions on a particular road at a particular time.

After that, we will make clusters of customers to make groups of similar customers either by their location or by the type of delivery.

Objective functions and Fitness functions

In this step, we will formulate our objective function that will provide us the solution. The objective function would be designed to minimize the time and traveling cost. Next, we will formulate our fitness function which will test how good the solution provided by our objective function is.

Training Data, Experiments and Implementing Optimization Algorithm

Our next step will be to carry out experiments with different types of data sets to check how well our algorithm performs under different circumstances. For this purpose we will also try to seek help from different delivery companies such as Uber Eats, Foodpanda, TCS and M&P, to get the real data of delivery locations for different parts of the city. If we are able to get the real time data, this will also serve the purpose of training data using which we can train our model.

Results Analysis

In this step, we will analyze our results that we have obtained. We will compare it with the results of the other researchers and see if we have improved in any way. We will measure our computational effort, complexity of the algorithm and, of course, how efficient results our algorithm provides in terms of time which is our main objective to be minimized.

4.2 Key Milestones and Deliverables

Below mentioned are some of the key milestones and deliverables.

S. #	Time (in weeks)	Milestone	Deliverables
1	1 – 3	Gather Requirements	Requirement Document
2	4 – 5	Finalize the design of the application	Prototypes
3	6 – 7	Gather Data	Dataset
4	8 – 10	Feature Selection/Data Balancing	Balanced Dataset
5	11 – 14	Formulate Functions to Optimize	Objective and Fitness Function
6	15 – 17	Design and Implement Optimization Algorithm	Optimization Algorithm
7	18 – 21	Design and Develop an app for demonstration	web/mobile app
8	22 – 24	Gather real-time data and experiment	Experiment Results
9	25 – 26	Study and compare results	Research Results
10	27 – 28	Document Project	Project Report

Table 1 Key milestones and their deliverables

4.3 Gantt Chart

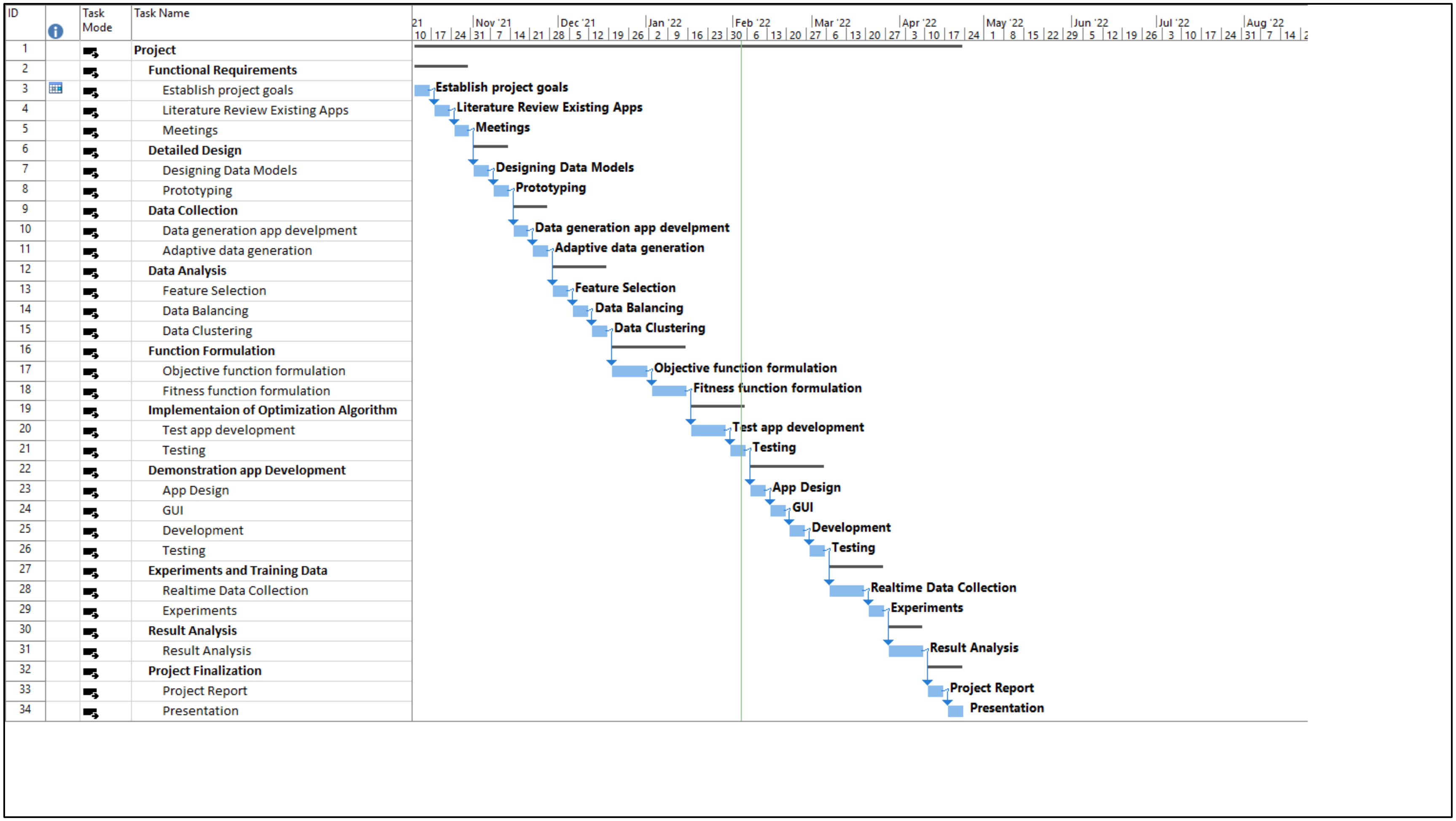

Figure 3 Gantt Chart of the project

Section – 5

5.1 Functional Requirements

Following are a few functional requirements of the system:

- The app should devise a route that minimizes the travel time.
- The app should be able to plan effective routes.
- The app should suggest the best rider in a particular time.

5.2 Non-Functional Requirements

Following are a few non-functional requirements of the system:

- The application should provide full data security.
- Accuracy in planning routes should be highly ensured
- The app should be efficient enough to run on maximum devices.
- The response time of the app should not exceed a few seconds.

5.3 Use Case

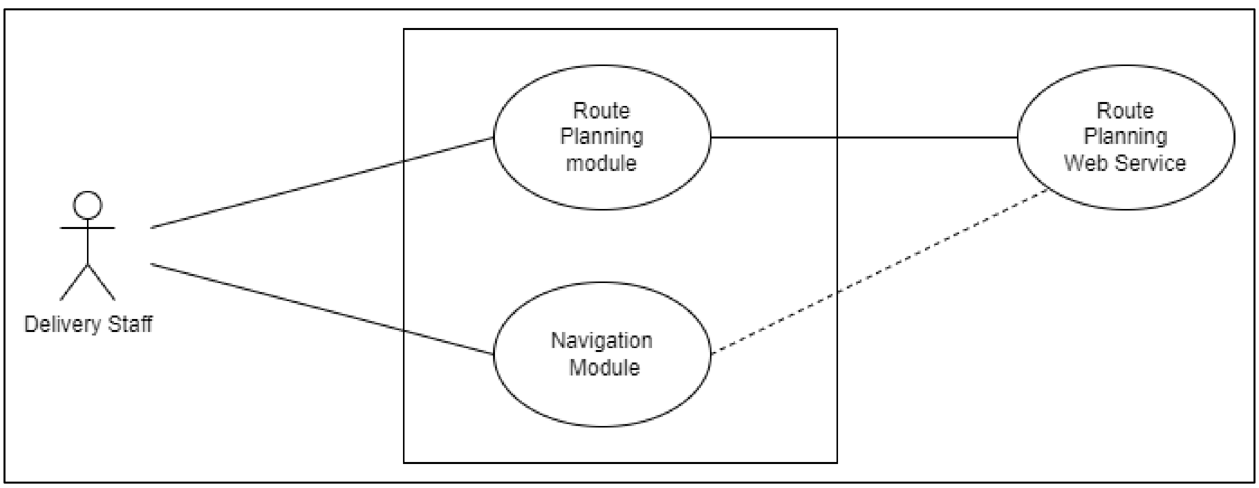

Figure 4 Use case diagram of the project

5.4 ERD

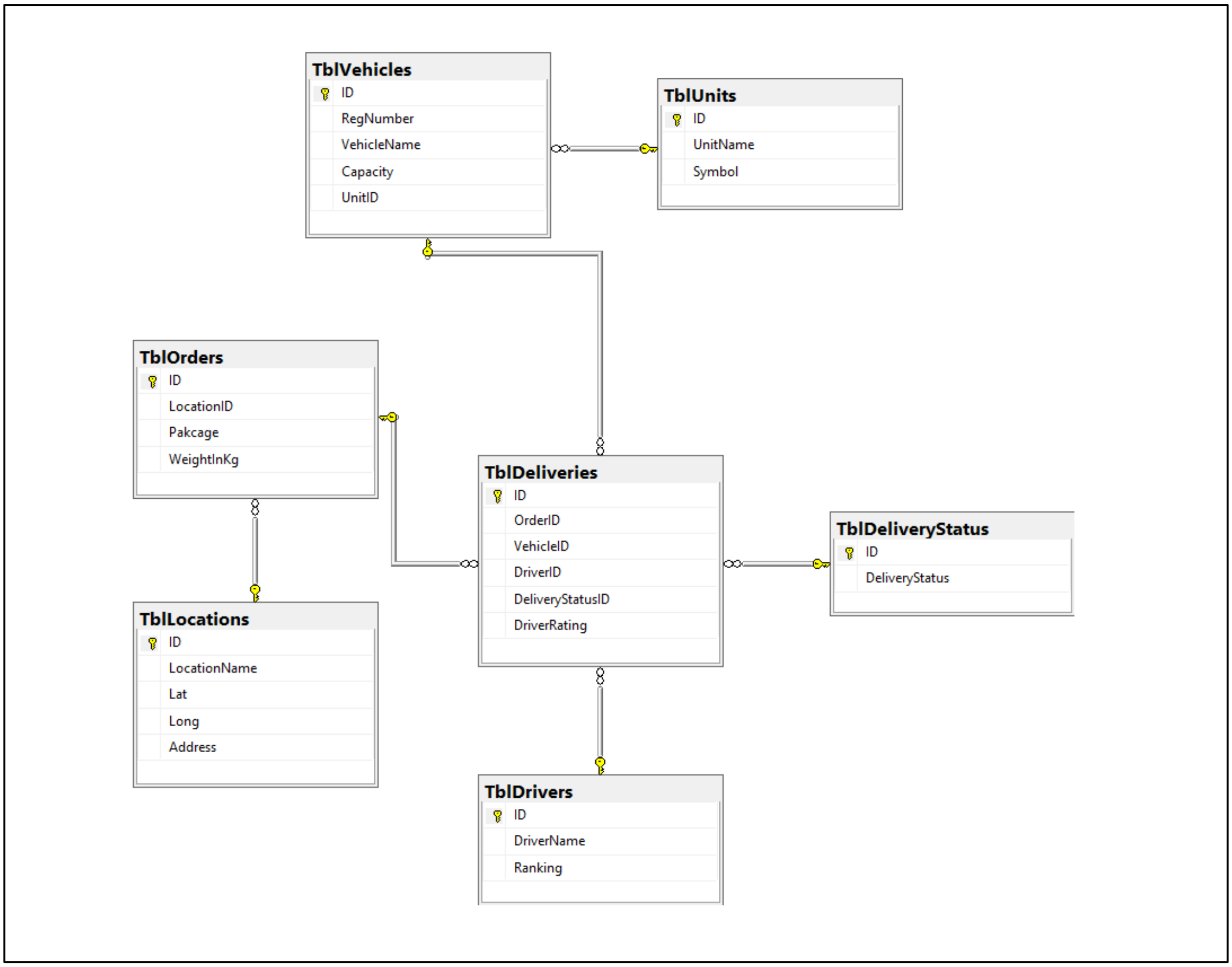

Figure 5 ERD diagram of the application

5.5 Prototypes

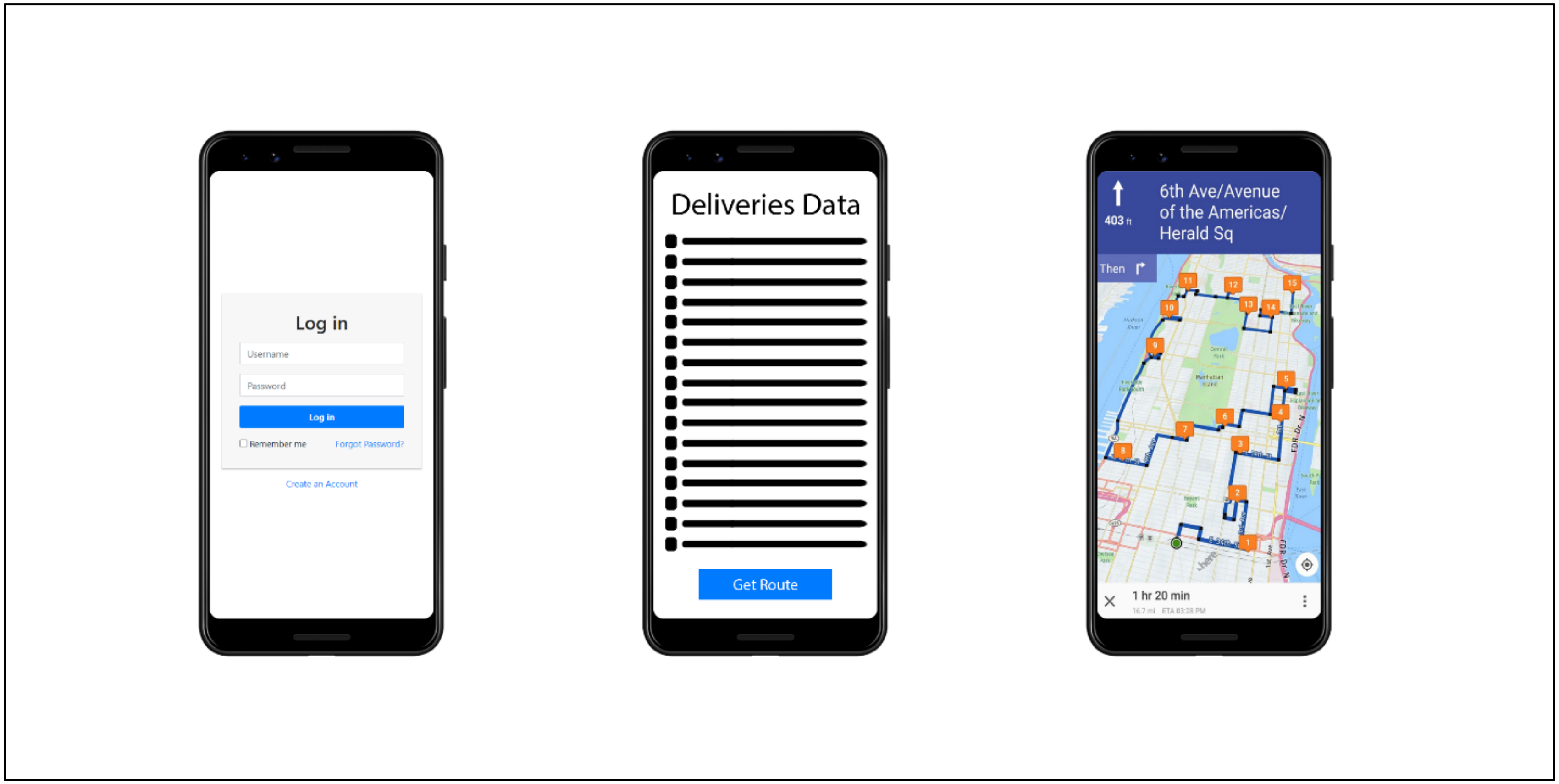

Figure 6 Prototypes

Section – 6

6.1 References

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Annexure – A: Proposed Budgeting

Project Time and Effort Estimates

	ENTER ESTIMATION VARIABLES, BELOW
PROJECT MANAGEMENT EFFORT %	30%
PROJECT MANAGEMENT OFFICE EFFORT %	50%
PROJECT CONTROL OFFICE EFFORT %	20%
TOTAL SHOULD BE 100% ------------------->	100%
WORK DAY LENGTH IN HOURS	8
ESTIMATED START DATE	10/09/2021
COMPUTED ESTIMATED END DATE	06/04/2022
ESTIMATED PROJECT DURATION IN WEEKS	34.0

Table 2 Project effort and time estimates

PHASE	ESTIMATED HOURS	ACTUAL HOURS
Business Requirements	120	-
Functional Specifications	40	-
Detailed Design	80	-
Code and Unit Test	320	-
System Testing	120	-
User Acceptance Testing	40	-
Project Manager	20	234
Project Control Office	20	156
Project Management Office	20	390

Table 3 Estimated project hours

Computed Budget

PHASE ACTIVITY	STANDARD WORK EFFORT %	PHASE TEAM SIZE	COMPUTED WORK EFFORT HOURS	COMPUTED TASK DURATION IN WEEKS	COMPUTED AVERAGE RESOURCE HOURLY COST	ESTIMATED COST	COMPUTED TASK DATE OF COMPLETION	COMPUTED WORK EFFORT IN DAYS	COMPUTED TASK DURATION IN DAYS
Business Requirements	17%	2	120	4	$ 41	$ 4,860	11/06/2021	15.0	7.5
Functional Specifications	6%	2	40	3	$ 41	$ 1,620	11/27/2021	5.0	2.5
Detailed Design	11%	3	80	3	$ 27	$ 2,160	12/18/2021	10.0	3.3
Code and Unit Test	44%	4	320	12	$ 20	$ 6,480	03/12/2022	40.0	10.0
System Testing	17%	2	120	4	$ 41	$ 4,860	04/09/2022	15.0	7.5
User Acceptance Testing	6%	2	40	2	$ 41	$ 1,620	04/23/2022	5.0	2.5
TOTAL SHOULD BE 100% ------------------>	100%		720	28		$ 21,600		90.0	33.3
Project Manager	30%		234	28	$ 8	$ 1,872		29.3	140.0
Project Control Office	50%		156	28	$ 7	$ 1,092		19.5	140.0
Project Management Office	20%		390	28	$ 8	$ 3,120		48.8	140.0
PROJECT MANAGEMENT			780			$ 6,084			
BASELINE PROJECT HOURS ESTIMATE			1,500			$ 27,684			

Table 4 Computed budget of the project

Annexure – B: Business Canvas Model

Business Model Canvas	Designed for:	Designed by:	Date:	Version:
	Route Optimization	Group # 5	06-01-2022	2

Problem	Solution	Unique Value Proposition	Unfair Advantage	Customer Segments
• Ineffective routes • Increased fuel cost • Greater time consumption	• An algorithm that would suggest an optimized route for a set of locations under certain circumstances	• Lesser travel time and cost • Lesser time of solution suggestion	• Supervisor of the same domain	• Food delivery companies • Courier services companies
	Key Metrics		**Channels**	
	• Performance on customers greater than 1000		• Digital Marketting • Targetted Marketting (meetings with courier companies)	

Cost Structure	Revenue Streams
• Research papers • Data Collection • Map APIs	• Contracts for projects

Figure 7 Business Canvas Model

Annexure – C: Poster

Student Names

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(43144)
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(44818)

Rotue and Delivery Package Optimization

Supervisor: Dr. Atiya Masood

Student Names

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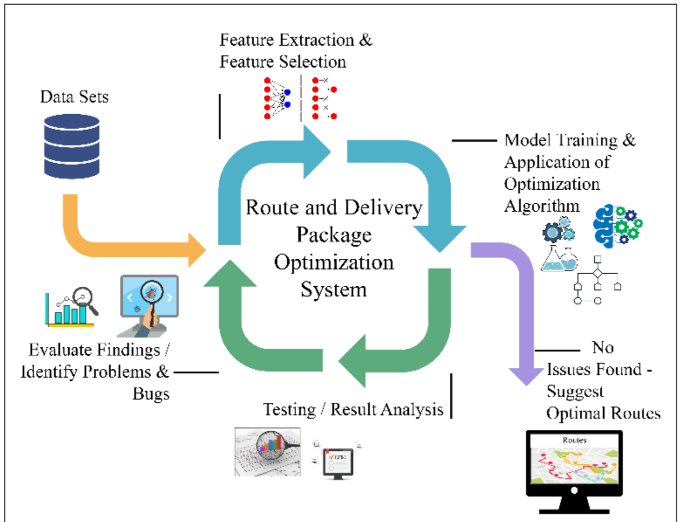
(45006)

Goals and Objectives

Goal of this project is to enhance route planning for delivery companies. **Objective** of this project is to formulate an algorithm that could find better and effective routes in less time.



Tools

HTML, CSS and Javascript

ASP.Net

Python

Android Studio

Key Features

- Easy route planning.
- Decreased travel time.
- Effective routes in less time.
- Interactive app.
- Visualization of devised routes.

Explanation

By using different otimization techniques, we are going to formulate an algorithm that would find the best possible routes for a set of customers to be served while minimizing the operational costs incurred in terms of time and fuel.

Scope

The project targets food delivery and courier service companies and solves the problem of planning an effective route for hundred of customers to be served on daily basis.

Figure 8 Poster

End of Document.