Location Problems with Distribution Capacity and Time Limitations

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ABSTRACT

Locational decisions are generally considered strategical level decisions. Hence, location problems received a large concern in the literature. There are several factors like: distances, demand amounts, facility capacities etc. that may affect the locational decisions. Most studies in the literature had considered these factors. However, there are few studies which considers distribution capacities of the production systems.

Today, especially service production systems such as fast-food producers declare a time limit in their delivery operations. In such systems, the distribution capacities and distribution time limits should be considered in location problems. In this study, it is aimed at investigate several realistic versions of location problems with distribution capacity and time limits, formulate these problems as optimization problems and develop exact/heuristic solution methods for those problems.

In this study, two distribution capacitated locational problem type had been developed. Type-1 is distribution capacitated version of well-known p-center problem on the other hand, type-2 is distribution capacitated version of well-known maximum-covering problem. MIP models and heuristic algorithms had been developed for both type of the problem. After that, computed results are compared and findings had been presented in conclusion section. In addition, a real life case study had been done too.

Keywords: location optimization, distribution capacities, p-center, maximum covering.

ÖZ

Yer seçimi kararları genel olarak stratejik kararlardır. Dolayısıyla yer seçimi kararları üzerine literatürde oldukça fazla sayıda çalışma bulunmaktadır. Uzaklık, talep miktarı, tesis kapasitesi vb. birtakım faktörler yer seçimi kararlarını etkilemektedir. Yukarıda bahsedilen faktörler literatürde birçok çalışmada yer almıştır. Fakat, bir üretimin sisteminin dağıtım kapasitesi düşünülürek yapılan çalışmalar oldukça az sayıdadır.

Günümüzde, servis üzerine hizmet veren üretim sistemleri dağıtım operasyonları için zaman kısıtı koymuşlardır. Buna örnek olarak Fast-Food tesislerini verebiliriz. Bu tarz sistemlerde yer seçimi problemi düşünülürken dağıtım kapasiteleri ve dağıtım süreleride hesaba katılmaladır. Bu çalışmanın amacı gerçekçi dağıtım kapasiteli ve zaman kısıtlı yer seçimi problemlerini araştırıp daha sonra bunları çözmek üzere kesin ve sezgisel çözüm yöntemlerini formülüze etmektir.

Bu çalışmada dağıtım kapasiteli iki farklı yer seçimi problemi geliştirilmiştir. Tip 1 problemi literatürde bilinen p-center probleminin dağıtım kapasiteli versiyonudur öte yandan Tip 2 probleimi literatürde bilinen maximum-covering probleminin dağıtım kapasiteli versiyondur. Her iki problem tipi içi karışık tamsayı izlenceleme modelleri ve sezgisel algoritmalar oluşturulmuştur. Daha sonra, bulunan sonuçlar karşılaştırılmış ve bulgular sonuç bölümünde yer almıştır. Ayrıca, gerçek hayattan bir vaka çalışması yapılmıştır.

Anahtar Kelimeler: yer seçimi eniyilemesi, dağıtımı kapasitesleri, p-center, maximum covering

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TABLE OF CONTENTS

ABSTRACT iii

ÖZ iv

ACKNOWLEDGMENT v

LIST OF TABLES viii

LIST OF FIGURES ix

1 INTRODUCTION 1

2 LITERATURE REVIEW 6

3 PROBLEM DEFINITIONS AND THE PROPOSED METHODS 18

3.1 Problem Definitions 18

3.2 The Proposed Solution Methods 19

3.2.1 Mixed Integer Programming Models of the Problems 19

3.2.2 Heuristic Methods 24

4 RESULTS 25

4.1 Experimental Design 25

4.2 Type-1 problem results 26

4.3 Type-2 problem results 37

5 CASE STUDY: ÇANKAYA 62

5.1 Background Information 62

5.2 Information about Çankaya 63

5.3 Çiğ Köfte Company 64

5.4 Experimental Procedure 64

5.5 ArcGIS 10 65

6 CONCLUSIONS 74

REFERENCES 77

APPENDIX 81

LIST OF TABLES

Table 1: MMT1 and HT1 results comparison table 35

Table 2: MMT2-0.6 and HT2-0.6 results comparison table 44

Table 3: MMT2-0.8 and HT2-0.8 results comparison table 56

Table 4: Type 1 Objective Values 67

Table 5: Distribution of motorized couriers to the restaurants for case 1 67

Table 6: Type 2 objective values 69

Table 7: Distribution of motorized couriers in Type 2 solutions 70

LIST OF FIGURES

Figure 1: Average solution time of MMT1 vs. nodes 27

Figure 2: Average solution time of PCM vs. nodes 28

Figure 3: Average solution time of MMT1 and PCM vs. nodes 29

Figure 4: Average solution time of HT1 vs. nodes 29

Figure 5: Average solution time of MMT1 and HT1 vs. nodes 30

Figure 6: Average solution time of PCM and HT1 vs. nodes 31

Figure 7: Average objective values of MMT1 solutions vs. nodes 32

Figure 8: Average objective values of HT1 vs. nodes 33

Figure 9: Average objective values of PCM vs. nodes 33

Figure 10: Average objective values of MMT1, HT1 and PCM vs. nodes 34

Figure 11: Average solution time of MMT1 (Facility level I and II) vs. nodes 35

Figure 12: Average solution time of MMT1 (Vehicle level I and II) vs. nodes 36

Figure 13: Average solution time of HT1 (Facility level I and II) vs. nodes............ 36

Figure 14: Average solution time of HT1 (Vehicle level I and II) vs. nodes 37

Figure 15: Average solution time of MMT2-0.6 vs. nodes...................................... 38

Figure 16: Average solution time between MMT1 and MMT2-0.6 vs. nodes 39

Figure 17: Average solution time of MCM-0.6 vs. nodes 40

Figure 18: Average solution time of HT2-0.6 vs. nodes.. 40

Figure 19: Average solution time of MMT2-0.6 and HT2-0.6 vs. nodes 41

Figure 20: Average solution time of MCM-0.6 and HT2-0.6 vs. nodes.................... 42

Figure 21: Average objective values of MMT2-0.6 solutions vs. nodes 42

Figure 22: Average objective values of HT2-0.6 vs. nodes...................................... 43

Figure 23: Average objective values of MMT2-0.6 and HT2-0,6 vs. nodes 44

Figure 24: Average solution time of MMT2-0.6 (Facility level I and II) vs. nodes .. 45

Figure 25: Average solution time of MMT2-0.6 (Vehicle level I and II) vs. nodes .. 46

Figure 26: Average solution time of HT2-0.6 (Facility level I and II) vs. nodes 46

Figure 27: Average solution time of HT2-0.6 (Vehicle level I and II) vs. nodes 47

Figure 28: Average solution time of MMT2-0.8 vs. nodes....................................... 48

Figure 29: Average solution time of MMT2-0.8 and MMT2-0.6 vs. nodes............. 48

Figure 30: Average solution time of MMT2-0.6, MMT2-0.8 and MMT1 vs. nodes 49

Figure 31: Average solution time of MCM-0.8 vs. nodes 50

Figure 32: Average solution time of HT2-0.8 vs. nodes... 50

Figure 33: Average solution time of HT2-0.8 and HT2-0.6 vs. nodes 51

Figure 34: Average solution time of MMT2-0.8 and HT2-0.8 vs. nodes 52

Figure 35: Average solution time of MCM-0.8 and HT2-0.8 vs. nodes.................... 52

Figure 36: Average objective values of MMT2-0.8 solutions vs. nodes 53

Figure 37: Average objective value of MMT2-0.8 and MMT2-0.6 vs. nodes........... 54

Figure 38: Average objective values of HT2-0,8 vs. nodes....................................... 54

Figure 39: Average objective values of MMT2-0.8 and HT2-0.8 vs. nodes 55

Figure 40: Average solution time of MMT2-0.8 (Facility level I and II) vs. nodes .. 56

Figure 41: Average solution time of MMT2-0.8 (Vehicle level I and II) vs. nodes .. 57

Figure 42: Average solution time MMT2-0.8 and MMT2-0.6 (F1 F2) vs. nodes 57

Figure 43: Average solution time MMT2-0.8 and MMT2-0.6 (V1 V2) vs. nodes 58

Figure 44: Average solution time of MMT2-0.8 (Facility level I and II) vs. nodes .. 59

Figure 45: Average solution time of HT2-0.8 (Vehicle level I and II) vs. nodes 59

Figure 46: Average solution time HT2-0.8 and HT2-0.6 (F1 F2) vs. nodes 60

Figure 47: Average solution time HT2-0.8 and HT2-0.6 (V1 V2) vs. nodes 61

Figure 48: Map of Çankaya... 65

Figure 49: Randomly created nodes in Çankaya district 66
Figure 50: Randomly created labelled nodes in Çankaya district............................. 66
Figure 51: Solution of case 1 68
Figure 52: Solution of case 1 (Simple) 68
Figure 53: Case 1 solutions.. 71
Figure 54: Case 5 solutions.. 71
Figure 55: Case 1 solutions (DL=30)... 72
Figure 56: Case 5 solutions (DL=30)... 73

Chapter 1

INTRODUCTION

Facility location decisions are generally strategic level decisions and they have a critical role in the success of companies for a long future term. Usually, opening a facility at a location causes some important amount of investment and set-up costs. Therefore, cancelling an applied wrong locational decision and locating the facilities at the correct places means having these high costs twice, once for the wrong locations and once for the correct locations. If a company does not change the wrong locations of its facilities in order not to have those costs again for the correct locations, this time wrong locations cause some other problems in the run of the company like higher supply and distribution times and costs, lower customer satisfaction, etc. In today's highly competitive market and especially in service/delivery sectors such as health, fire, fast food/postal/cargo delivery, passenger transportation, etc. these issues become extremely important in the success of companies. Hence, deciding the correct locations of the facilities at first time arises as a strategic level optimization problem for such companies.

Because of the high importance of the locational decisions there is a wide literature on this subject. There are many articles on several types of location problems. To the best of our knowledge, almost all of those studies consider distances, times, costs in the related locational decisions but they omit the service/delivery/transportation capacities of the companies. I.e., it is assumed in the location literature that companies have unlimited service/delivery/transportation capacities.

Especially the service/delivery/transportation times highly depend on the distances and related capacities. In this study, it is claimed that considering only the distances and omitting the capacities causes wrong location decisions. For example, service/delivery times of a fast food company (like pizza or burger delivery) highly depend on the distances between its facilities and the customers. But it also highly depend on its service/delivery capacity (like the number of its delivery vehicles and drivers). Arrival times to patients by ambulances cannot be considered as only a function of the distances between the hospital and patients. Number of the available ambulances has to be taken into account. Number of the vehicles/trucks is as much important as the distances in service/delivery times of a postal/cargo delivery system. High competition forces companies in these type of service/delivery industries to declare a short service/delivery time. Several fast food companies announce that they distribute their products to customers in 30 minutes. Similarly, cargo systems guarantee 3 or 7 days for their services. Hungry people does not accept waiting too much for their orders. Long cargo delivery times are not acceptable by the customers. Late arrivals of ambulances or fire trucks cause loss of lives.

This study is initiated by a real life case of a local fast food company in Ankara, Turkey. Our observation about the mentioned lack in the location literature increased our motivation for the research. Two types of location problems with distribution capacities are studied.

There is a set of customers and a set of alternative facility locations in both types of the considered problems. The distances/travel times between the locations and customers are known. In addition, number of the facilities that will be open and total number of the service/distribution units (vehicles, drivers, postmen, doctors, nurses, firemen, etc.) are known. In this thesis, services/distribution units are considered as motorized couriers for a fast food restaurant. It is assumed that a single service unit can serve only a single customer at a time. Completing a service means having a trip from the related facility to the related customer and from the customer to the facility by the corresponding service unit. Different customers can be served by different service units in parallel. However, the customers assigned to a specific service unit are served one-by-one by the service unit.

Locations of the given number of facilities, allocations of the given number of service units to facilities and assignments of the customers to the service units are to be determined in order to finish serving all customers in the minimum time in the first type of the considered problems. The same decisions have to be made in the second type of the considered problems but this time the goal is to maximize the number of the served customers in a given amount of time. Some customers can be lost in this type of the problem.

The first type of the studied problems is a minimax type problem and it is distribution capacitated version of the well-known *p*-center problem. On the other hand, the second type problem is a maxisum type problem and it is distribution capacitated version of the well-known max covering problem.

In order to solve these problems polynomial size mixed integer programming (MIP) models of the problems are developed. It is seen in the numerical experiments that solution times increase very rapidly when the developed MIP models are used and this method fails to solve large problems in acceptable times. In order to find some good solutions in much shorter times a heuristic approach is developed and adopted for both types of the problems. The main idea of the developed heuristic approach is to consider the entire hard problem in two separated and simpler decision levels. Locations of the facilities are determined in the first level with omitting the given service/distribution capacities. Then allocations of the service units to the locations found in the first level and assignments of the customers to the service units are determined in the second level of the entire heuristic approach.

These two well-known location problems and their distribution capacitated versions are considered, and extended numerical experiments are made to show that omitting the distribution capacities and considering only the distances in such location problems causes wrong decisions. Several conclusions about the difficulties of the problems and most significant factors on the difficulties of the problems based on the numerical experiments are made. In addition, the performances of the MIP models and the heuristics are evaluated. Solution times by the MIP models increase very rapidly by the number of nodes. These models can be used to solve small or medium size problems but require very long solution times for larger problems. The performance of the developed heuristic found satisfactory by the numerical experiments. Hence, it can be used to find good solutions to large size problems in very short times. Based on these experiments it is decided to use the developed heuristic methods for solving the considered real-life case which was the starting point of the research.

A fast food company selected as a real life application of this study. This company wants to start a new operation in Çankaya providence of Ankara city and they need to decide on locations of branches, and motorized courier allocations to the branches. So, sample problems have been created and solved and presented to the company.

The related literature is reviewed in the following chapter. Problem definitions, MIP models of the problems and the proposed heuristic methods are given in detail in Chapter 3. The numerical experiments and all related evaluations are presented in Chapter 4. Then, in Chapter 5, the details of the considered real life problem are given. The research is concluded and the future study directions are discussed in the last chapter.

Chapter 2

LITERATURE REVIEW

Location problems are widely discussed in the literature. In this section, related studies have been presented.

Studies which are related to emergency, logistics, humanitarian logistics etc. are given below.

The priority queuing covering location problem; in this paper, emergency facility service calls have been prioritized according to its emergency levels. This is very vital on emergency calls, because not all calls must have same importance. Problem model has created from previous maximum coverage models but improved according to priority of emergency call nodes and queuing theory. In this paper, facility locations already decided and fixed. Waiting time for each node calculated separately according to the importance level. Also, a greedy heuristic method developed in order to solve this problem. [1]

Natural disasters and disasters which have caused by people have been dramatically increased in last 70 years. So, building facilities (Aid stations, water and food distribution facilities etc.) have become more problematic. Then, location problems in OR field have become more noticeable for these subjects. Because of this, numerous amount of exact methods and heuristic algorithms have been developed within years related by humanitarian logistics. Focus of this paper is to present existing work in this field and to make survey from them. What is more, this paper have been presented four critical problems as well which are deterministic facility location problems, dynamic facility location problems, stochastic facility location problems, and robust facility location problems. All of the problems have discussed specifically and few research gaps have been detected for future researches. [11]

Facility location problems focus on locating best possible location for facilities. However, it is not easy on real world. There can be several unexpected situations while satisfying a demand such as emergency calls. Every hospital have limited resources to answer emergency calls and since every call have importance level it is very important to respond these calls at minimum amount of time. So, backup supply for facilities have become very vital in order to satisfy a demand even with unexpected problems. This paper have been focused on two common problems which are p-median and maximal covering. Moreover, five criteria have been created in order to make comparison between p-median maximal covering problems and for testing randomly generated instances have been created. [12]

Humanitarian logistics is one of the major problem in today’s world. Poor counties were suffering from food, water or pharmaceutical shortages. Although help stations were serving the people who need help, distribution of goods still is a problem. Most of the help stations are working self-service. In other words, people need to visit the station in order to obtain necessary goods. However, building help stations everywhere is not possible due to its cost, geography etc. This paper mainly focuses on solving this distribution problems of help stations. Authors proposed a solution method which consisting people (demand) who visit help stations. People who has more accessibility to help stations have been involved to the distribution of goods. Authors called them “cooperatives”. These cooperatives acting as intermediate facilities and helping the original facilities to reach people who has no accessibility to original facility. Next, cooperatives after collected their goods from facility then, collected goods for people who were living far away the facility. However, these cooperatives only serves people who are close to their region. Four different location problem have been modelled and all four of them have median and covering objectives. Also, a nonlinear model have been used for cooperation price. [13]

Drones based distribution have been popular recent history. However, it has brought own difficulties as well such as; battery life, whether conditions etc. Private sectors have other limits as well such as drone capacity. On the other hand, drone technology have been so convenient for supplying medical equipment (defibrillators, blood or pharmaceuticals) in medical sector. So maximize the demand which has been satisfied is very critical both private and public sector. Service quality is measured in private sector by this way. However, it is an obligation to serve each demand in public sector. This paper have presented single stage model for capacitated facility (drone sites) locations then, assigning drones to these drone sites and lastly assigning demands to drones which assigned to the drone sites. Maximum coverage model have been used to form mathematical model and also a greedy heuristic method has been developed in order to have more efficient results. [14]

Response time of a demand is the most critical issue in medical sector. There has been many researches have been conducted to reduce response time of medical staff (ambulances) to reach on patient side. The reason for that, fast intervene to the patient is very important for several cases such as “cardiac arrests”. Recent years drones have been started to use several areas like surveillance, transportation goods, medical supplies and medical equipment. One of the breakthrough invention was placing external defibrillator on drone. However, a drone have limited range of accessibility due to the battery life. So, overcome to this issue, backup service approach has been adopted from this paper. This paper developed a model to provide continuous service for demand sites. Model essential have two objective function. First one is, primarily covers all the demand and second one is, covers all demands that have been appeared while primary objective processing. In other words, second objective stands here as backup service to first objective. Moreover, number of drones also located in model as well. [15]

Healthcare facility locations (HCF) has been a part of operation researchers for so many years. Since it is strategic decision for public services many comprehensive studies have been conducted on this issue. However, review papers that have been published so far were insufficient. This paper has been conducted vast research for HCF and classified different types HCF problems as emergency and non-emergency types. Also, detailed tables have been created with ten descriptive dimensions. Usual problem models like p-median, p-center, set covering and maximum covering models have been discussed. Then, at the end future research suggestions have been discussed. [17]

Search and rescue operations (SAR) get used for rescue people who need help at sea. Therefore, it is very important to organize these operations smoothly since the people lives depending on it. This paper have been proposed a model to allocate SAR helicopter to the incident location in order minimize total response time of incident. Model also considered helicopter types which means that according to the type of incident (evacuation, fire, search etc.) helicopter type (Fire helicopter, Emergency Helicopter etc.) changes as well. What is more, historical incident data which has been collected from Aegean Sea region is used. Another thing to mention is helicopter stations. Since these stations already existed, proposed model have used these locations for helicopters. These stations can be active or passive according to incident location. Such as, if a station is close to incident location immediately this station is become active and SAR helicopter uses this station in order to aid to people who are at incident site. In order to create the model both ILP and simulation (MATLAB) have been used. [18]

Responsiveness is very for important hospitals so, healthcare institution has an obligation to be efficient and effective since human life is depending on it. Emergency Medical Service (EMS) duties are to give best service possible to the patients at limited time. This paper have been investigated EMS of Belo Horizonte, Brazil. Two modelling technique have been used to solve the problem which are optimization and simulation. Problem has hospitals and ambulance bases. These bases have been located all around city without any scientific assumptions. There are hospitals as well. Ambulances were dispatching from these basis to patient then, going to the hospitals and drop out the patient. Location of optimized ambulance bases and allocation of ambulances have been determined from optimization model. Then, according to the optimize configuration a simulation have been conducted. For optimization ILP have been used. [21]

Studies which are related to p-center problems, p-median problems and maximum covering problems are given below.

In this paper, researchers have tried to optimize facility locations according to demand. Main motivation of authors is optimizing emergency service locations. Well known problems like p-median, p-center and maximum coverage problems have been used. Researchers have been declared three objectives to achieve in order the find the pareto-optimal solution for this problem. These objectives are, minimizing nearest distance between demand and nearest facility, maximizing the covered demand nodes and minimize the maximum distance. This paper presented all the mathematical formulations and proposed an iterative heuristic method and compared the results at the end. [2]

Location-routing problem with time windows is deal with deciding depots locations, then allocating remaining nodes to these depots and finally determining the routes under specified time windows. It is assume that capacity of facilities and vehicles are limited. Moreover, a fixed cost considered to open a depot and buying a vehicle. In this paper, considered samples are from 5 nodes to 50 nodes. Location of candidate depots have been determined by a method called “Labelling”. Routing part have been solved by branch and price algorithm which is based on set portioning approach. At the end, prosed method calculates better results in small and medium cases. [3]

An Emergency Service System can be anything. Such as, a hospital if it is for medical purpose or a police station if it is for security purpose. For both cases, purpose is response to an emergency. Emergency Service System (ESS) problems may have two different objectives minimizing time to satisfy a demand node or minimizing the distance between nearest facility and demand node. In this paper, it is assumed that capacity for satisfying a demand for facility is capacitated. Problem that authors ask starts from here. In real life it is possible to a demand cannot be satisfied from nearest facility, sometimes response capacity of nearest facility already full, in that case a backup service for this demand node has to be provided. In this paper, a general p-median problem adapted according to the case which back-up services involved. [4]

In this paper have done a large survey about facility location models (FCM) and solution methods. Authors have been provided many references about FCM along with p-center and p-median problems. Objective function of any FCM have been classified as minsum or minmax in literature mainly. This paper also said that, any model which don't have capacity constraint have no restriction to allocate demand. Moreover, It has been discussed that p-center problem and ability to transform various covering problem. [5]

A GIS approach; Bike users were increasing day by day in largely populated urban areas. The reason of this is highly intensive car using thus, local authorities and governments have taken actions in order to increase bike using even more. Because of this fact, bike-sharing programs were applying for years. Population, social activities, closeness to public transportation station etc. are the key factors to establish any bike stations to the urban areas. This paper have been used ARC-GIS 10 software in order to determine spatial distribution of latent demand for trips, decided stations locations by using facility location models in ARC-GIS 10 software and lastly defined demand's for stations by considering characteristics. Objective here minimize impedance and maximize coverage to find the final locations of stations. Facility location models that have been used here are P-median and Maximum Covering models. [6]

Facility location optimization mostly have been targeted to minimize cost of production and distribution especially in private sector. However, public facility decision not always taken by under these circumstances. The reason for that unlike private sector, governments have obligation to provide all possible services to citizens. Such as, building a hospital, fire department or police station. Since the governments have less resources than private sectors, all of these facilities have to provide their services at maximum level to citizens. In that point, maximum covering location problem have been born. Objective of this paper is to decide facility locations under the condition of maximizing the covered nodes (which represents population, importance, weight etc.). This problem have been mathematically presented in this paper and have been a guide for many academician within the years. [7]

Public facility (Hospitals, Schools, Police stations etc.) location decisions have been discussed for many years. Reducing the overall average distance that potential users to travel in order to reach to desired facility may not always correct for deciding public facility locations. Reducing the total or average distance tends to favor customers clustered in populated centers over the ones dispersed in node space. That is why p-center problem have been emerged. This paper have been presented about large surveys about p-center problem also have been presented original model of Daskin and what is more, Several variants of p-center problems have been presented as well. Such as, capacitated p-Center problem, conditional p-Center problem, continuous p-Center problem and the p-Center problem with uncertain parameters. Lastly, some future research directions have been presented as well for new researchers who want to work with this problem type. [8]

Location Routing Inventory Problem with Transshipment (LRIP-T) is unity of three items of supply chain namely facility-allocation, vehicle routing (VRP) and inventory management problems. Transshipment process occurs under these there three items. Thus, cost of the system itself and overall operation time are minimized. In this study, N customer nodes have been defined and these points have been settled as passive transshipment points. More, they have ability to be an active transshipment point based surplus quantity of product which they hold. So, by this way when a customer have needed product ASAP. One of the points becoming active and satisfy the customer. P-center model have been used to make customer points to possible transshipment point. Moreover, results have been compared with existed models before and found that this model is more efficient. [9]

Network designers try to minimize maximum (valued) interaction time or length which travelled in existing or new networks for transportation and telecommunication applications. This problem which have been defined considered as p-hub center problem. This paper have been interested on p-hub center problem. A single-relocation heuristic algorithm developed for p-hub center problem and results have been compared with existing literature example. Also, tabu search method have been used while the creation of algorithm. [10]

Humanitarian logistics is one of the major problem in today’s world. Poor counties were suffering from food, water or pharmaceutical shortages. Although help stations were serving the people who need help, distribution of goods still is a problem. Most of the help stations are working self-service. In other words, people need to visit the station in order to obtain necessary goods. However, building help stations everywhere is not possible due to its cost, geography etc. This paper mainly focuses on solving this distribution problems of help stations. Authors proposed a solution method which consisting people (demand) who visit help stations. People who has more accessibility to help stations have been involved to the distribution of goods. Authors called them “cooperatives”. These cooperatives acting as intermediate facilities and helping the original facilities to reach people who has no accessibility to original facility. Next, cooperatives after collected their goods from facility then, collected goods for people who were living far away the facility. However, these cooperatives only serves people who are close to their region. Four different location problem have been modelled and all four of them have median and covering objectives. Also, a nonlinear model have been used for cooperation price. [13]

An Annotated Bibliography; P-median problem is a network problem. Problem first appeared at 17^{th} century by Fermat. Early version of problem consisted 3 points in plane. Fermat has tried minimize to minimize distances between point and median for all three points. Next, Weber has been worked with same problem at early 20^{th} century by adding weights to the points. Then, he has converted to this problem a real life example. Objective of this problem converted to facility-allocation problem to satisfy demand by using median point. Hakimi has proved that optimum solution of this problem has to be lie on edges of feasible solution space by graph theory. This paper has been done a survey on p-median problem. Many of the researchers’ papers which related to p-median problem have been presented. Moreover, p-median problem model also have been presented and explained. [16]

Hierarchal facility network problems have been discussed in literature widely. This paper mainly focus on Multiple Location of Transfer Points (MLTP) and Facility and Transfer Points Location Problem (FTPLP). In this particular problem types, each of the demand nodes go one of facilities or through one of the transfer points in order receive services. In this paper, MLTP uses p-median model in order to determine locations of facilities and transfer points and minimize traveling time of a customer. Then, locations which has been found at MLTP again used in FTPLP problem in order to minimize total summation of traveling time of a customers. Test instances which has been conducted were between 100 to 900 nodes. Moreover, an exact solution have been found at the end. [19]

Location problems have been widely studied at operational research discipline. Creating a balance between service quality and efficiency was challenging since the beginning of the location problems. However, set up a large number of facilities on service network enhances availableness and responsiveness of an existing demand but at the same time operational costs (fixed costs) increases as well. So, there is a dilemma here. Because, setting up less number facilities would decrease availableness and responsiveness of an existing demand. Thus, customer satisfaction also would decrease as well. This paper proposes three different location models as indicators of locational performance in order to balance between service level and efficiency of service network. Models that has been used are; set covering model for availability, maximum covering model for measuring efficiency and lastly p-median model for to observe responsiveness. Also a real life case (Narvik Postal Office) has been optimized with created models and possible facility location has been determined. Problem Solver of MS Excel has been used for experimentation. [20]

Location of facilities and transfer points have been discussed in this paper. Customers (demand) use these transfer and facility sites as collecting point. Such as; emergency service system. In a most common scenario, patients are carried to an emergency service chopper site (transfer point) with an ambulance and from there transported to a hospital (facility). Model which was developed consists multiple transfer points and one facility. Multiple location transfer points (MLTP) and facility and transfer points location problem (FTPLP) are discussed literature. This paper used one of the models in literature and developed heuristics algorithm to find best one to recommend readers. [22]

Chapter 3

PROBLEM DEFINITIONS AND THE PROPOSED METHODS

3.1 Problem Definitions

Let N be set of the nodes representing demand points and alternative facility locations. Let p be number of the facilities that will be located, m is the number of the service units ($p < |N|$, $m \geq p$). D_{ij} is the distance traveled (or time spent) for satisfying demand of point j by the facility located at node i. The first type of the considered problems is to determine (i) locations of p facilities, (ii) allocations of m service units to the facilities and (iii) assignments of demand nodes to the service units in order to minimize the maximum total distance traveled (or time spent) by a service unit.

In addition the previous settings let w_j be the weight of the demand node j, and DL be the maximum total distance that can be traveled (or time spent) by a service unit. The second type of the considered problems is to determine (i) locations of p facilities, (ii) allocations of m service units to the facilities, (iii) subset of the nodes that will be satisfied and (iv) assignments of these demand nodes to the service units in order to maximize the total weight of the satisfied demand nodes such that DL limit is not violated by any service unit.

If m is equal to $|N|$ then each demand node can be assigned to a different service unit. (If m is bigger than $|N|$ then ($|N|$-m) of the service units can be dropped from the problem because they will be idle in any solution.) Hence, since there is a one-to-one correspondence between the demand nodes and the service units in such a case, the decisions related with the service units reduces from the considered problems. The first type of the problem reduces to a problem where it is needed to determine (i) locations of p facilities and (ii) assignments of demand nodes to the facilities in order to minimize the maximum distance (or travel time) between a demand node and its facility. This problem is the well-known p-center problem. Thus, the first type of the considered problems is the p-center problem with a distribution capacity. Similarly, the second type of the problem reduces to a problem where it is needed to determine (i) locations of p facilities, (ii) subset of the nodes that will be satisfied and (iii) assignments of these demand nodes to the facilities in order to maximize the total weight of the satisfied demand nodes such that the distance (or travel time) between any of these nodes and its facility is not more than the DL limit. This problem is the well-known maximum covering problem. Thus, the second type of the considered problems is the maximum covering problem with a distribution capacity.

3.2 The Proposed Solution Methods

3.2.1 Mixed Integer Programming Models of the Problems

In order to solve the problems mixed integer programming (MIP) models of the problems are developed and first one is; *MIP model of the p-center problem with a distribution capacity* and definitions of the decision variables are given below.

$$x_{ijk} = \begin{cases} 1 & \text{if demand node } i \text{ is assigned to service unit } k \text{ at the facility located at node } j \\ 0 & \text{otherwise} \end{cases}$$

$$z_{jk} = \begin{cases} 1 & \text{if service unit } k \text{ is given to the facility located at node } j \\ 0 & \text{otherwise} \end{cases}$$

$$y_j = \begin{cases} 1 & \text{if a facility is located at node } j \\ 0 & \text{otherwise} \end{cases}$$

MD: maximum total distance (or time) traveled by a service unit

The MIP model of the problem is then,

$$\min MD \tag{1.1}$$

$$s.t.$$

$$\sum_{j \in N} y_j = p \tag{1.2}$$

$$\sum_{j \in N} z_{jk} = 1 \qquad k = 1,...,m \tag{1.3}$$

$$\sum_{j \in N} \sum_{k=1}^{m} x_{ijk} = 1 \qquad \forall i \in N \tag{1.4}$$

$$z_{jk} \leq y_j \qquad \forall j \in N; k = 1,...,m \tag{1.5}$$

$$x_{ijk} \leq z_{jk} \qquad \forall i, j \in N; k = 1,...,m \tag{1.6}$$

$$x_{ijk} \leq y_j \qquad \forall i, j \in N; k = 1,...,m \tag{1.7}$$

$$\sum_{i \in N} \sum_{j \in N} D_{ij} x_{ijk} \leq MD \qquad k = 1,...,m \tag{1.8}$$

$$MD \geq 0 \tag{1.9}$$

$$y_j \in \{0,1\} \qquad \forall j \in N \tag{1.10}$$

$$z_{jk} \in \{0,1\} \qquad \forall j \in N; k = 1,...,m \tag{1.11}$$

$$x_{ijk} \in \{0,1\} \qquad \forall i, j \in N; k = 1,...,m \tag{1.12}$$

In this model, the objective function is the minimization of the maximum total distance (or time) traveled by a service unit. Constraint (1.2) ensures locating *p* facilities. Constraint (1.3) guarantees that each service unit is given to a single facility. Constraint (1.4) guarantees that each demand node is assigned to a service unit. According to constraint (1.5) any service unit can be given to a facility at a node only if there is a facility there. According to constraint (1.6) any demand node can be assigned to a service unit at a facility only if that service unit is given to that facility. According to constraint (1.7) any demand node can be assigned to a service unit at a facility only if there is a facility there. Constraint (1.8) guaranties that the maximum total distance (or time) traveled by a service unit cannot be less than the total distance (or time) traveled by any of the service units. The remaining constraints determine the domains of the decision variables. Second model is: *MIP model of the p-center problem* and Definitions of the decision variables are given below.

$$x_{ij} = \begin{cases} 1 & \text{if demand node } i \text{ is assigned to the facility located at node } j \\ 0 & \text{otherwise} \end{cases}$$

$$y_j = \begin{cases} 1 & \text{if a facility is located at node } j \\ 0 & \text{otherwise} \end{cases}$$

MD: maximum total distance (or time) between a demand node and its facility

The MIP model of the problem is given below.

$$\begin{array}{llr}
\min MD & & (2.1) \\
s.t. & & \\
\sum_{j \in N} y_j = p & & (2.2) \\
\sum_{j \in N} x_{ij} = 1 & \forall i \in N & (2.3) \\
x_{ij} \le y_j & \forall i, j \in N & (2.4) \\
D_{ij} x_{ij} \le MD & \forall i, j \in N & (2.5) \\
x_{ij} \in \{0,1\} & \forall i, j \in N & (2.6) \\
MD \ge 0 & & (2.7) \\
y_j \in \{0,1\} & \forall j \in N & (2.8)
\end{array}$$

In this model, the objective function is the minimization of the maximum distance (or time) between a demand node and its facility. Constraint (2.1) ensures locating *p* facilities. Constraint (2.3) guarantees that each demand node is assigned to a single facility. According to constraint (2.4) any demand node can be assigned to a facility at a node only if there is a facility there. Constraint (2.5) guaranties that the maximum distance (or time) between a demand node and its facility cannot be less than the distance (or time) between any demand node and its facility. The remaining constraints determine the domains of the decision variables. Third model is: *MIP model of the maximum covering problem with a distribution capacity* and definitions of the decision variables are given below.

$$x_{ijk} = \begin{cases} 1 & \text{if demand node } i \text{ is assigned to service unit } k \text{ at the facility located at node } j \\ 0 & \text{otherwise} \end{cases}$$

$$z_{jk} = \begin{cases} 1 & \text{if service unit } k \text{ is given to the facility located at node } j \\ 0 & \text{otherwise} \end{cases}$$

$$y_j = \begin{cases} 1 & \text{if a facility is located at node } j \\ 0 & \text{otherwise} \end{cases}$$

The MIP model of the problem is the following.

$$\max \sum_{i \in N} \sum_{j \in N} \sum_{k=1}^{m} w_i x_{ijk} \tag{3.1}$$

$$s.t.$$

$$\sum_{j \in N} y_j = p \tag{3.2}$$

$$\sum_{j \in N} z_{jk} = 1 \qquad k = 1,\dots,m \tag{3.3}$$

$$\sum_{j \in N} \sum_{k=1}^{m} x_{ijk} \le 1 \qquad \forall i \in N \tag{3.4}$$

$$z_{jk} \le y_j \qquad \forall j \in N; k = 1,\dots,m \tag{3.5}$$

$$x_{ijk} \le z_{jk} \qquad \forall i, j \in N; k = 1,\dots,m \tag{3.6}$$

$$x_{ijk} \le y_j \qquad \forall i, j \in N; k = 1,\dots,m \tag{3.7}$$

$$\sum_{i \in N} \sum_{j \in N} D_{ij} x_{ijk} \le DL \qquad k = 1,\dots,m \tag{3.8}$$

$$x_{ijk} \in \{0,1\} \qquad \forall i, j \in N; k = 1,\dots,m \tag{3.9}$$

$$y_j \in \{0,1\} \qquad \forall j \in N \tag{3.10}$$

$$z_{jk} \in \{0,1\} \qquad \forall j \in N; k = 1,\dots,m \tag{3.11}$$

In this model, the objective function is the maximization of the total weight of the satisfied demand nodes. Constraint (3.2) ensures locating p facilities. Constraint (3.3) guarantees that each service unit is given to a single facility. Constraint (3.4) guarantees that each demand node can be assigned to at most one service unit. According to constraint (3.5) any service unit can be given to a facility at a node only if there is a facility there. According to constraint (3.6) any demand node can be assigned to a service unit at a facility only if that service unit is given to that facility. According to constraint (3.7) any demand node can be assigned to a service unit at a facility only if there is a facility there. Constraint (3.8) guaranties that the total distance (or time) traveled by a service unit cannot be more than *DL* unit. The remaining constraints determine the domains of the decision variables. The last model is: *MIP model of the maximum covering problem* and definitions of the decision variables are given below.

$$x_{ij} = \begin{cases} 1 & \text{if demand node } i \text{ is assigned to the facility located at node } j \\ 0 & \text{otherwise} \end{cases}$$

$$y_j = \begin{cases} 1 & \text{if a facility is located at node } j \\ 0 & \text{otherwise} \end{cases}$$

The MIP model of the problem is then,

$$\max \sum_{i \in N} \sum_{j \in N} w_i x_{ij} \tag{4.1}$$

$$s.t.$$

$$\sum_{j \in N} y_j = p \tag{4.2}$$

$$\sum_{j \in N} x_{ij} \leq 1 \qquad \forall i \in N \tag{4.3}$$

$$x_{ij} \leq y_j \qquad \forall i, j \in N \tag{4.4}$$

$$D_{ij} x_{ij} \leq DL \qquad \forall i, j \in N \tag{4.5}$$

$$x_{ij} \in \{0,1\} \qquad \forall i, j \in N \tag{4.6}$$

$$y_j \in \{0,1\} \qquad \forall j \in N \tag{4.7}$$

In this model, the objective function is the maximization of the total weight of the satisfied demand nodes. Constraint (4.2) ensures locating *p* facilities. Constraint (4.3) guarantees that each demand node can be assigned to at most facility. According to constraint (4.4) any demand node can be assigned to a facility at a node only if there is a facility there. According to constraint (4.5) any demand node *i* can be assigned to the facility at node *j* only if D_{ij} is not more than the given limit *DL*. The remaining constraints determine the domains of the decision variables.

3.2.2 Heuristic Methods

A heuristic approach is developed in order to find good solutions to large problem instances in short times. The approach separates and solves the entire problem in two levels. In the first levels the locations of the facilities are determined without considering the distribution capacities. In the second level, the facility locations are fixed to the locations found in the first level and the remaining part of the entire problem (*i.e.*, determining the allocations of the service units to the facilities and assignments of the demand nodes to the service units) is solved for these fixed facility locations. As it is explained earlier, when the distribution capacity of the first problem cancelled the problem reduces to the *p*-center problem. Hence, the locations of the facilities are determined by solving this *p*-center problem instance in the first level of the proposed heuristic for the first type of the considered problems. Similarly, the second type of the considered problems reduces to the maximum covering problem if the distribution capacities are omitted. Therefore, this time, corresponding maximum covering problem instance is solved in order to determine the locations of the facilities in the first level of the heuristic for the second type of the problems.

Chapter 4

RESULTS

4.1 Experimental Design

Experiment have been designed and performed for seven levels of node clusters (N). N (n) = {10, 15, 20, 25, 30, 35, 40}. Each node in N represents a demand site. In addition, each n has two facility (p) and vehicles levels (m). Facility levels and vehicles are determined based on below formulas;

$$p_1 = roundup\left(\frac{n}{10}\right), p_2 = roundup\left(\frac{n}{5}\right),$$

$$m_1 = roundup\left(\frac{n}{2}\right), m_2 = roundup\left(\frac{n}{4}\right),$$

Moreover, both problems require set of distance matrices in order to be experimented. So, five different distance matrices *(Dij)* randomly created by using excel macros for every combination of n, p, m. Thus, Total number of test instances generated for problem type-1 are determined 140 (i.e. 7*2*2*5=140). However, in order to solve type-2 problem weight sets are required. Because of this, five different weight set *(Wi)* randomly created by using excel macros. First, type-1 problem test instances have been solved by using data created by excel macros. One of the data file content are represented in appendix section. Then, all 140 test instances results have been collected. Also, one of the solution file content are represented in appendix section. These solution files contains locations of facilities, allocation of service units and minimized DL values. After that, determined DL values are imported to type-2 data files by multiplying 0.6 and 0.8. By this way, type-2 model are able to make selection among demand sites. So total of test instances generated for problem type-2 are determined 280 (i.e. 7*2*2*2*5=280). One of the data and solution file content are represented in appendix section. So, total number of test instances is equal to 420 (i.e. 140+280=420).

Next, Heuristic algorithms for type-1 and type-2 are determined. P-center and maximum covering problems are solved in first level. Then, allocation of service units are distributed to facility locations which determined in first level. Then, problem solved with CPLEX. Experimentation has been conducted at Industrial Engineering department LAB3.

4.2 Type-1 problem results

In this section type-1 problem computational results are discussed. Some abbreviations must be given before result discussion. “MMT1” represents MIP model of the p-center problem with a distribution capacity. “PCM” represents MIP model of the p-center problem and “HT1” represents Heuristic Algorithm of p-center problem with a distribution capacity. MMT1 and PCM have given “optimum” solutions. However, HT1 has given “local optimum” solutions. Average solution times and objective functions are determined and presented in figures. Moreover, tables are created in order to understand results more clearly.

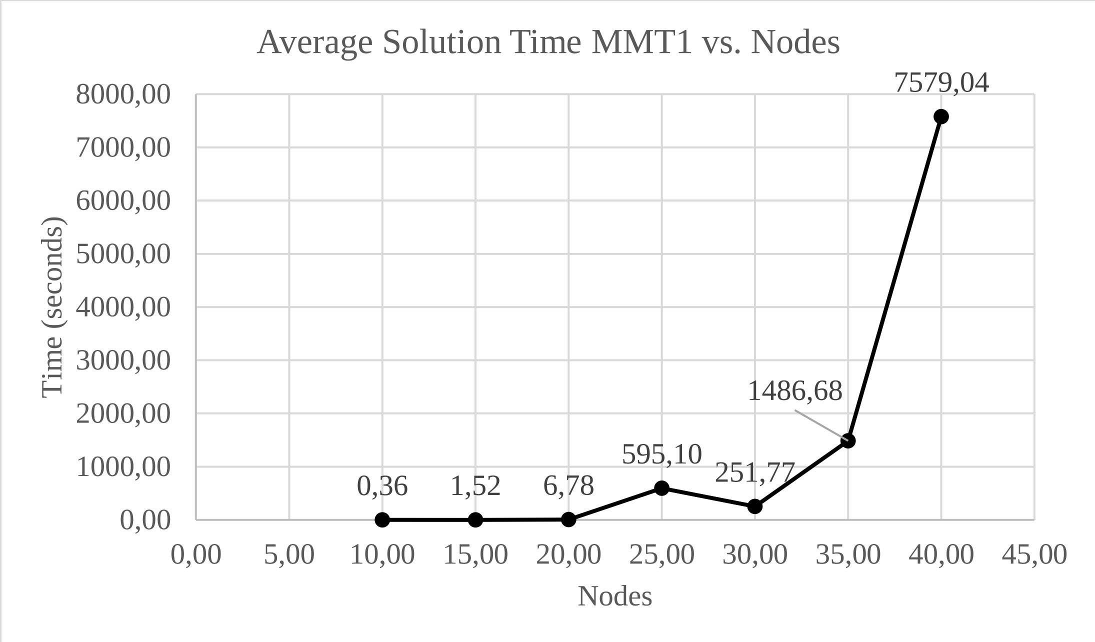

Figure 1: Average solution time of MMT1 vs. nodes

Figure 1 above shows that MMT1 solution times with respect to nodes. Such as, if n=10 then corresponding solution time is 0.36 seconds. However, if n=40 then corresponding solution time is 7579.04 seconds. This means that nodes are significantly effects on solution times. In other words, solution times increases together with nodes.

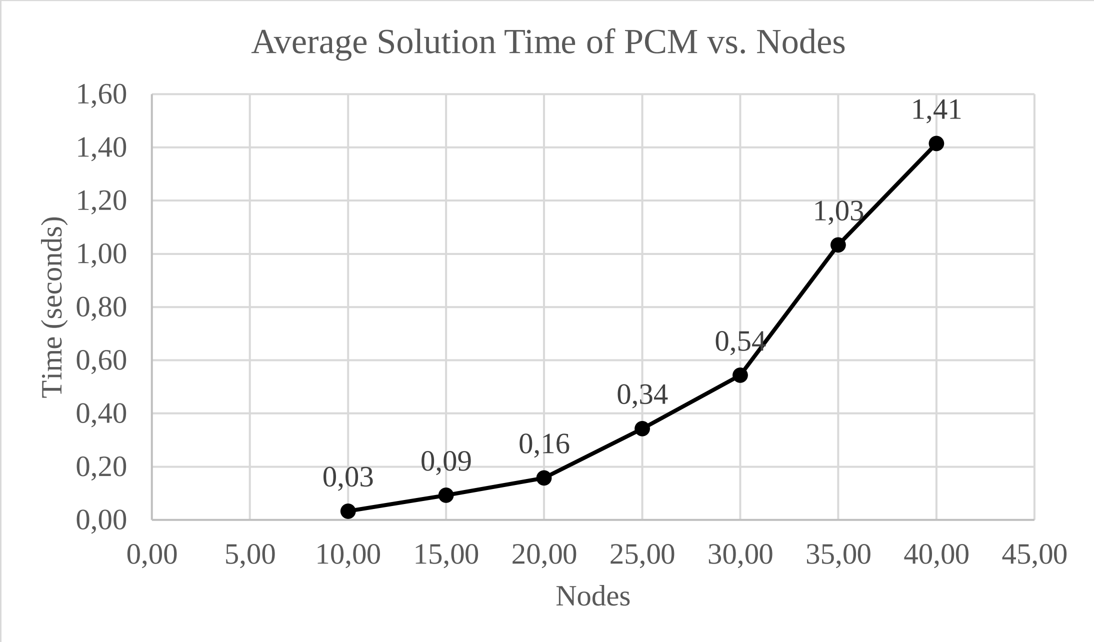

Figure 2: Average solution time of PCM vs. nodes

Figure 2 above shows that shows that PCM solution times with respect to nodes. Such as, if n=10 then corresponding solution time is 0.03 seconds. However, if n=40 then corresponding solution time is 1.41 seconds. This means that nodes are significantly effects on solution times. So, solution times increases together with nodes. In other words, more complex problems needs more time in order to be solved.

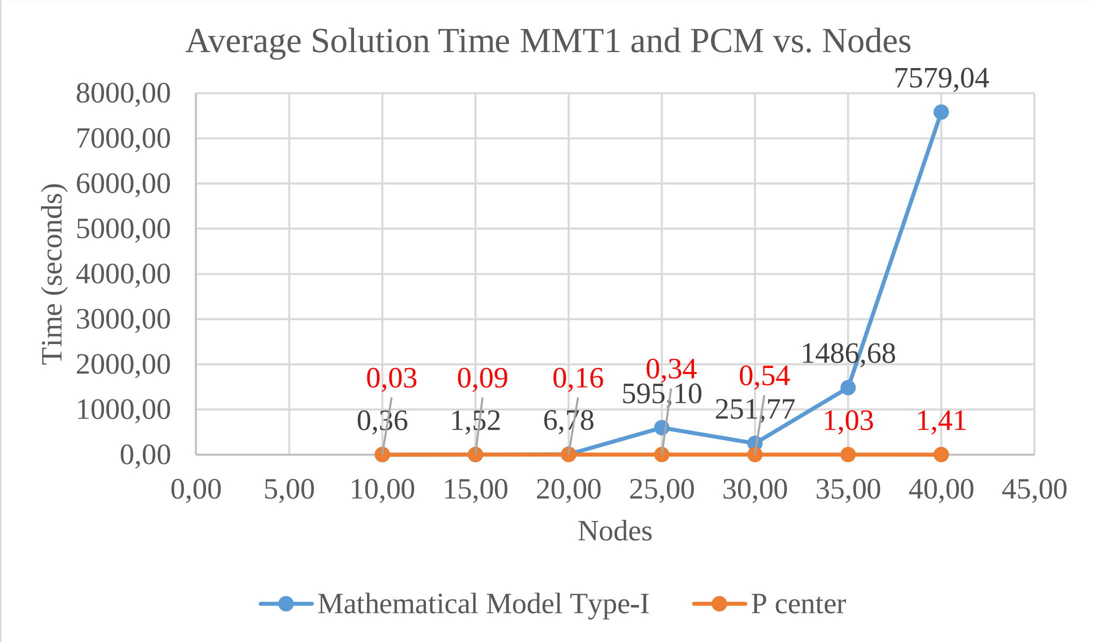

Figure 3: Average solution time of MMT1 and PCM vs. nodes

Figure 3 above shows that MMT1 and PCM solution times with respect to nodes. PCM solution times are better than MMT1. This means that, allocation of service units to the facilities makes MMT1 more complex. Because, only difference between PCM and MMT1 is service unit decisions.

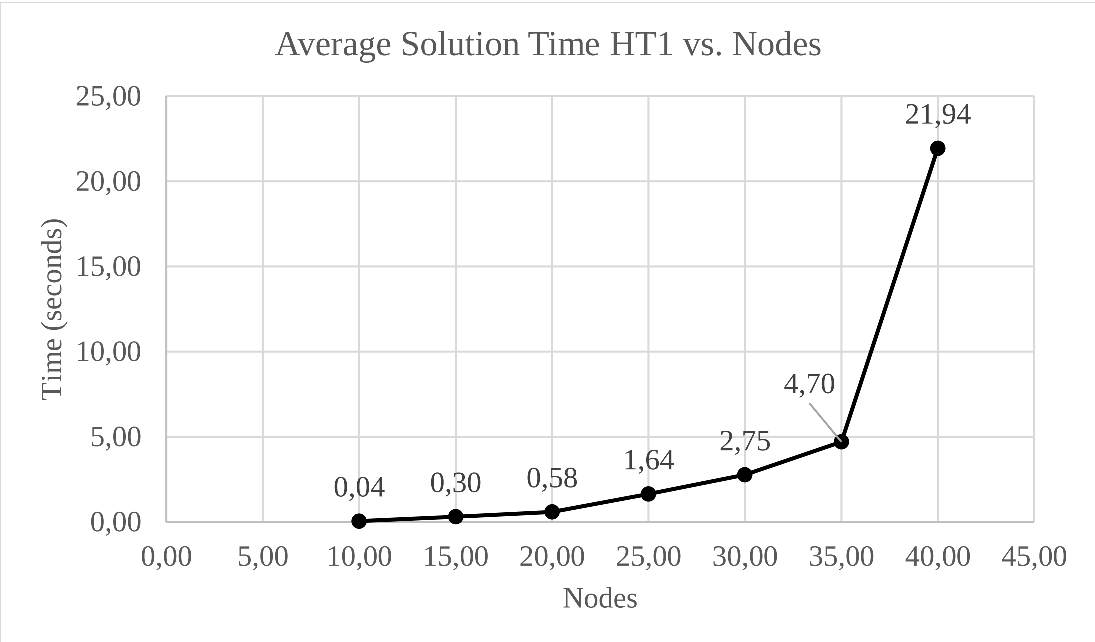

Figure 4: Average solution time of HT1 vs. nodes

Figure 4 above shows that HT1 solution times with respect to nodes. Such as, if n=10 then corresponding solution time is 0.34 seconds. However, if n=40 then corresponding solution time is 21.94 seconds. This means that nodes are one of the significant effects on solution times. Solution times are increases with nodes

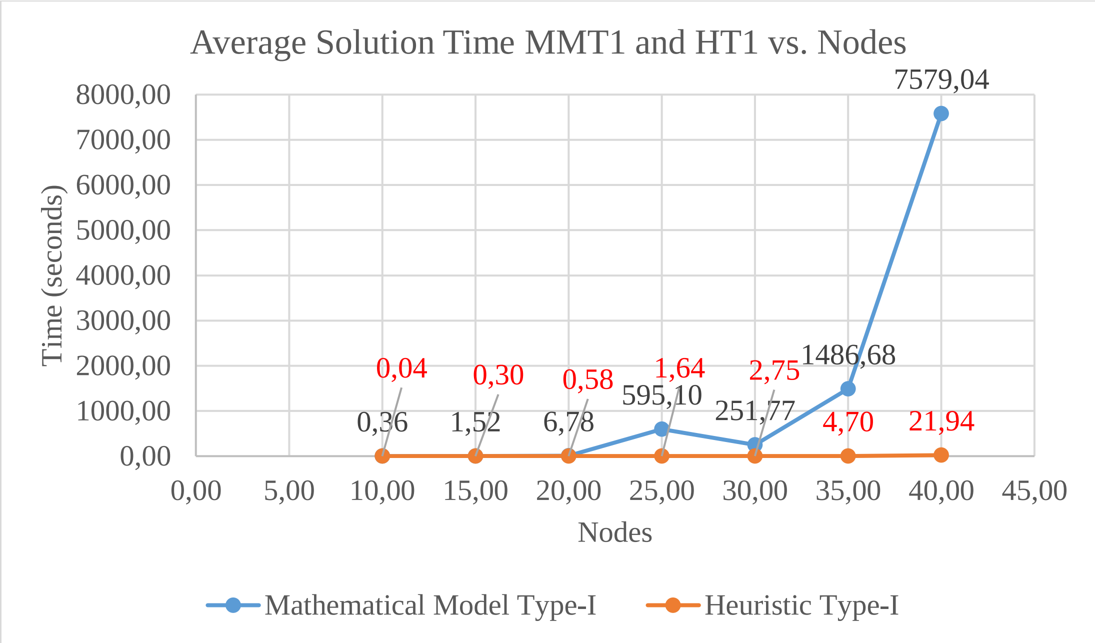

Figure 5: Average solution time of MMT1 and HT1 vs. nodes

Figure 5 above shows that MMT1 and HT1 solution times with respect to nodes. HT1 solution times are better than MMT1. This means that, HT1 is faster than MMT1 but objective function values should be compared in order to make a full comparison.

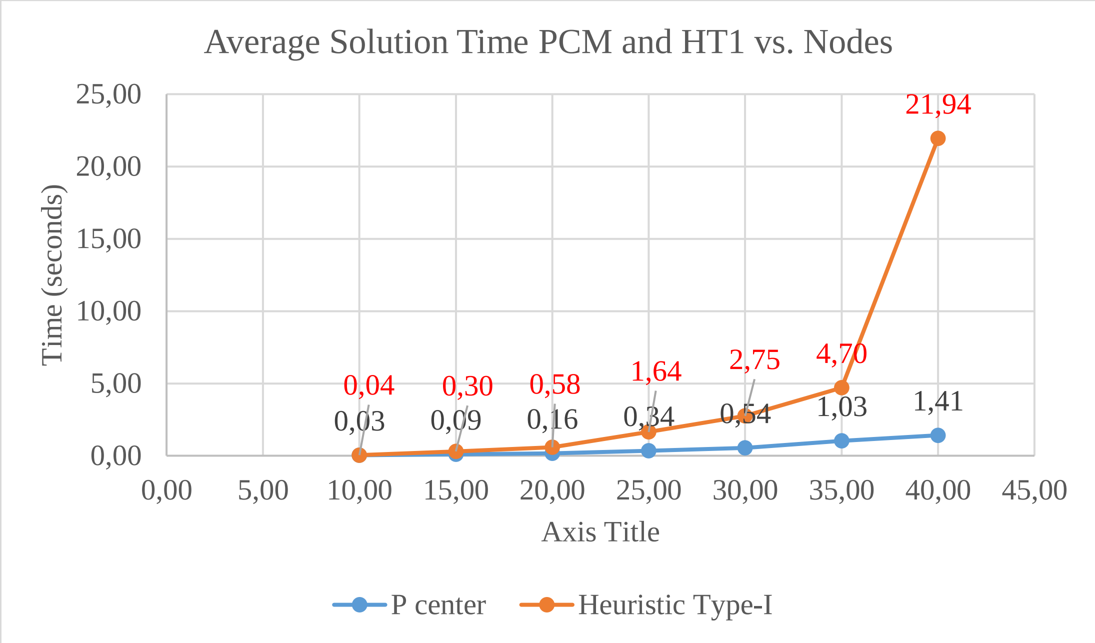

Figure 6: Average solution time of PCM and HT1 vs. nodes

Figure 6 above shows that, PCM and HT1 algorithm average computation times with respect to the node clusters. PCM solution times are better than HT1. The reason of this is actually PCM is the first level of HT1.

Average solution times of MMT1, PCM and HT1 presented in figures up to here. However, in order to make better conclusions average objective functions are determined and presented in figures.

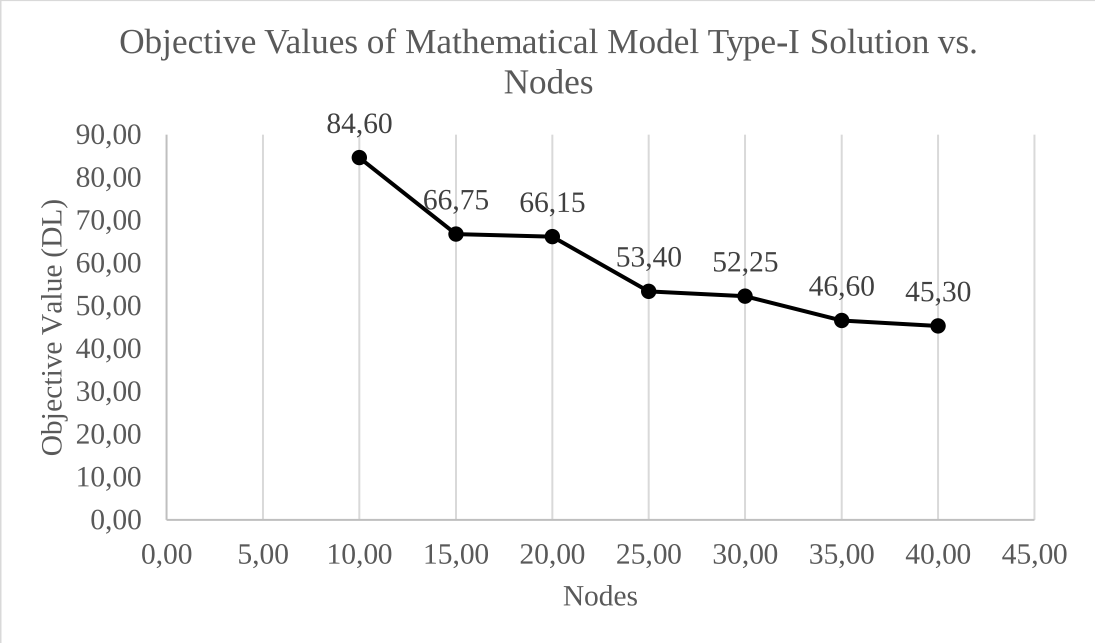

Figure 7: Average objective values of MMT1 solutions vs. nodes

Figure 7 above shows that, MMT1 objective function values (DL) with respect to the nodes. Such as, if n=10 then corresponding objective value is 84.60. However, if n=40 then corresponding solution time is 45.30. This means that nodes are one of the significant on objective values. Objective values are decreased with nodes. In other words, better objective values are obtained while nodes are increase since objective function is minimization.

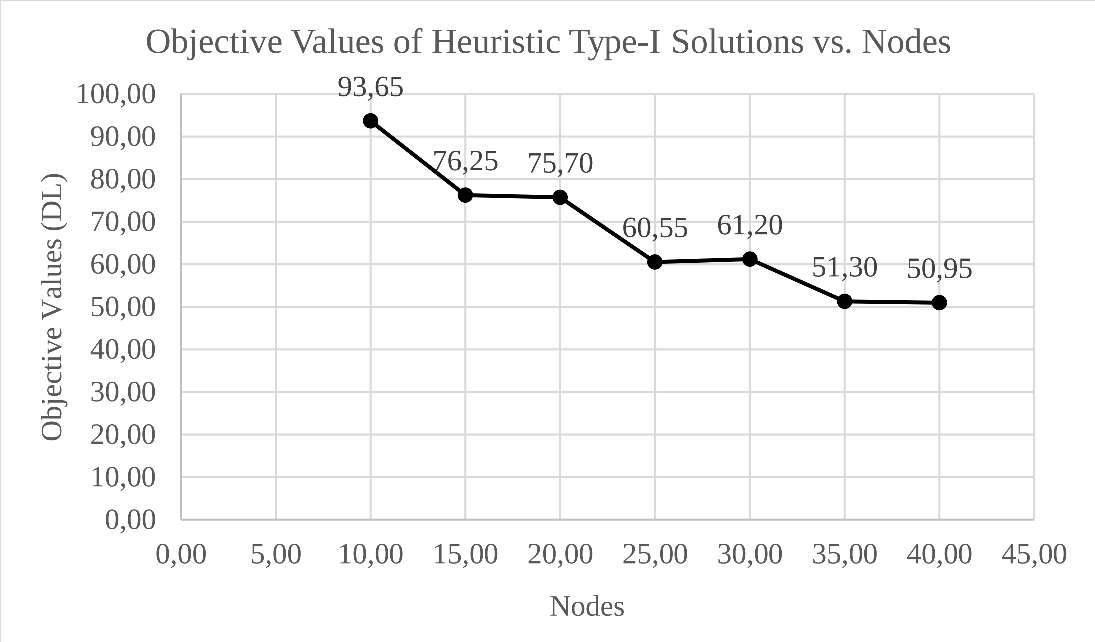

Figure 8: Average objective values of HT1 vs. nodes

Figure 8 above shows that, HT1 objective function values (DL) with respect to the nodes. Similarly, nodes are one of the significant effects on objective values. Again, objective values are decreased with nodes but obtained results are slightly worse than MMT1

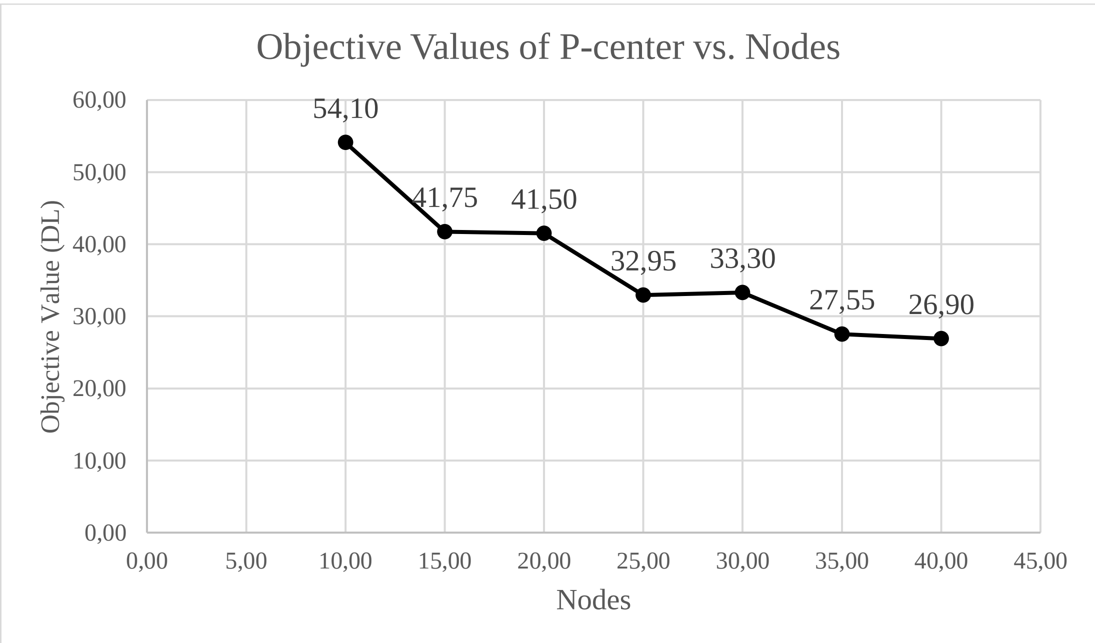

Figure 9: Average objective values of PCM vs. nodes

Figure 9 above shows that, PCM objective function values (DL) with respect to the nodes. Similarly, nodes are one of the significant effects on objective values. Again, objective values are decreased with nodes but obtained results are slightly better than MMT1 and HT1.

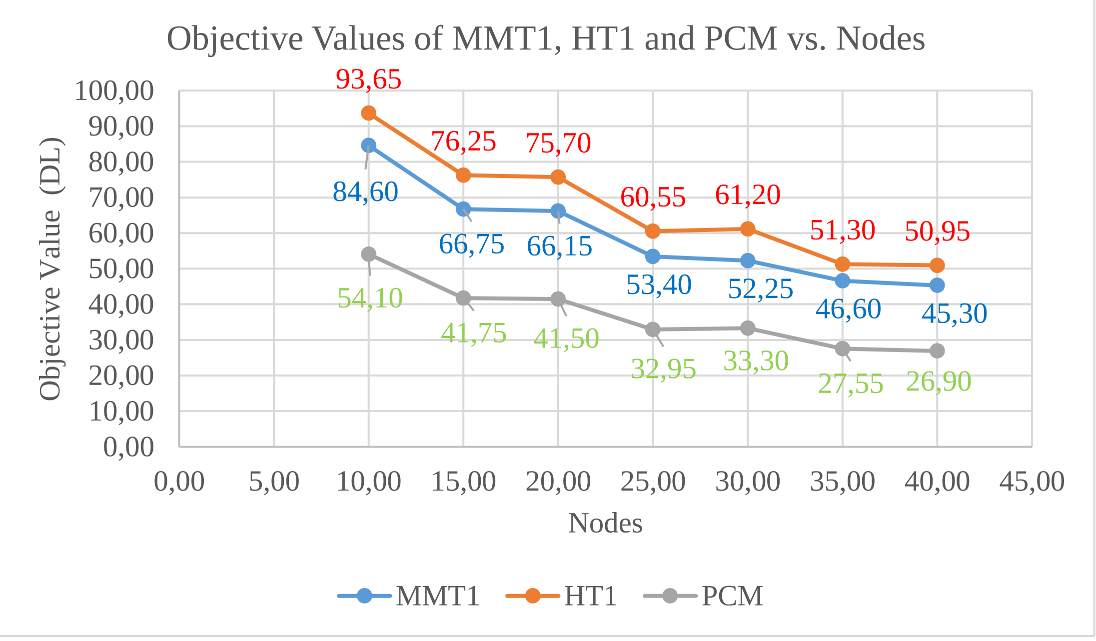

Figure 10: Average objective values of MMT1, HT1 and PCM vs. nodes

Figure 10 above shows that, MMT1, HT1 and PCM objective values (DL) with respect to the nodes. PCM alone have better objective values than MMT1 and HT1. However, PCM is only the first level of HT1. On the other hand, HT1 are given worst objective values than MMT1. This figure is proves that, facility location decisions should considered together with allocations of service units to the facilities.

Table 1 below shows that, MMT1 and HT1 objective results' relations. Averagely MMT1 objective values are %13 better than HT1. On the other hand, Averagely HT1 solution times are %94 better than MMT1.

Table 1: MMT1 and HT1 results comparison table

Nodes	Mathematical Model		Heuristic		Gap (Objective)	Gap (Time)
	Objective	Time	Objective	Time		
10	84,60	0,36	93,65	0,04	11%	-88%
15	66,75	1,52	76,25	0,30	14%	-80%
20	66,15	6,78	75,70	0,58	14%	-91%
25	53,40	595,10	60,55	1,64	13%	-100%
30	52,25	251,77	61,20	2,75	17%	-99%
35	46,60	1486,68	51,30	4,70	10%	-100%
40	45,30	7579,04	50,95	21,94	12%	-100%

Also, facility levels have been examined separately. Average solution times of facility level 1 and 2 have been computed for MMT1 and HT1.

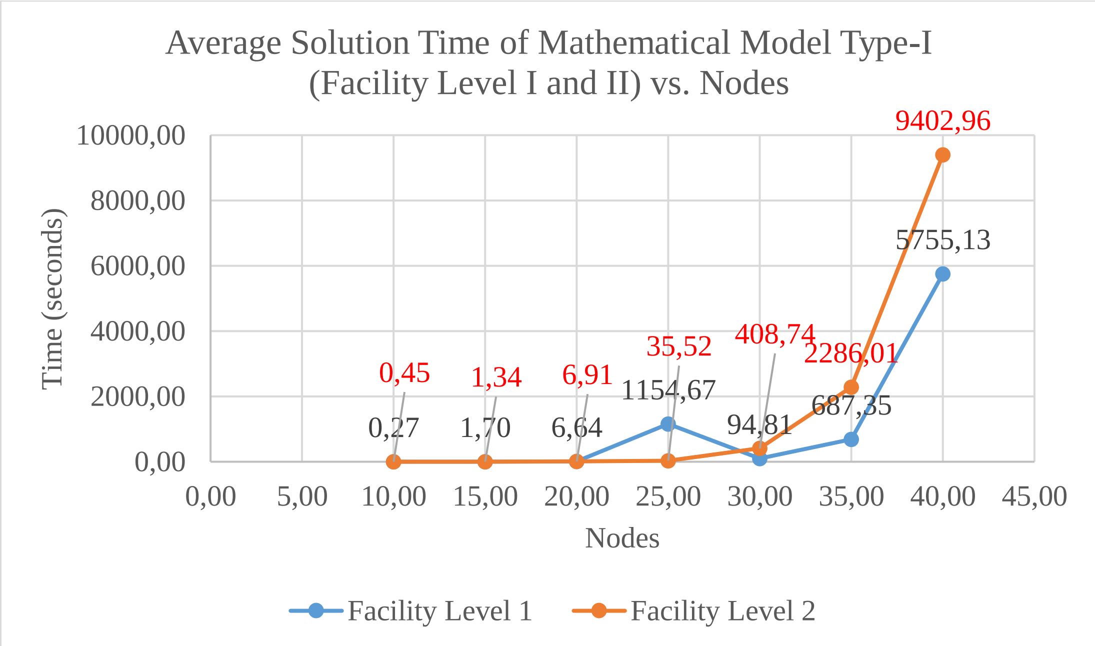

Figure 11: Average solution time of MMT1 (Facility level I and II) vs. nodes

Figure 11 above shows that, MMT1's average solution times according to facility level 1 and 2 with respect to the nodes. Unfortunately, figure 10 does not provide any conclusions because of the random ups and downs.

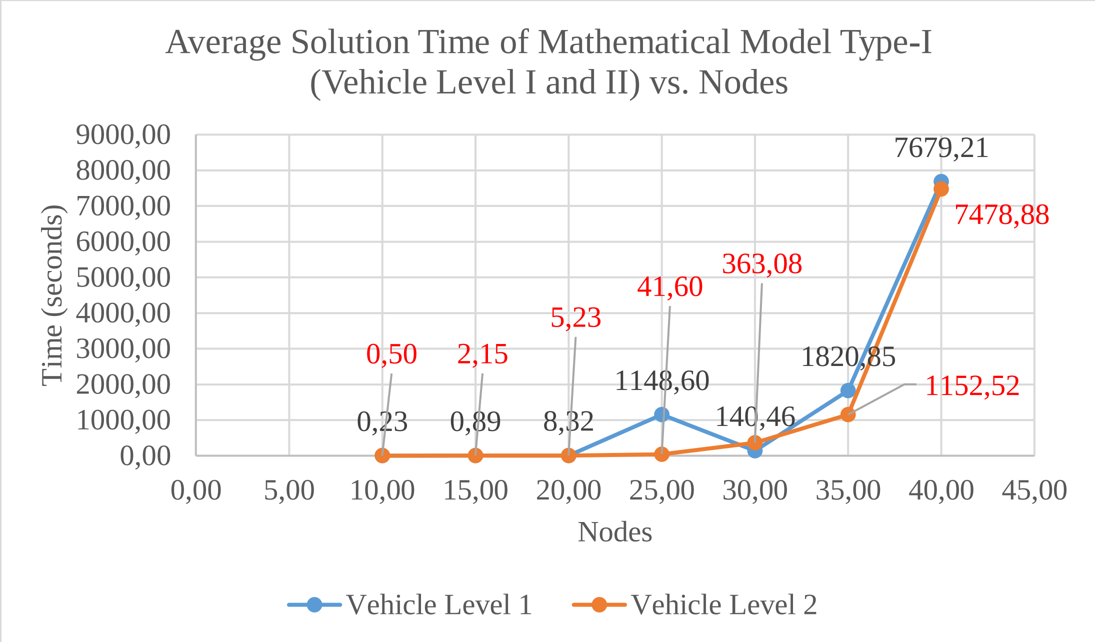

Figure 12: Average solution time of MMT1 (Vehicle level I and II) vs. nodes

Figure 12 above shows that, MMT1's average solution times according to vehicle level 1 and 2 with respect to the nodes. Lines are almost identical which means vehicle levels have no significant effect on solution time. Next, average solution time for facility and vehicle levels have been computed for HT1 algorithm.

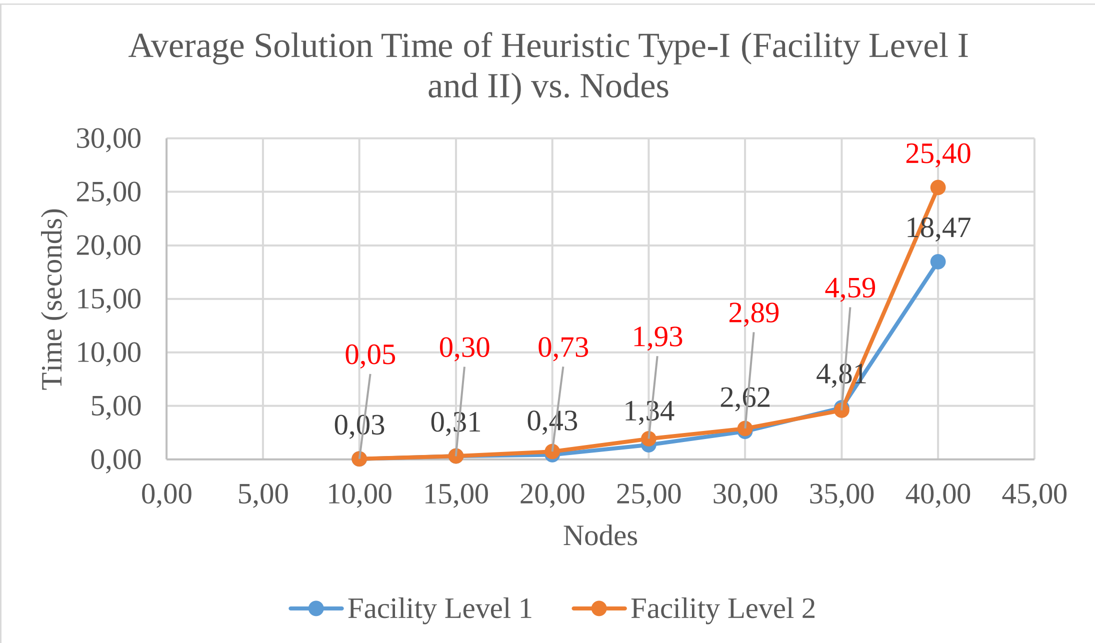

Figure 13: Average solution time of HT1 (Facility level I and II) vs. nodes

Figure 13 above shows that, HT1's average solution times according to facility level 1 and 2 with respect to the nodes. Lines are almost identical which means facility levels have no significant effect on solution time.

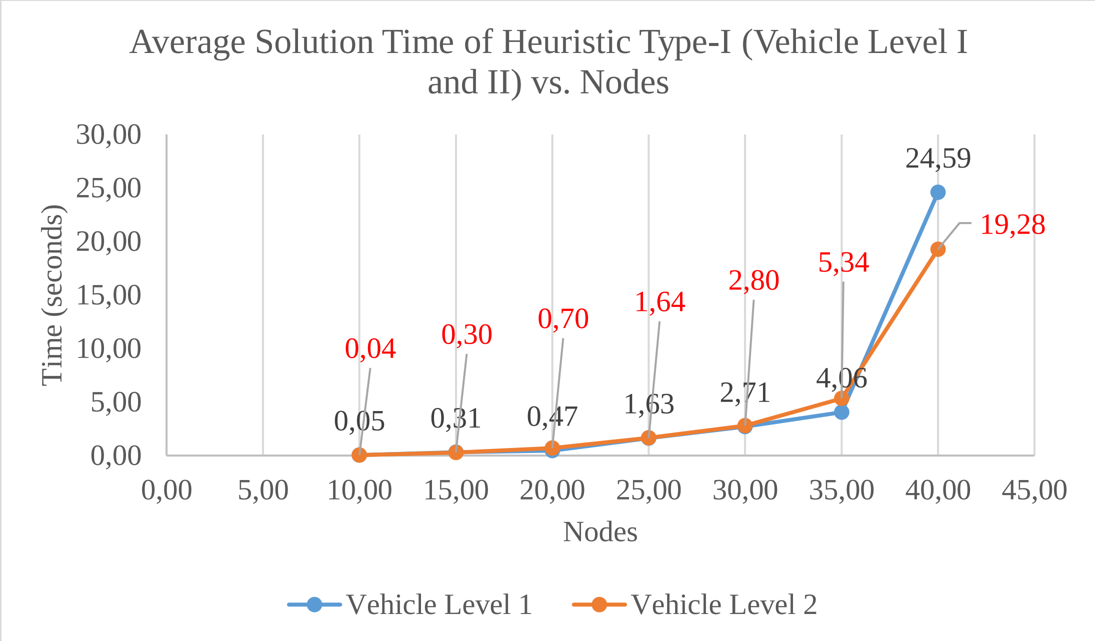

Figure 14: Average solution time of HT1 (Vehicle level I and II) vs. nodes

Figure 14 above shows that, HT1's average solution times according to vehicle level 1 and 2 with respect to the nodes. Lines are almost identical which means vehicle levels have no significant effect on solution time.

4.3 Type-2 problem results

In this section type-2 problem computational results are discussed. Some abbreviations must be given before result discussion. "MMT2" represents MIP model of the maximum covering problem with a distribution capacity. DL is a parameter in MMT2 and DL values have been taken from MMT1 results, and also multiplied with 0.6 and 0.8. So, "MMT2-0.6" represents MMT2 which has a DL value with multiplied by 0.6 and "MMT2-0.8 represents MMT2 which has a DL value with multiplied by 0.8. "MCM" represents MIP model of the maximum covering problem. Similarly DL is a parameter in MCM too and DL values have been taken from PCM results, and also multiplied with 0.6 and 0.8. So, “MCM-0.6” represents MCM which has a DL value with multiplied by 0.6 and “MCM-0.8 represents MCM which has a DL value with multiplied by 0.8. Lastly, “HT2” represents Heuristic Algorithm of maximum covering problem with a distribution capacity. Similarly “HT2-0.6” represents HT2 which has a DL value with multiplied by 0.6 and “HT2-0.8” represents HT2 which has a DL value with multiplied by 0.8.

MMT2 and MCM have given “optimum” solutions. However, HT2 has given “local optimum” solutions. Average solution times and objective functions are determined and presented in figures. Moreover, tables are created in order to understand results more clearly.

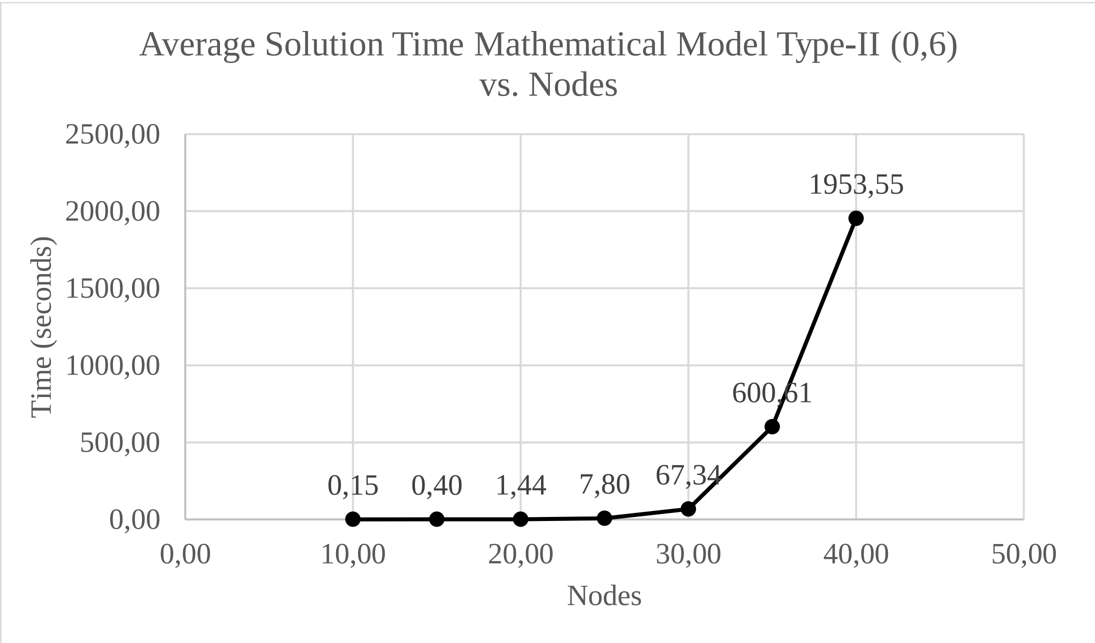

Figure 15: Average solution time of MMT2-0.6 vs. nodes

Figure 15 above shows that MMT2-0.6 solution times with respect to nodes. Such as, if n=10 then corresponding solution time is 0.15 seconds. However, if n=40 then corresponding solution time is 1953.55 seconds. This means that nodes are significantly effects on solution times. In other words, solution times are increases together with nodes.

Although MMT1 and MMT2 have different objective functions, most of the constraints are very similar. Solution time considered as one of the significant factor that makes the problem complex. So, comparing solution times' of MMT1 and MMT2-0.6 gives an idea about complexity of problems.

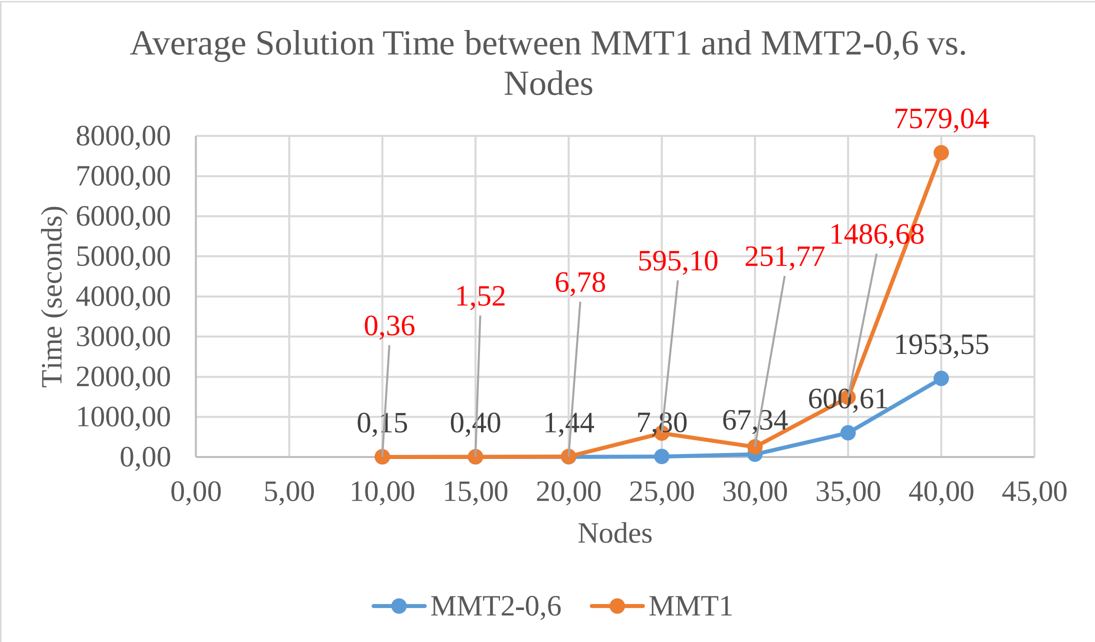

Figure 16: Average solution time between MMT1 and MMT2-0.6 vs. nodes

Figure 16 above shows that MMT1 and MMT2-0.6 average solution times with respect to the nodes. MMT1 takes more time than MMT2-0.6 to be solved. So, MMT1 is more complex problem than MMT2-0.6 because of the one constraint. MMT1 must covers all the nodes. However, MMT2 does not have this necessity.

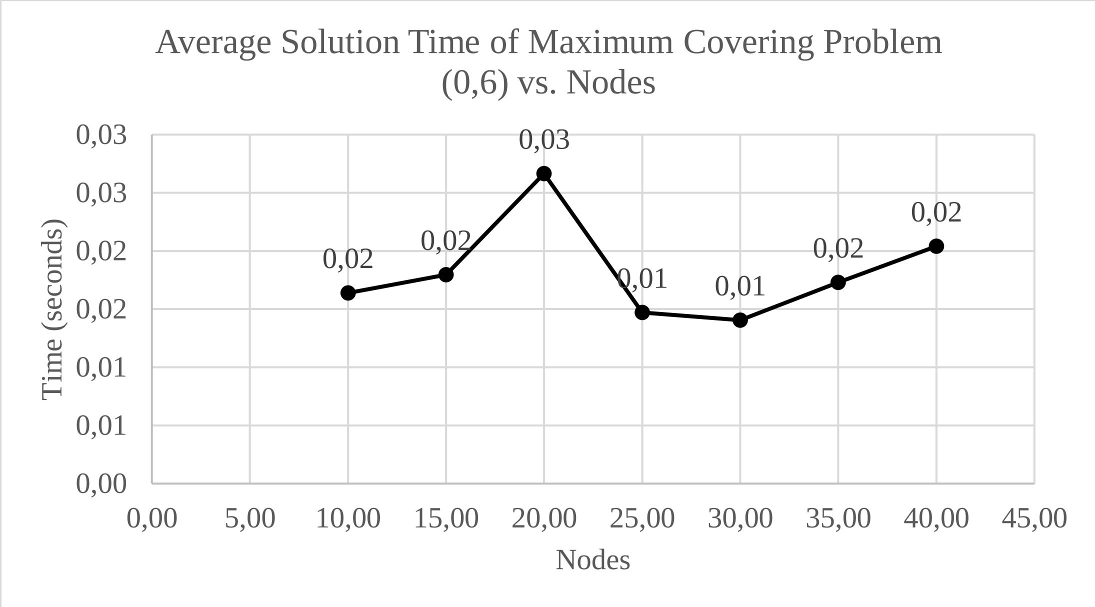

Figure 17: Average solution time of MCM-0.6 vs. nodes

Figure 17 above shows that MCM-0.6 average solution times with respect to nodes. Solution times are close to zero which means that MCM-0.6 is very fast. Major reason for that is vehicle decisions are omitted.

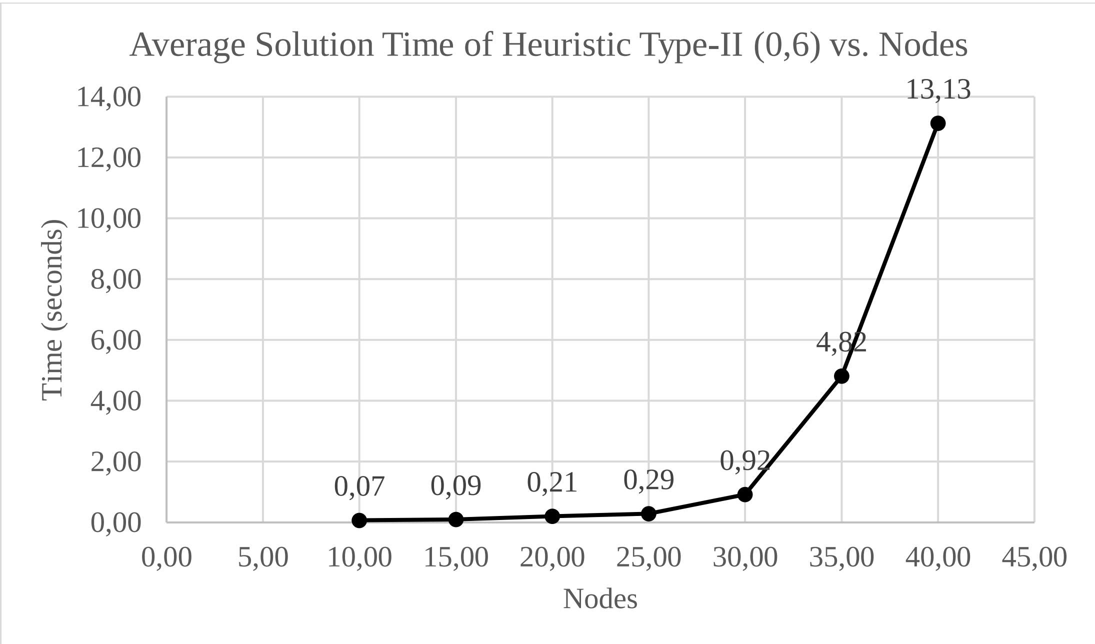

Figure 18: Average solution time of HT2-0.6 vs. nodes

Figure 18 above shows that HT2-0.6 average solution times with respect to nodes. This means that nodes are one of the significant effects on solution times. In other words, solution times are increases together with nodes. Also, MMT2-0.6 and HT2-0.6 curves are look very similar but solution times are very different than each other.

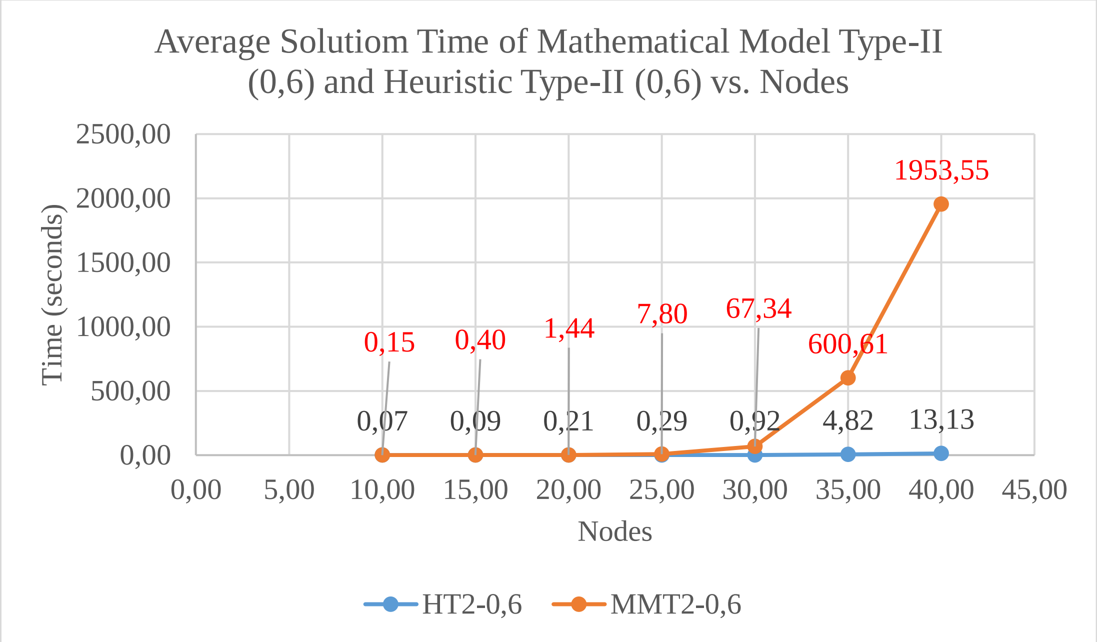

Figure 19: Average solution time of MMT2-0.6 and HT2-0.6 vs. nodes

Figure 19 above shows that MMT2-0.6 HT2-0.6 average solution times with respect to nodes. HT2-0.6 solution times are better than MMT2-0.6. This means that, HT2-0.6 is faster than MMT2-0.6 but objective function values should be compared in order to make a full comparison.

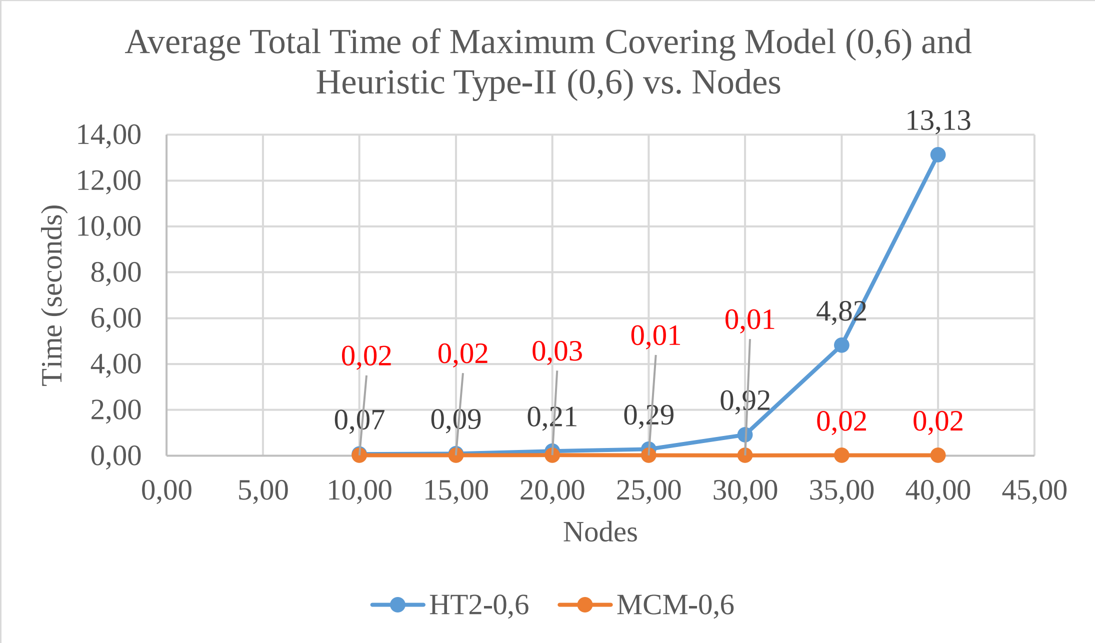

Figure 20: Average solution time of MCM-0.6 and HT2-0.6 vs. nodes

Figure 20 above shows that, MCM-0.6 and HT2-0.6 algorithm average computation times with respect to the node clusters. MCM-0.6 solution times are better than HT2-0.6. The reason of this is actually MCM-0.6 is the first level of HT2-0.6.

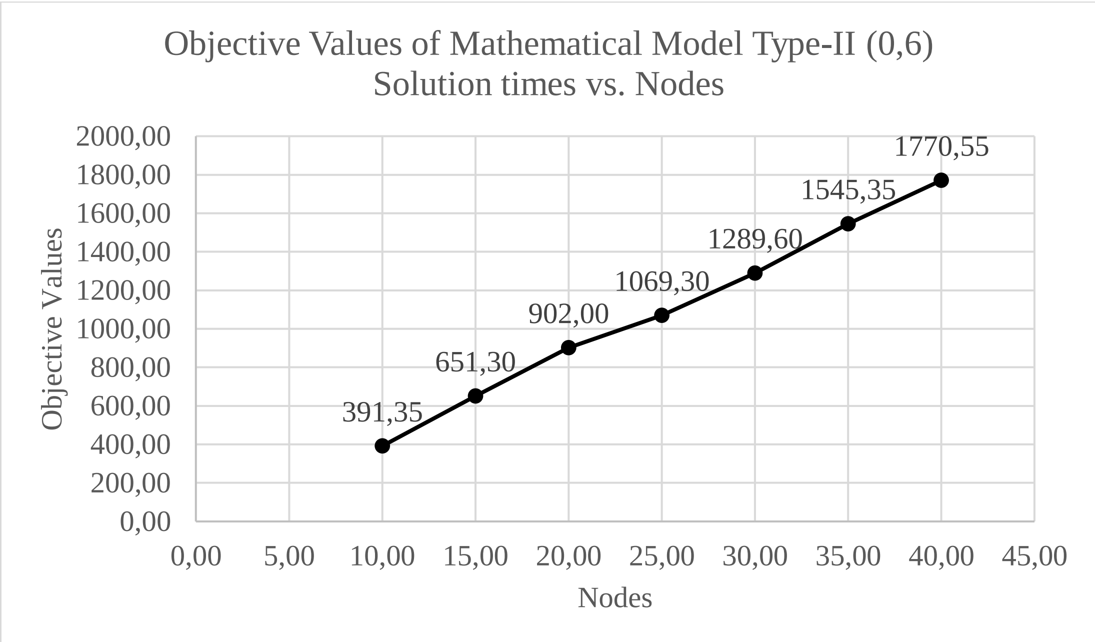

Figure 21: Average objective values of MMT2-0.6 solutions vs. nodes

Figure 21 above shows that, MMT2-0.6 objective function values (Wi*Xijk) with respect to the nodes. Such as, if n=10 then corresponding objective value is 391.35 However, if n=40 then corresponding solution time is 1770.55. This means that, nodes are one of the significant effects on objective values. This means, Objective function values are increased together with nodes. In other words, better objective values are obtained while nodes are increased since objective function is maximization.

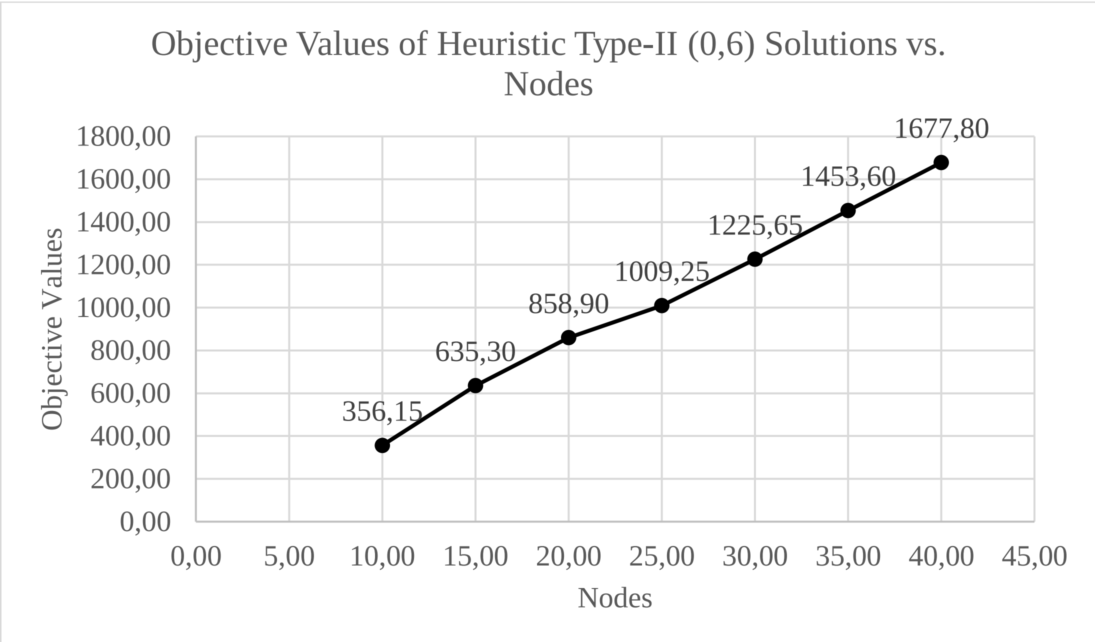

Figure 22: Average objective values of HT2-0.6 vs. nodes

Figure 22 above shows that, HT2-0.6 objective function values (Wi*Xijk) with respect to the nodes. Similarly, nodes are one of the significant effects on objective values. Again, objective values are increased with nodes but obtained results are slightly worse than MMT2-0.6

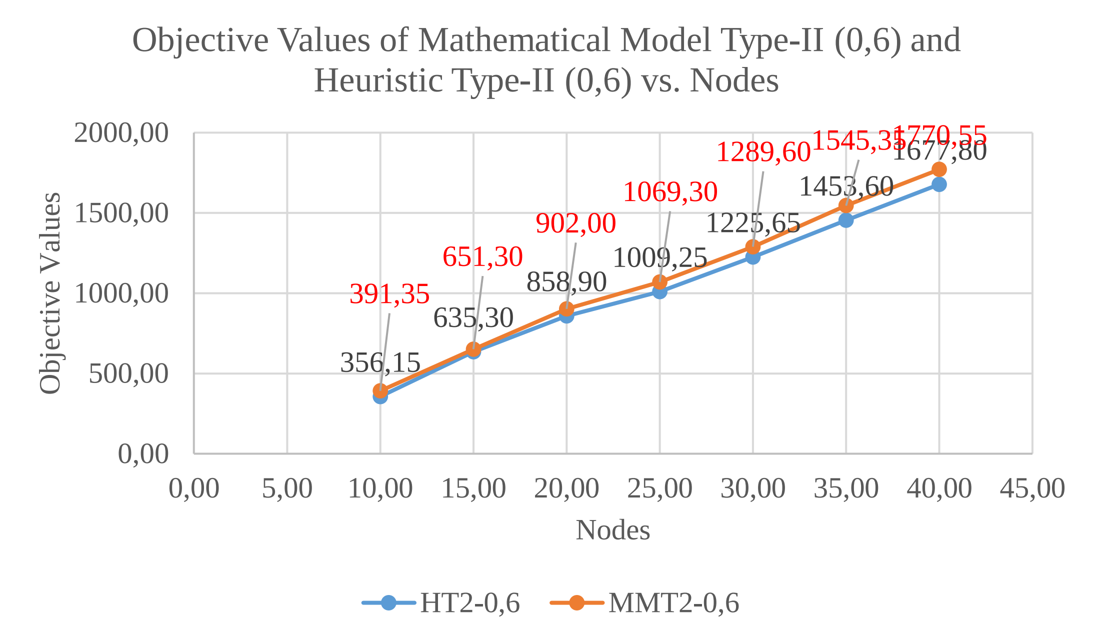

Figure 23: Average objective values of MMT2-0.6 and HT2-0,6 vs. nodes

Figure 23 above shows that, MMT2-0.6 and HT2-0.6 objective values (Wi*Xijk) with respect to the nodes. HT2-0.6 are given a little bit worse objective values than MMT2-0.6. This also proves that, facility location decisions should considered together with allocations of service units to the facilities since MMT2-0.6 average objective values better than HT2-0.6.

Table 2: MMT2-0.6 and HT2-0.6 results comparison table

Nodes	**MMT2-0,6**		**HT2-0,6**		**Gap (Objective)**	**Gap (Time)**
	Objective	Time	Objective	Time		
10	391,35	0,15	356,15	0,07	-9%	-51%
15	651,30	0,40	635,30	0,09	-2%	-77%
20	902,00	1,44	858,90	0,21	-5%	-86%
25	1069,30	7,80	1009,25	0,29	-6%	-96%
30	1289,60	67,34	1225,65	0,92	-5%	-99%
35	1545,35	600,61	1453,60	4,82	-6%	-99%
40	1770,55	1953,55	1677,80	13,13	-5%	-99%

Table 2 above shows that, MMT2-0.6 and HT2-0.6 objective results' relations. Averagely MMT2-0.6 objective values are %6 better than HT2-0.6. On the other hand, averagely HT2-0.6 solution times are %87 better than MMT2-0.6.

Also, facility levels have been examined separately. Average solution times of facility level 1 and 2 have been computed for MMT2-0.6 and HT2-0.6.

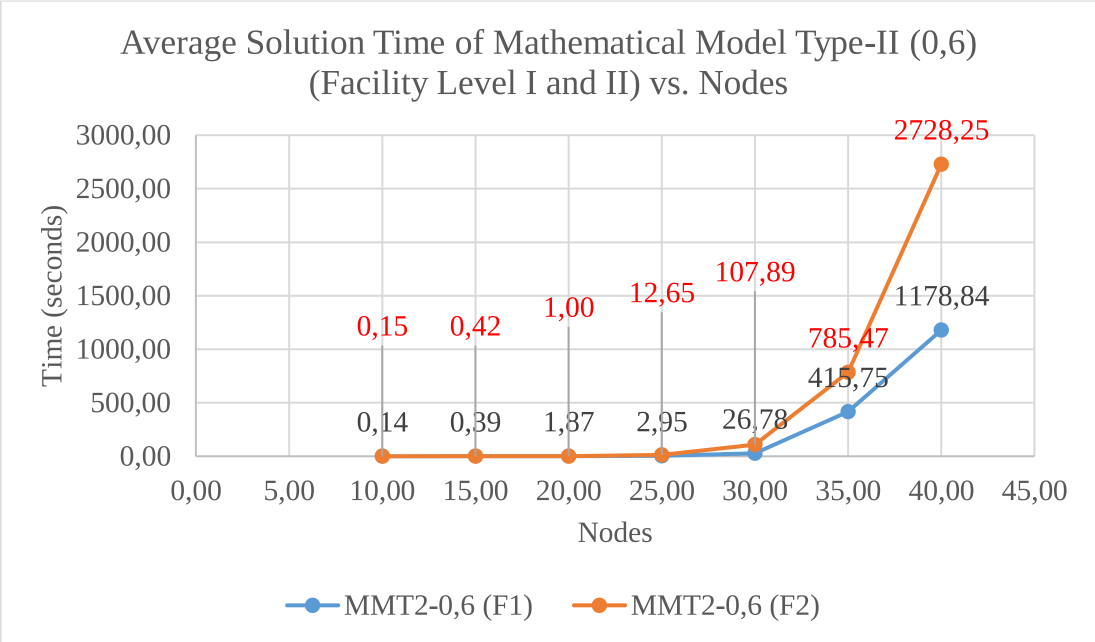

Figure 24: Average solution time of MMT2-0.6 (Facility level I and II) vs. nodes

Figure 24 above shows that, MMT2-0.6's average solution times according to facility level 1 and 2 with respect to the nodes. Lines are almost identical up to 35 nodes. Unfortunately, it is not possible to make conclusions from this result.

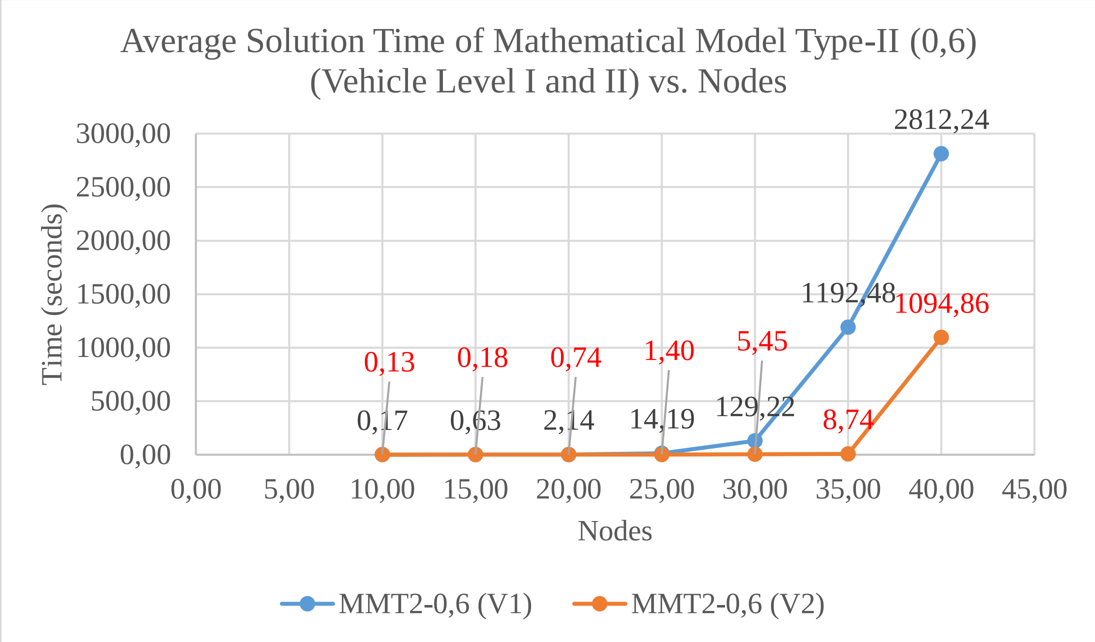

Figure 25: Average solution time of MMT2-0.6 (Vehicle level I and II) vs. nodes

Figure 25 above shows that, MMT2-0.6's average solution times according to vehicle level 1 and 2 with respect to the nodes. Lines are almost identical which means vehicle levels have no significant effect on solution time.

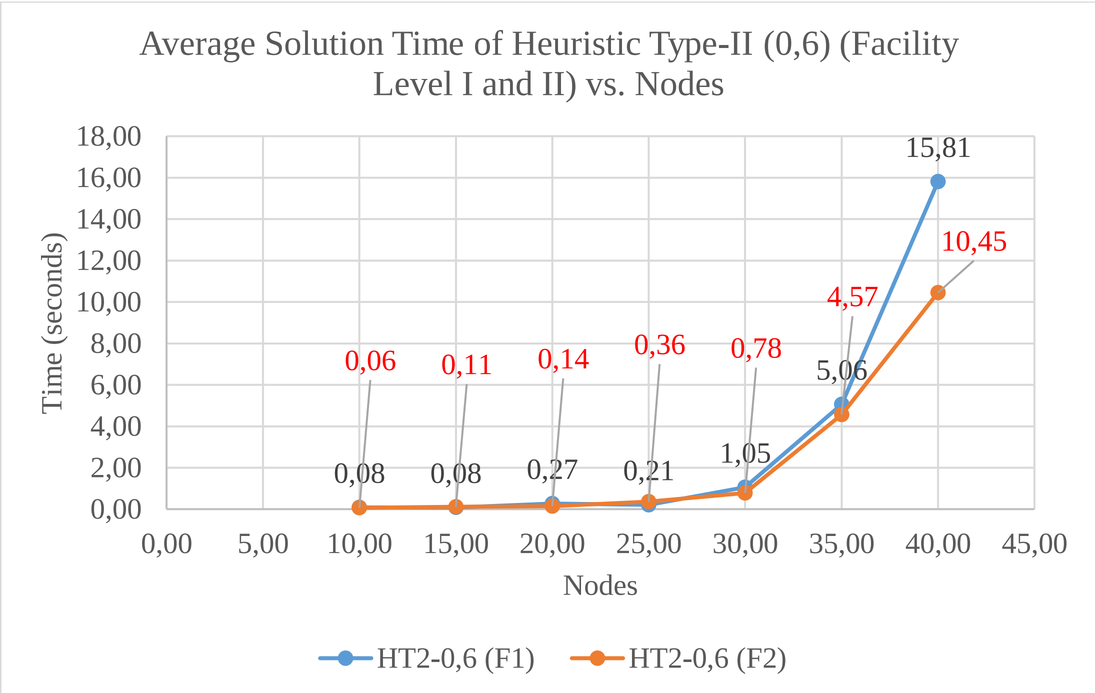

Figure 26: Average solution time of HT2-0.6 (Facility level I and II) vs. nodes

Figure 26 above shows that, HT2-0.6's average solution times according to facility level 1 and 2 with respect to the nodes. Lines are almost identical which means facility levels have no significant effect on solution time.

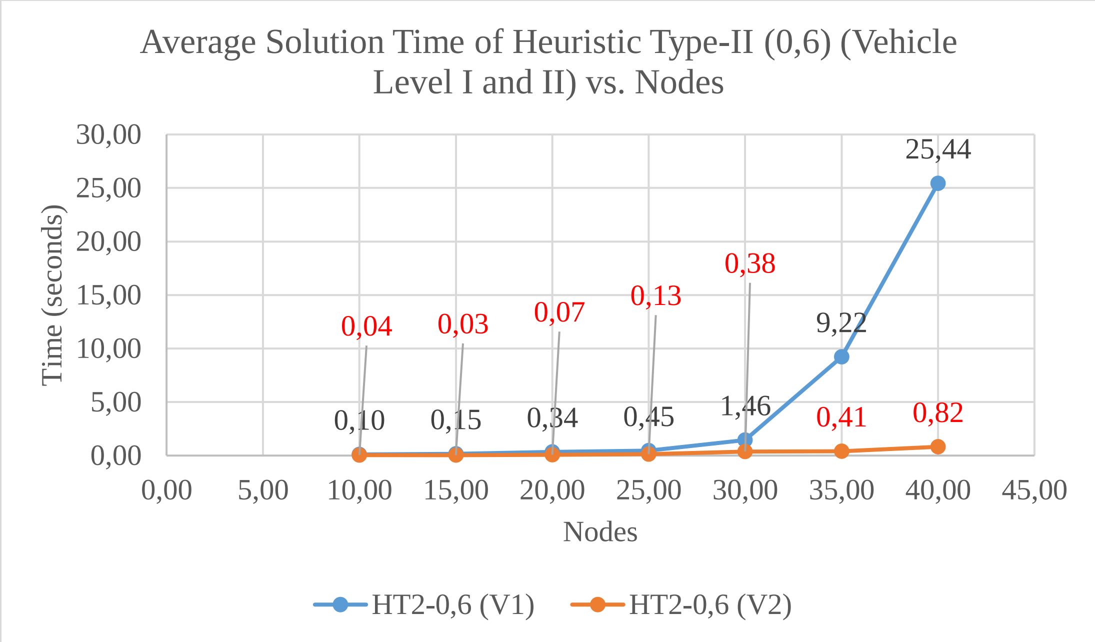

Figure 27: Average solution time of HT2-0.6 (Vehicle level I and II) vs. nodes

Figure 27 above shows that, HT2-0.6's average solution times according to vehicle level 1 and 2 with respect to the nodes. Lines are almost identical which means vehicle levels have no significant effect on solution time. Differences are started after 35 nodes but this alone is not enough evidence to support any claim.

Next, Average solution times and objectives values of MMT2-0.8, HT2-0.8 and MCM-0.8 have been computed and presented on figures. Results are also compared with MMT2-0.6, HT2-0.6 and MCM-0.6 on several figures.

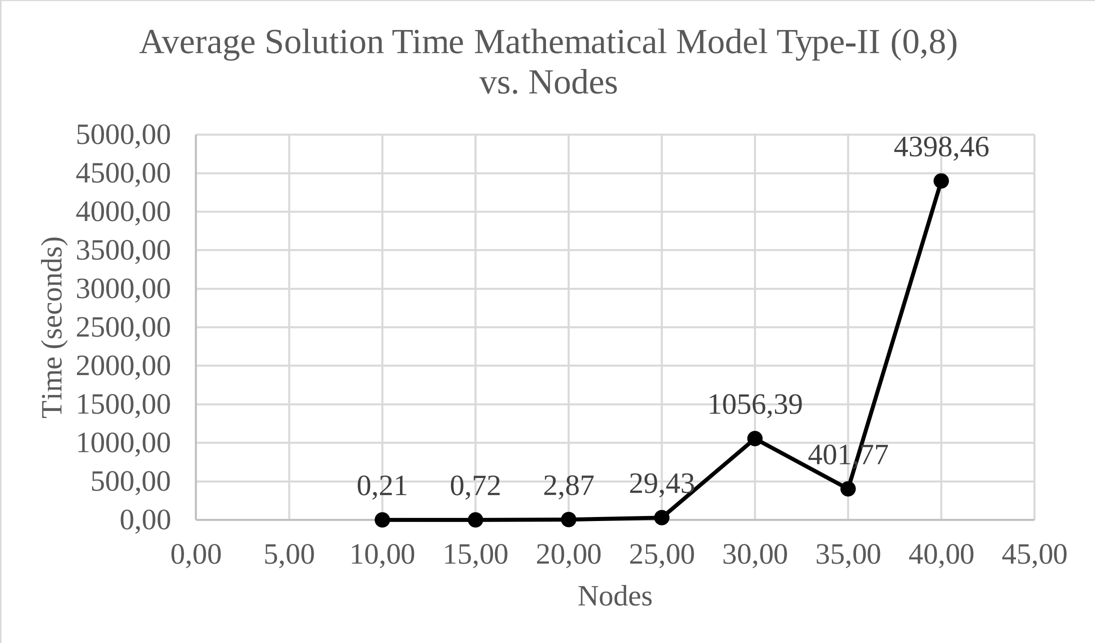

Figure 28: Average solution time of MMT2-0.8 vs. nodes

Figure 28 above shows that MMT2-0.8 solution times with respect to nodes. This figure shows that nodes are significantly effects on solution times. In other words, solution times are increases together with nodes.

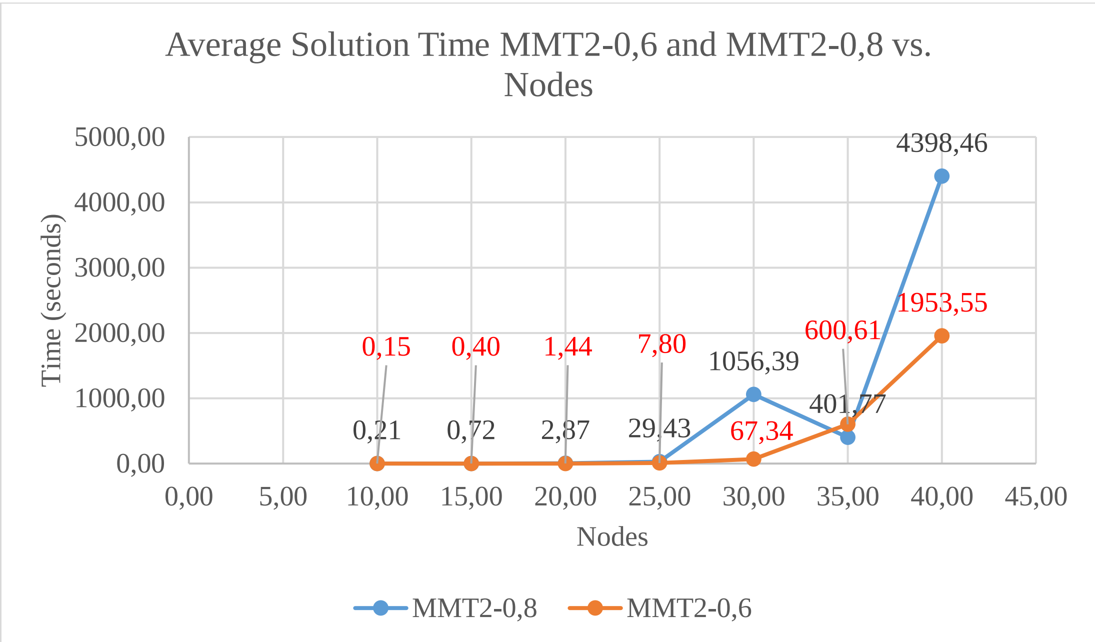

Figure 29: Average solution time of MMT2-0.8 and MMT2-0.6 vs. nodes

Figure 29 above shows that MMT2-0.6 and MMT2-0.8 average solution times with respect to nodes. MMT2-0.6 took less time than MMT2-0.8 to be solved. Main reason of this is MMT2-0.8 have higher DL value than MMT2-0.6. In other words, MMT2-0.6 deals with less demand than MMT2-0.8.

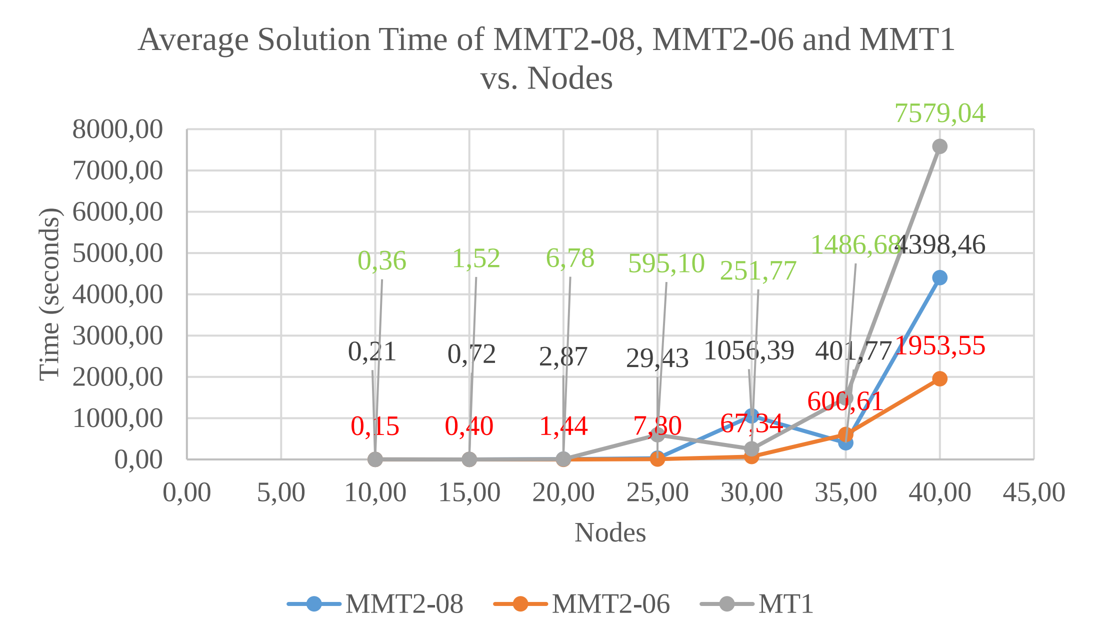

Figure 30: Average solution time of MMT2-0.6, MMT2-0.8 and MMT1 vs. nodes

Figure 30 above shows that MMT2-0.6, MMT2-0.8 and MMT1 average solution time with respect to nodes. MMT1 takes more time than MMT2-0.6 and MMT2-0.8 to be solved. Objective function of MMT1 is the main reason of this. MMT2-0.8 takes more time than MMT2-0.6 to be solved. Major reason of this is MMT2-0.8 have higher DL values than MMT2-0.6.

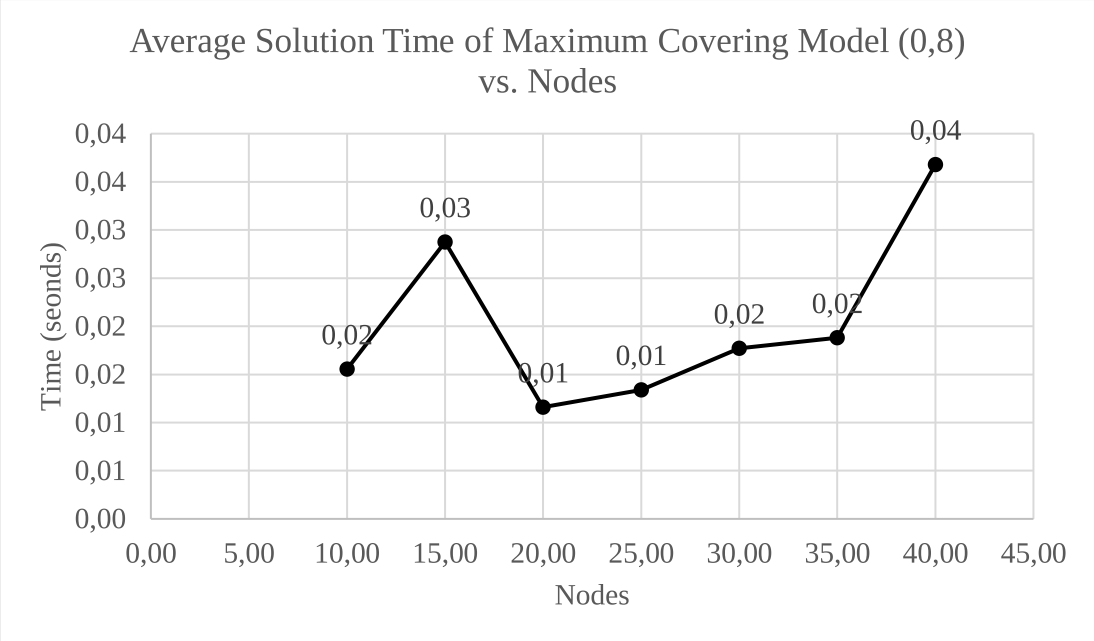

Figure 31: Average solution time of MCM-0.8 vs. nodes

Figure 31 above shows that MCM-0.8 average solution times with respect to nodes. Solution times are close to zero which means that MCM-0.8 is very fast. Major reason for that is vehicle decisions are omitted.

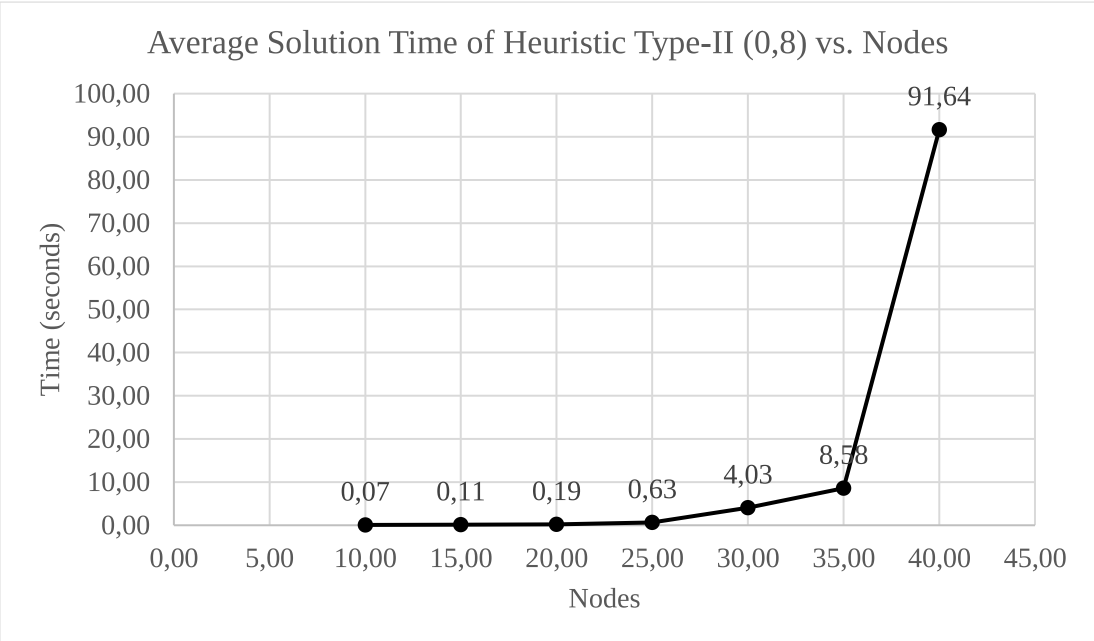

Figure 32: Average solution time of HT2-0.8 vs. nodes

Figure 32 above shows that HT2-0.8 average solution time with respect to nodes. This means that nodes are one of the significant effects on solution times. In other words, solution times are increases together with nodes.

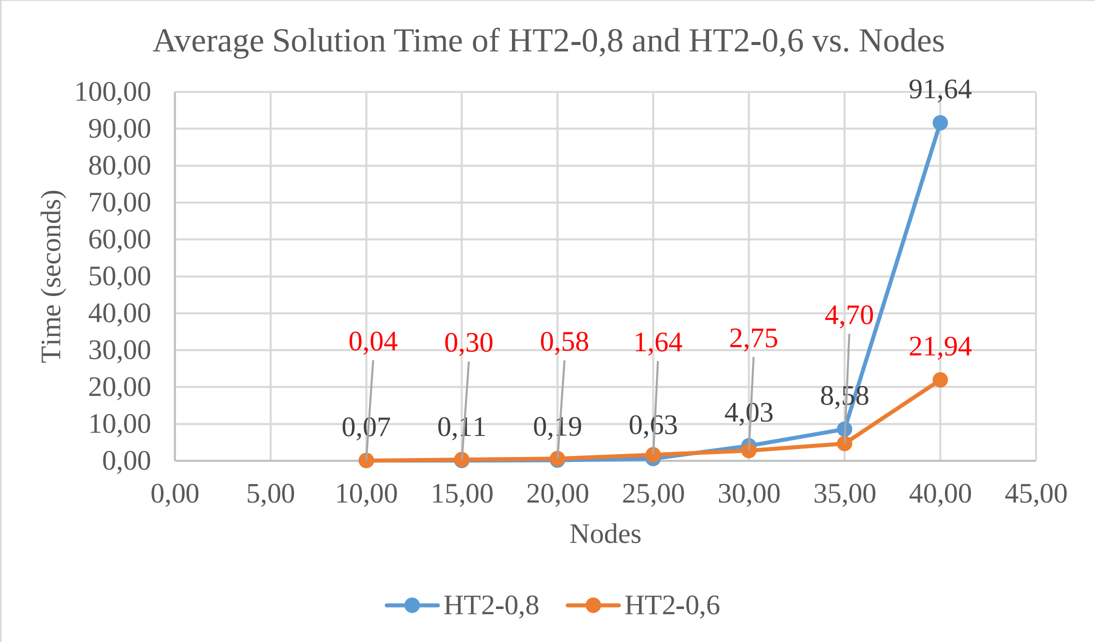

Figure 33: Average solution time of HT2-0.8 and HT2-0.6 vs. nodes

Figure 33 above shows that HT2-0.8 and HT2-0.6 average solution times with respect to nodes. Lines are nearly parallel to each other up to 35 nodes. HT2-0.8 average solution time are dramatically increased after 35 nodes compare to HT2-0.6.

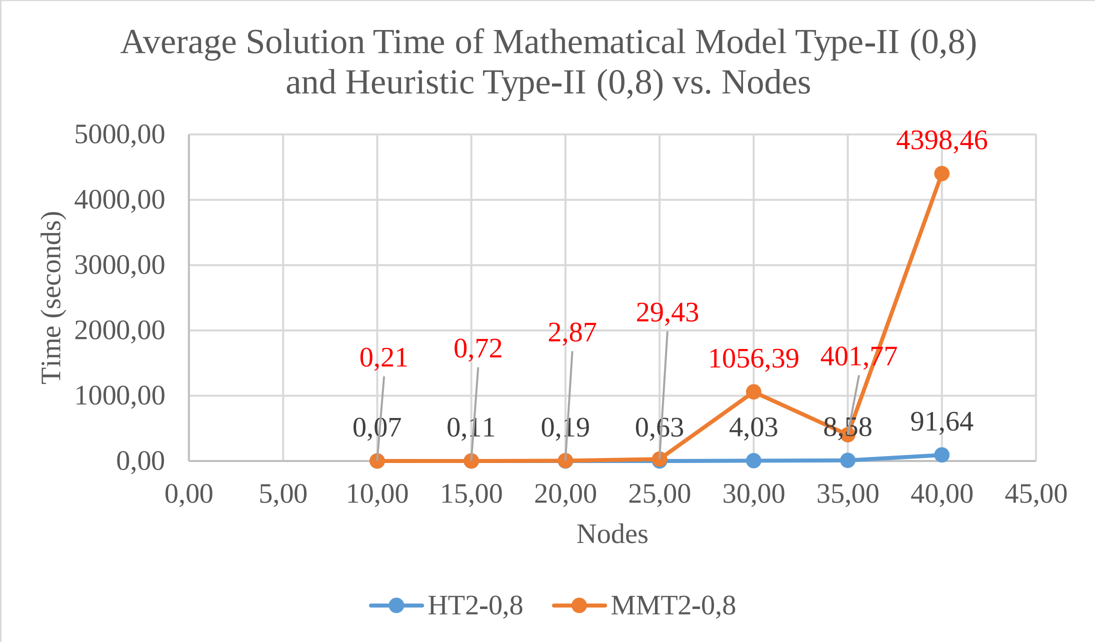

Figure 34: Average solution time of MMT2-0.8 and HT2-0.8 vs. nodes

Figure 34 above shows that, MMT2-0.8 and HT2-0.8 average solution times with respect to nodes. HT2-0.8 solution times are better than MMT2-0.8. This means that, HT2-0.8 is faster than MMT2-0.8 but objective function values should be compared in order to make a full comparison.

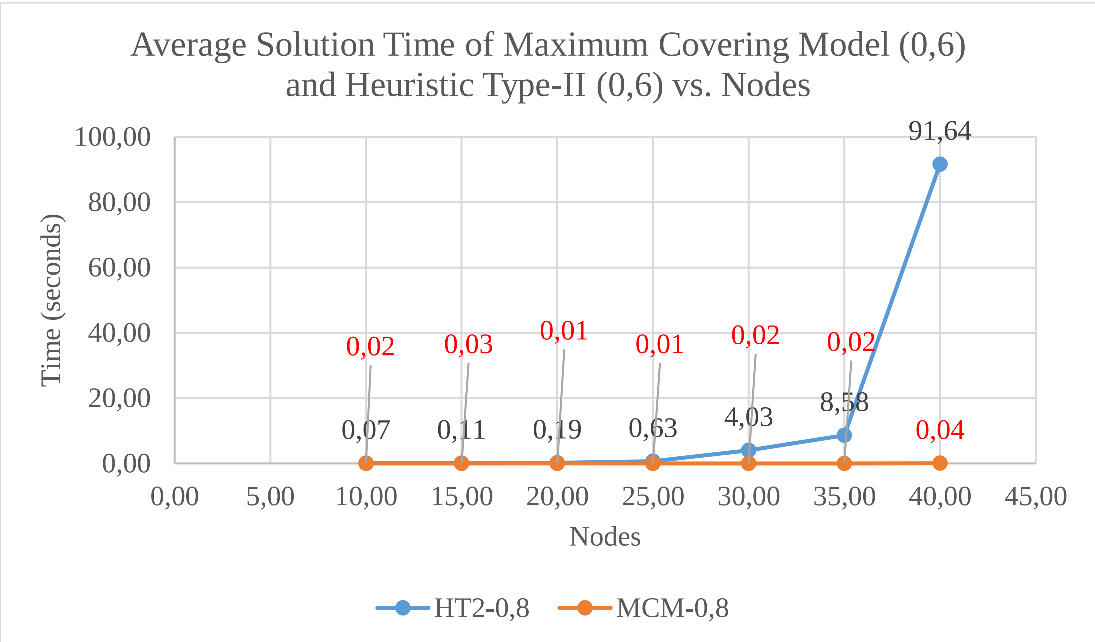

Figure 35: Average solution time of MCM-0.8 and HT2-0.8 vs. nodes

Figure 35 above shows that, MCM-0.8 and HT2-0.8 algorithm average computation times with respect to the node clusters. MCM-0.8 solution times are better than HT2-0.8. The reason of this is actually MCM-0.8 is the first level of HT2-0.8.

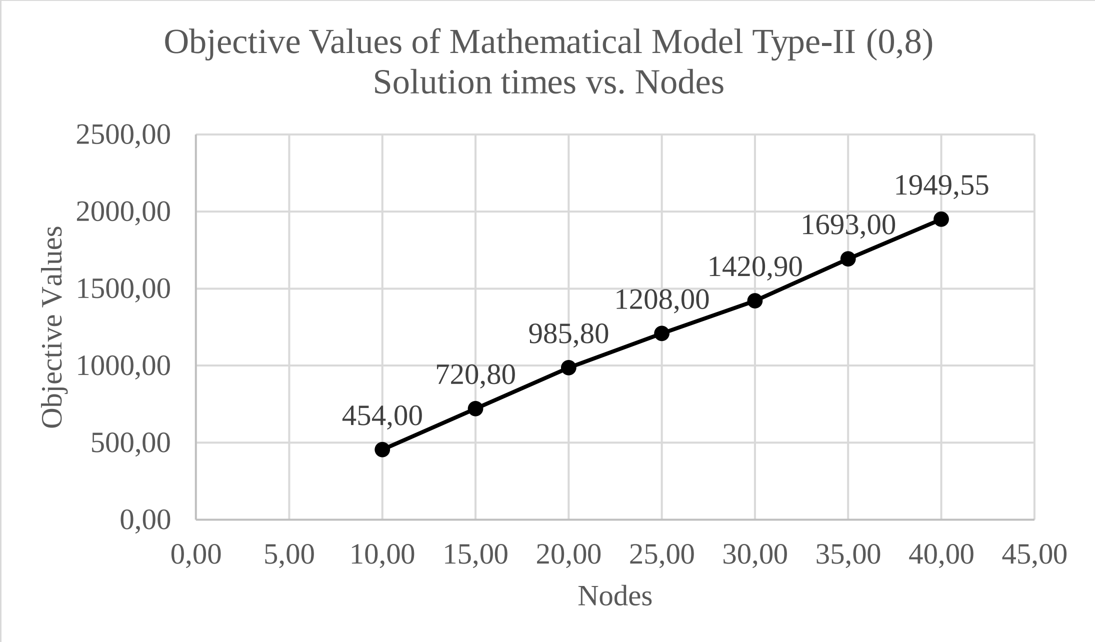

Figure 36: Average objective values of MMT2-0.8 solutions vs. nodes

Figure 36 above shows that, MMT2-0.6 objective function values (Wi*Xijk) with respect to the nodes. Such as, if n=10 then corresponding objective value is 454.00 However, if n=40 then corresponding solution time is 1949.55. This means that, nodes are one of the significant effects on objective values. This means, Objective function values are increased together with nodes. In other words, better objective values are obtained while nodes are increased since objective function is maximization.

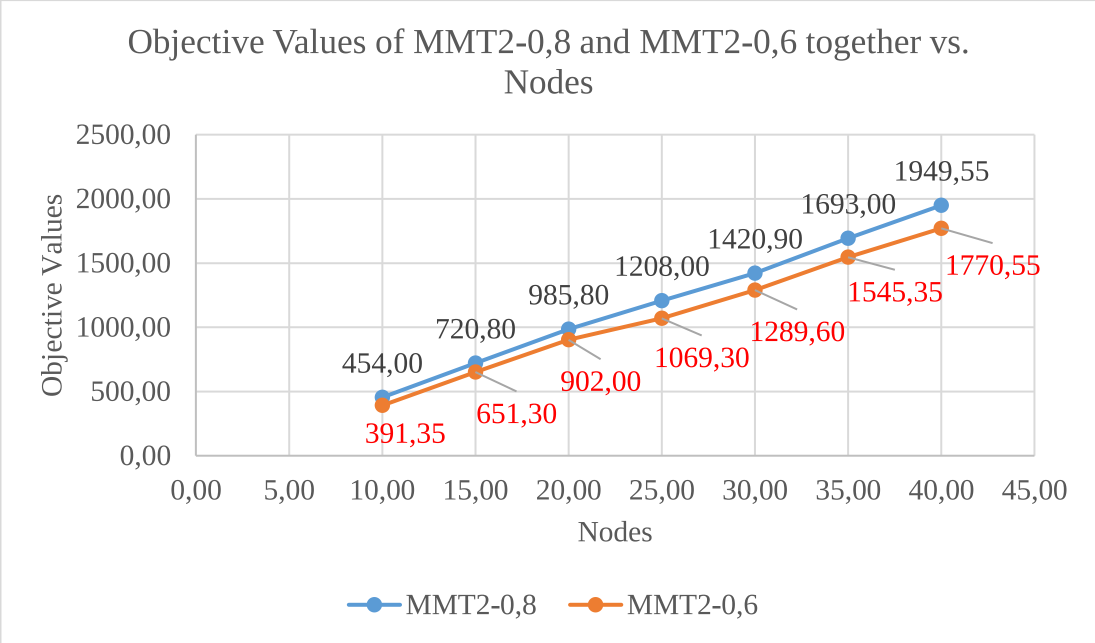

Figure 37: Average objective value of MMT2-0.8 and MMT2-0.6 vs. nodes

Figure 37 above shows that, MMT2-0.6 and MMT2-0.8 objective function values (Wi*Xijk) with respect to the nodes. MMT2-0.6's objective values observed are worse than MMT2-0.8. Reason of this is MMT2-0.8 have higher DL values than MMT2-0.6. In other words MMT2-0.8 reaches more demand than MMT-0.6.

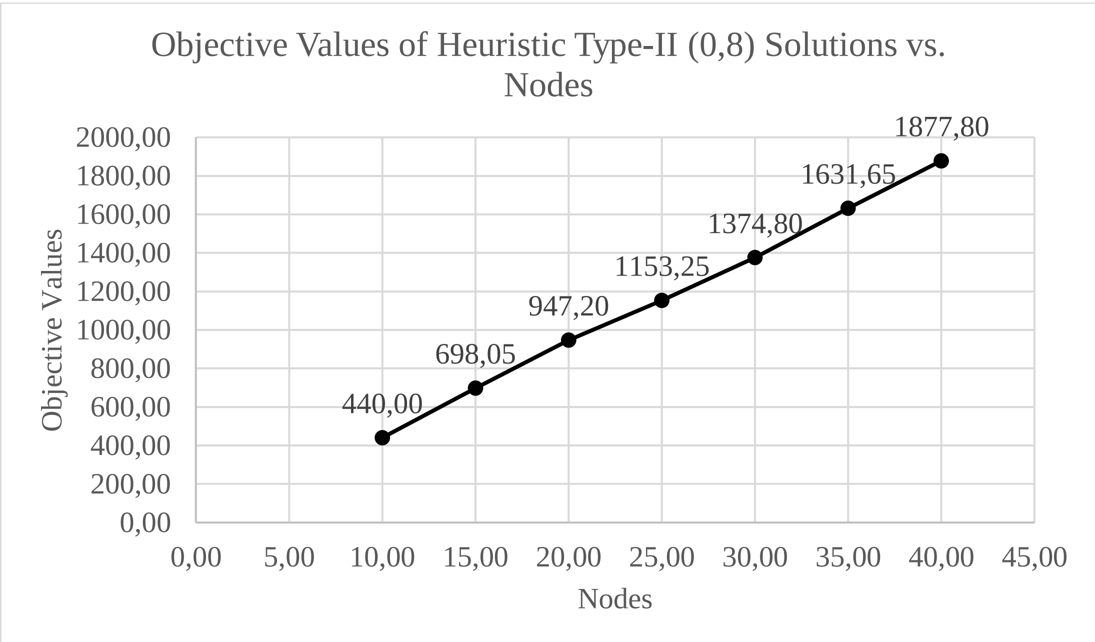

Figure 38: Average objective values of HT2-0,8 vs. nodes

Figure 38 above shows that, HT2-0.8 objective function values (Wi*Xijk) with respect to the nodes. Similarly, nodes are one of the significant effects on objective values.

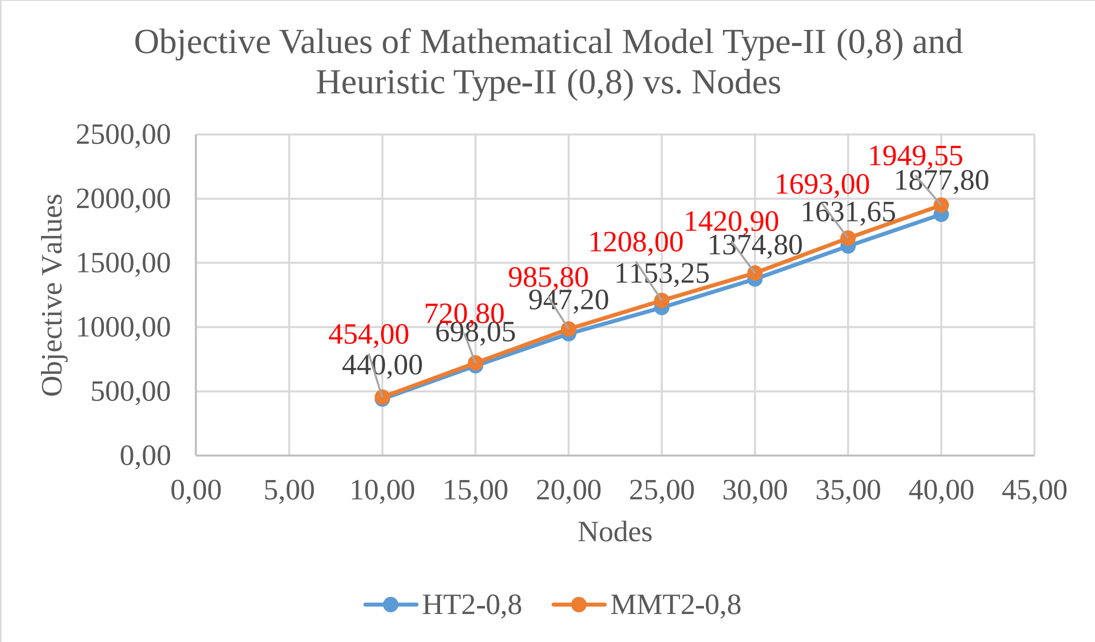

Figure 39: Average objective values of MMT2-0.8 and HT2-0.8 vs. nodes

Figure 39 above shows that, MMT2-0.8 and HT2-0.8 objective values (Wi*Xijk) with respect to the nodes. HT2-0.8's objective values are observed little bit worse than MMT2-0.8. This also proves that, facility location decisions should considered together with allocations of service units to the facilities since MMT2-0.8 average objective values better than HT2-0.8.

Table 3 below shows that, MMT2-0.8 and HT2-0.8 objective results' relations. Averagely MMT2-0.8 objective values are %4 better than HT2-0.8. On the other hand, averagely HT2-0.8 solution times are %92 better than MMT2-0.8.

Table 3: MMT2-0.8 and HT2-0.8 results comparison table

Nodes	**MMT2-0,8**		**HT2-0,8**		**Gap (Objective)**	**Gap (Time)**
	Objective	Time	Objective	Time		
10	454,00	0,21	440,00	0,07	-3%	-67%
15	720,80	0,72	698,05	0,11	-3%	-84%
20	985,80	2,87	947,20	0,19	-4%	-93%
25	1208,00	29,43	1153,25	0,63	-5%	-98%
30	1420,90	1056,39	1374,80	4,03	-3%	-100%
35	1693,00	401,77	1631,65	8,58	-4%	-98%
40	1949,55	4398,46	1877,80	91,64	-4%	-98%

Also, facility levels have been examined separately. Average solution times of facility level 1 and 2 have been computed for MMT2-0.8 and HT2-0.8 and compared with MMT2-0.6 and HT2-0.8.

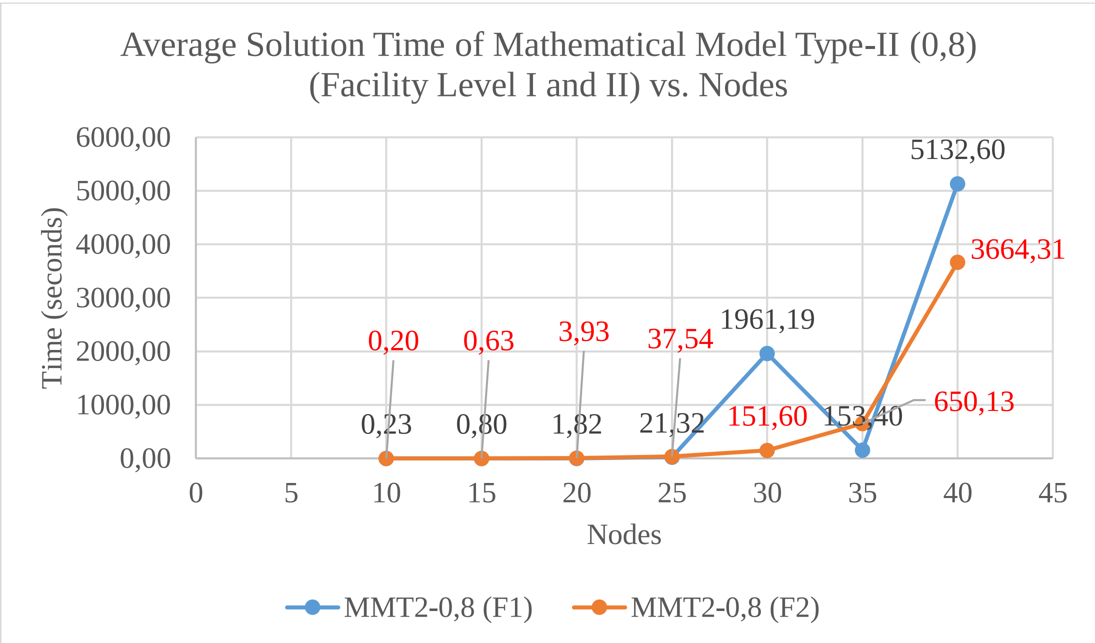

Figure 40: Average solution time of MMT2-0.8 (Facility level I and II) vs. nodes

Figure 40 above shows that, MMT2-0.8's average solution times according to facility level 1 and 2 with respect to the nodes. Lines are almost identical up to 25 nodes. Unfortunately, it is not possible to make conclusions from this result.

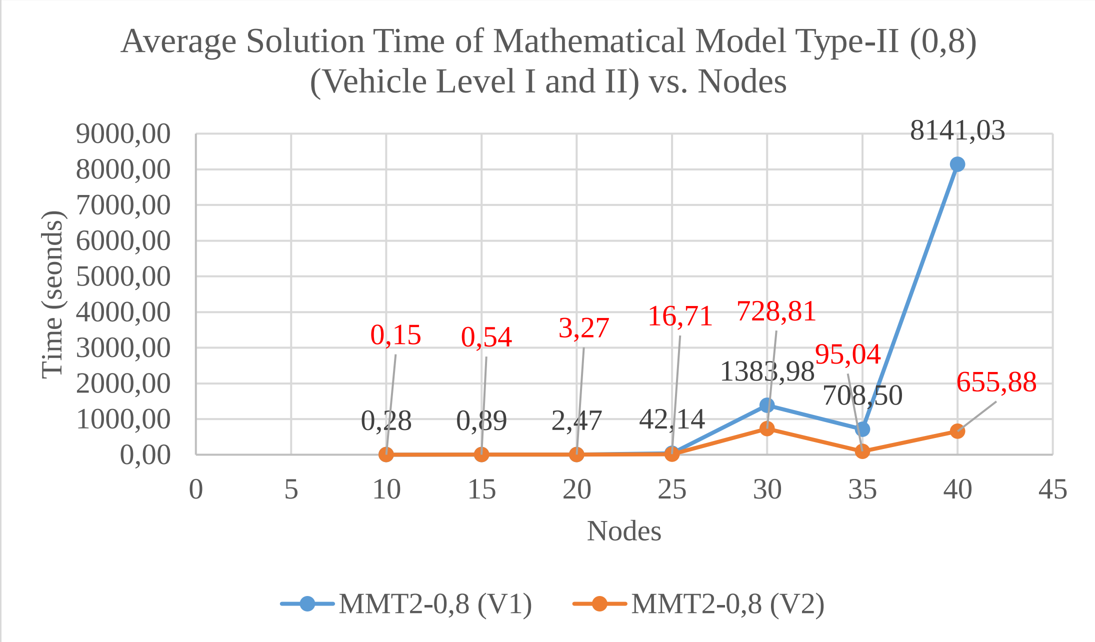

Figure 41: Average solution time of MMT2-0.8 (Vehicle level I and II) vs. nodes

Figure 41 above shows that, MMT2-0.8's average solution times according to vehicle level 1 and 2 with respect to the nodes. Lines are almost identical which means vehicle levels have no significant effect on solution time.

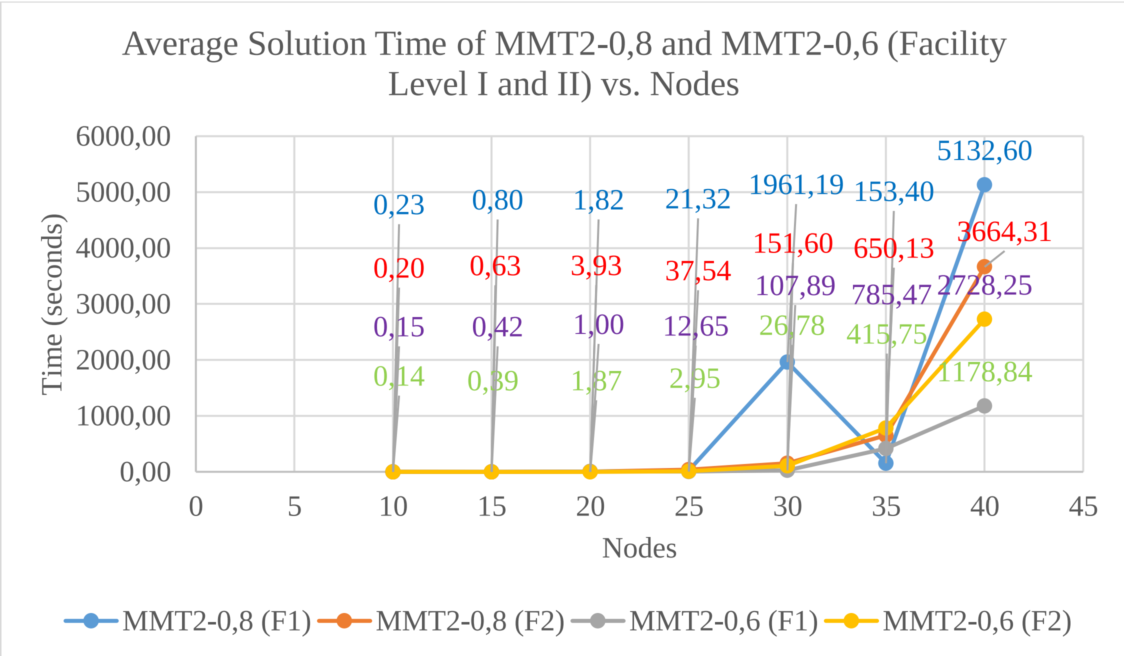

Figure 42: Average solution time MMT2-0.8 and MMT2-0.6 (F1 F2) vs. nodes

Figure 42 above shows that, MMT2-0.8 and MMT2-0.6 average solution times according to facility level 1 and level 2 with respect to nodes. Generally, MMT2-0.8's average solution times observed more than MMT2-0.6.

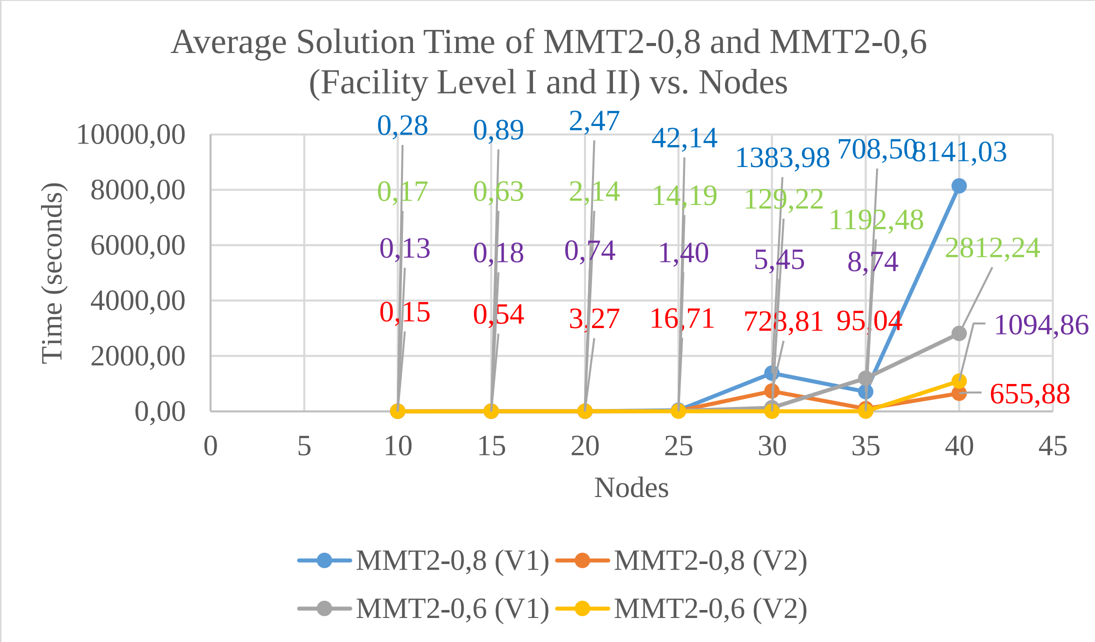

Figure 43: Average solution time MMT2-0.8 and MMT2-0.6 (V1 V2) vs. nodes

Figure 43 above shows that, MMT2-0.8 and MMT2-0.6 average solution times according to vehicle level 1 and level 2 with respect to nodes. Generally, MMT2-0.8's average solution times observed more than MMT2-0.6.

Also, facility levels have been examined separately. Average solution times of facility level 1 and 2 have been computed for MMT2-0.8 and HT2-0.8.

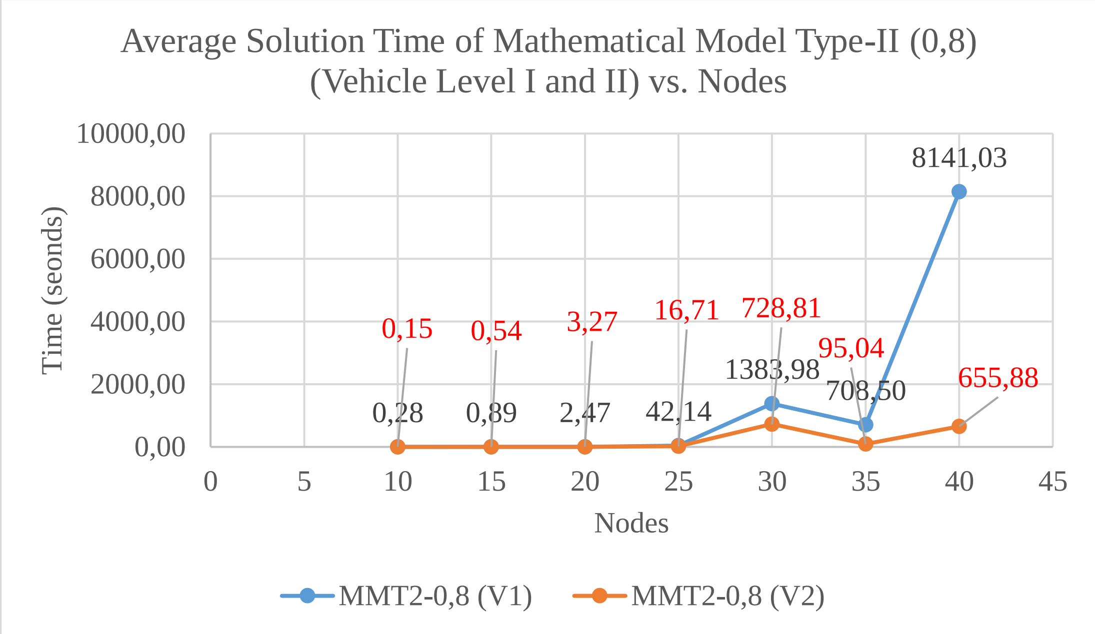

Figure 44: Average solution time of MMT2-0.8 (Facility level I and II) vs. nodes

Figure 44 above shows that, MMT2-0.8's average solution times according to vehicle level 1 and 2 with respect to the nodes. Lines are almost identical which means vehicle levels have no significant effect on solution time.

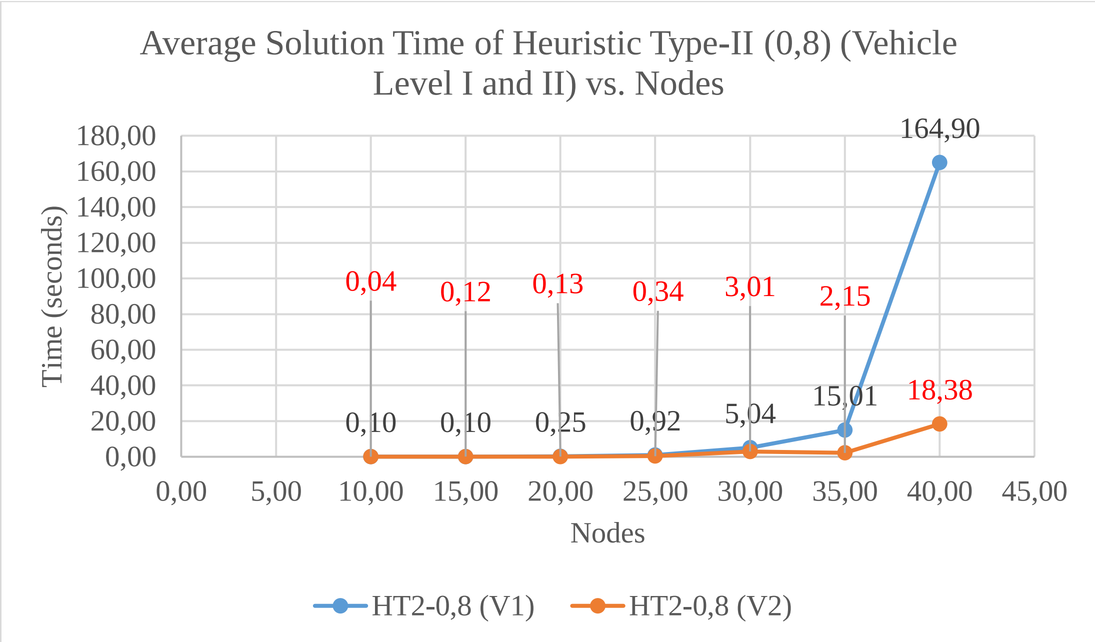

Figure 45: Average solution time of HT2-0.8 (Vehicle level I and II) vs. nodes

Figure 45 above shows that, HT2-0.8's average solution times according to vehicle level 1 and 2 with respect to the nodes. Lines are almost identical which means vehicle levels have no significant effect on solution time. Differences are started after 35 nodes but this alone is not enough evidence to support any claim.

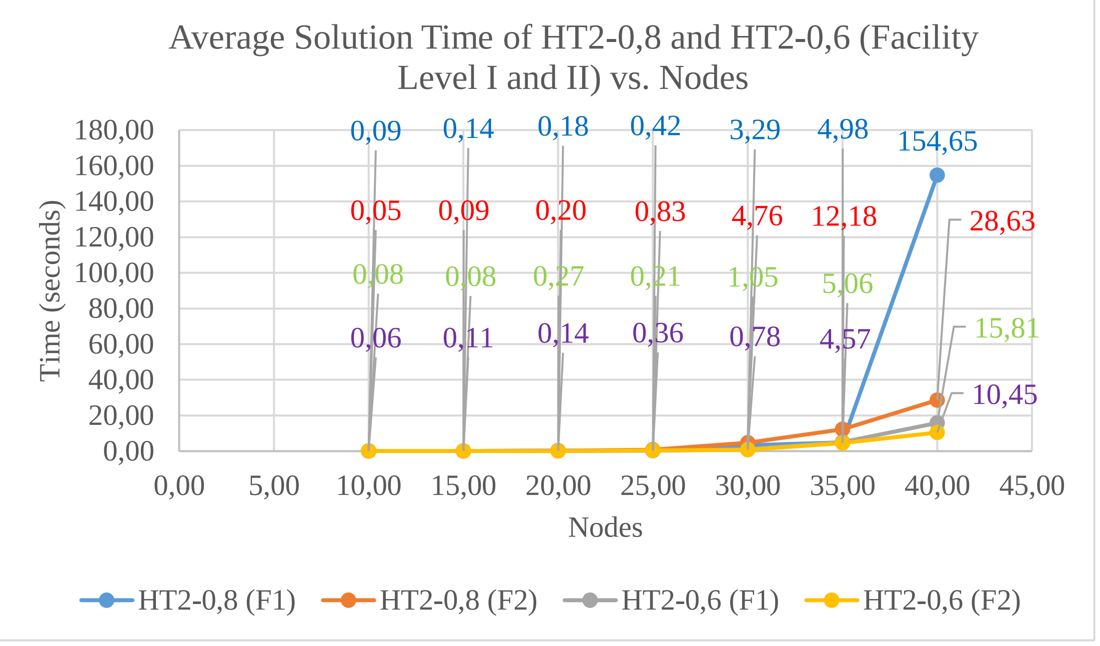

Figure 46: Average solution time HT2-0.8 and HT2-0.6 (F1 F2) vs. nodes

Figure 44 above shows that, HT2-0.8 and HT2-0.6 average solution times according to facility level 1 and 2 with respect to the nodes. Lines are very close to each other. So, no difference have been observed.

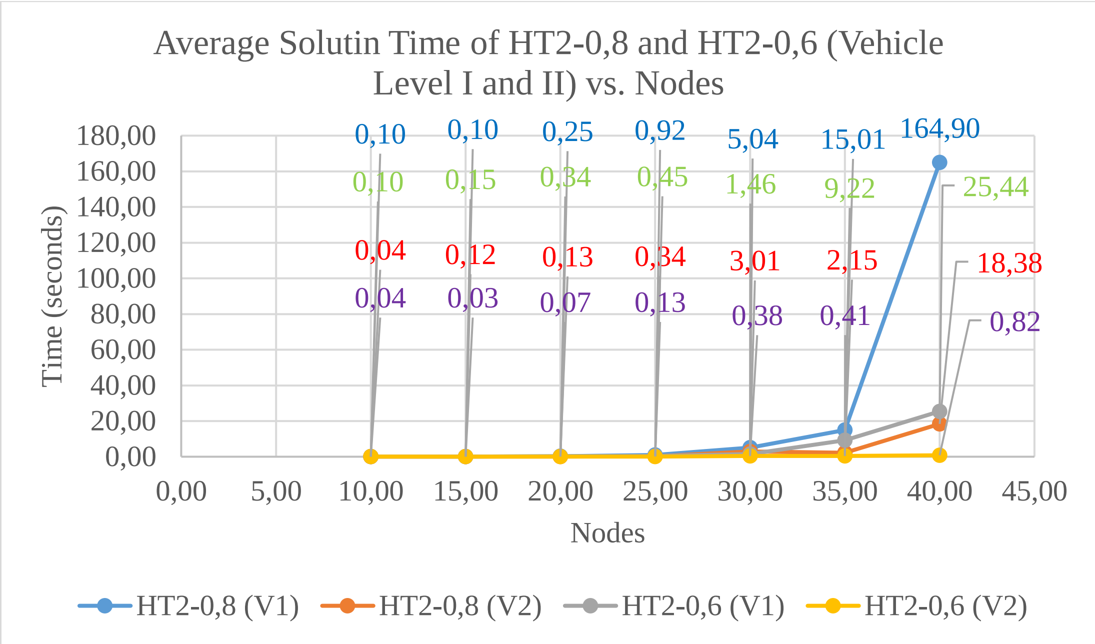

Figure 47: Average solution time HT2-0.8 and HT2-0.6 (V1 V2) vs. nodes

Figure 47 above shows that, HT2-0.8 and HT2-0.6 average solution times according to vehicle level 1 and 2 with respect to the nodes. Lines are very close to each other. So, no difference have been observed.

Chapter 5

CASE STUDY: ÇANKAYA

5.1 Background Information

People have started to immigrate to cities from villages because of the industry revolution in late 1890s. In that time, people were struggling to find jobs at villages because of the growing population. Then suddenly, industrial revolution have been started and many jobs opportunities are emerged. So, countries became industrial civilizations from agriculture civilizations. Also, people's life styles have been re-shaped within after few decades later. As years passed competition among corporations have been raged and also industrial conditions have become more complex than before. So, corporations have made pioneer decisions in order to compete their rivals on the market. As a result of this, expectation from employees have been dramatically increased. So, people have started spend more time at work than before.

Fast-Food corporations have been emerged in order to fulfill this new demand. Because people were spending most of their time at work, they weren't spend time for cooking themselves at home. So, fast-food shops have started to open all around the world.

Turkey affected from these changes especially after 1990s because of the social and economic changes. Female population slowly showed themselves on business life in these years. So, woman's role have been changed on society. Nowadays, both man and woman are actively working from 8 to 5. According to this fact, fast-food industry constantly growing day by day. Moreover, almost all of the major universities have been located on urban areas in Turkey so these students also have become regular customers for fast-food companies either. This case study is about a fast-food company which sells "steak tartar a la turca" or in Turkish "çiğ köfte". This company wants to open chain restaurants in Cankaya district of Ankara city in Turkey. However, establishing new restaurants are strategic decisions and should be considered very carefully. Çiğ Köfte is a very nice example of a fast-food product. It is cheap and easy to prepare. Because of this, preparation time have been neglected in this study. Main focus of company is satisfying demand at minimum time. Company also wants to distribute motorized couriers to the open restaurants with respect to the demand. So, Type-1 and Type-2 problems have been improvised according to company's requests.

5.2 Information about Çankaya

Çankaya is a district of Ankara city of Turkey. Population of Çankaya is almost 1 million which is very high compare to other district of Ankara. Distance between from one corner to another corner of Çankaya is nearly 45 kilometers. There are many universities which are located on Çankaya or near to Çankaya district. Such as; Middle East Technical University, Bilkent University, Atılım Univesity and Çankaya University. Many white collar are live in Çankaya. Many businesses and financial institutions have been located in Çankaya. Moreover, since the beginning of the Republic of Turkey many of the high ranking government officials are living. According these facts obviously can been seen that Çankaya have enough demand for fast-food industry.

5.3 Çiğ Köfte Company

This company is a newly established company. Company's partners have worked in çiğ köfte business for many years. Partners are capable enough in inside operations like preparation, quality of product, human resources etc. yet they need help for outside operations like distribution. Because of this when they had decided on starting an operation in Çankaya district we had suggested our assistance on distribution operations. Company had very helpful during the field research. Numerous audio conferences had been done. Then, we had improvised our problem models according to company's requests.

5.4 Experimental Procedure

According to the conducted field study, amount of the order calls to the restaurants dramatically increases at afternoon periods. That's why, we decided on responding to 100 orders in 30 minutes at afternoon period are chosen as example case. Unfortunately, seeking for optimum solution are going to take too much time since the node cluster is greater than 40 nodes and. So, we have tried to compute local optimum solution instead of seeking for optimum solution and HT1 and HT2 have been used as solution methods.

Next, many interviews have conducted with restaurant owners to determine restaurant and motorized courier levels. Most significant factors to determine restaurant and motorized courier levels have set as population, neighborhood value, social classes and businesses according to restaurant owners. So according to research, two realistic restaurant level have been decided for Çankaya district and these are levels are 5 and 8. Moreover, two motorized courier level for these restaurants also have decided as 20 and 30.

Goal of the Type 1 is try to minimize the maximum distance which motorized couriers have traveled. In other words, Type 1 solution show us to minimum required time to distribute all of 100 orders.

5.5 ArcGIS 10

ArcGIS 10 is mapping program and it allows us to work on real life maps. We've found Çankaya district map at first in order work on ArcGIS 10. Figure 48 below shows Çankaya district map.

Figure 48: Map of Çankaya

Then, randomly located 100 nodes are created in Çankaya map by using ArcGIS 10 features. Figure 49 below shows that, randomly created 100 nodes in Çankaya map.

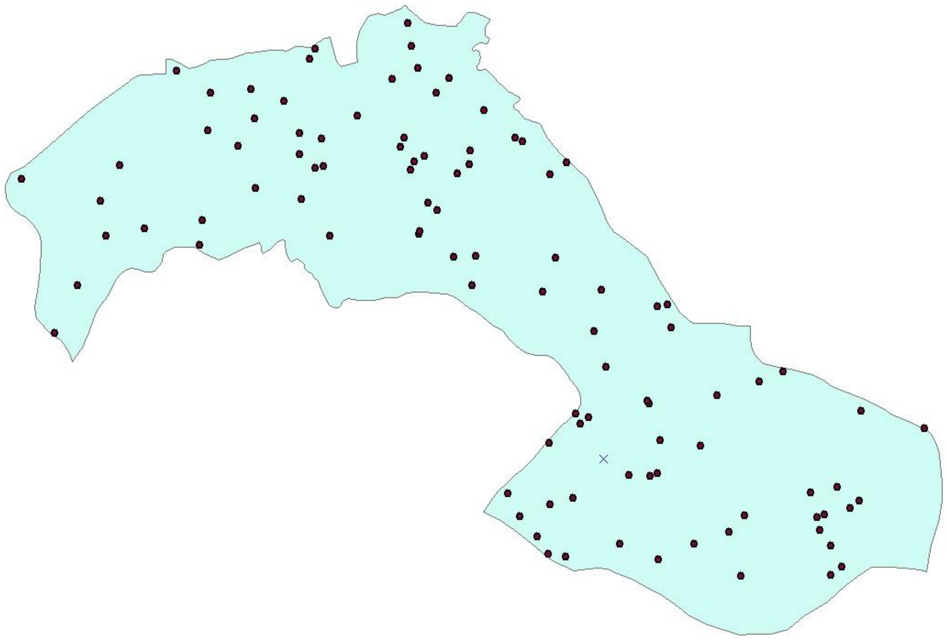

Figure 49: Randomly created nodes in Çankaya district

After that, all created nodes have labelled from 1 to 100. Figure 50 below shows that, labelled nodes in Çankaya district map.

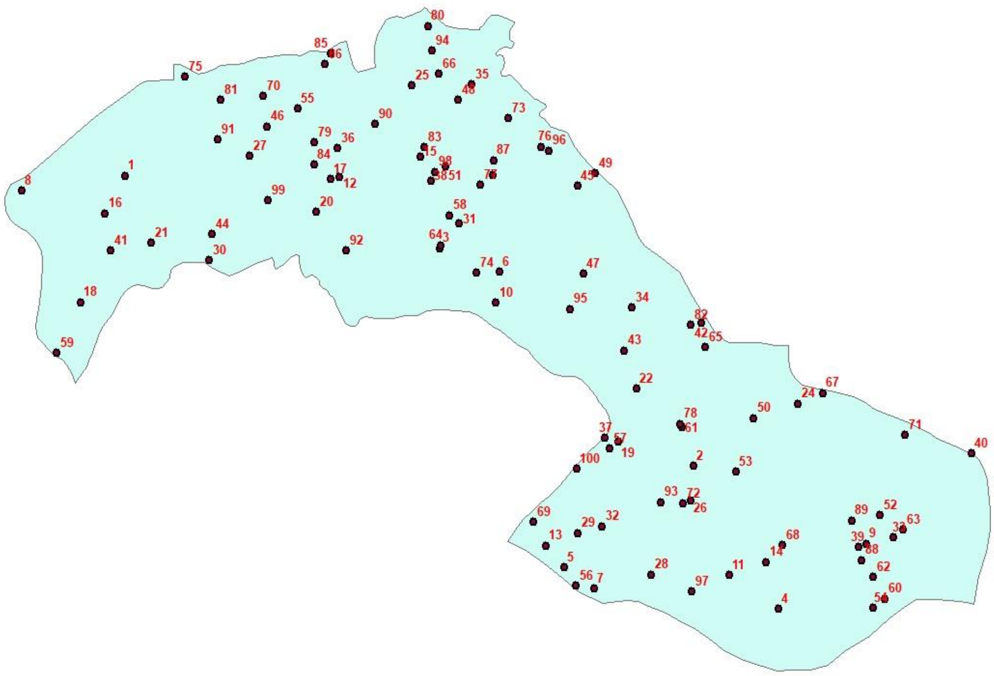

Figure 50: Randomly created labelled nodes in Çankaya district

Then, coordinates of all nodes are defined with ArcGIS's feature and export to Excel. After that, distance matrix have created and first level of HT1 algorithm run. For case 1 facility locations have been found at node 16, 26, 39, 47 and 90. Then, HT1 algorithm's second level have run and motorized courier allocations and objective function value are computed. Table 4 below shows computed objective function values with respect to "p" and "m" values. Such as; for case 1 it is equal to 58 minutes.

Table 4: Type 1 Objective Values

Case	N	p	m	DL
1	100	5	20	58
2	100	5	30	39
3	100	8	20	45
4	100	8	30	31

Table 5 below are shows that how motorized courier allocation for case 1. Such that; restaurant located in 16 have 3 motorized courier in order to distribute orders or restaurant located in 26 have 5 motorized courier in order to distribute orders. Figure 51 and 52 below are presenting case 1 solutions visually

Table 5: Distribution of motorized couriers to the restaurants for case 1

Case	Restaurant Location	Motorized Courier Amount
1	16	3
	26	5
	39	2
	47	4
	90	6

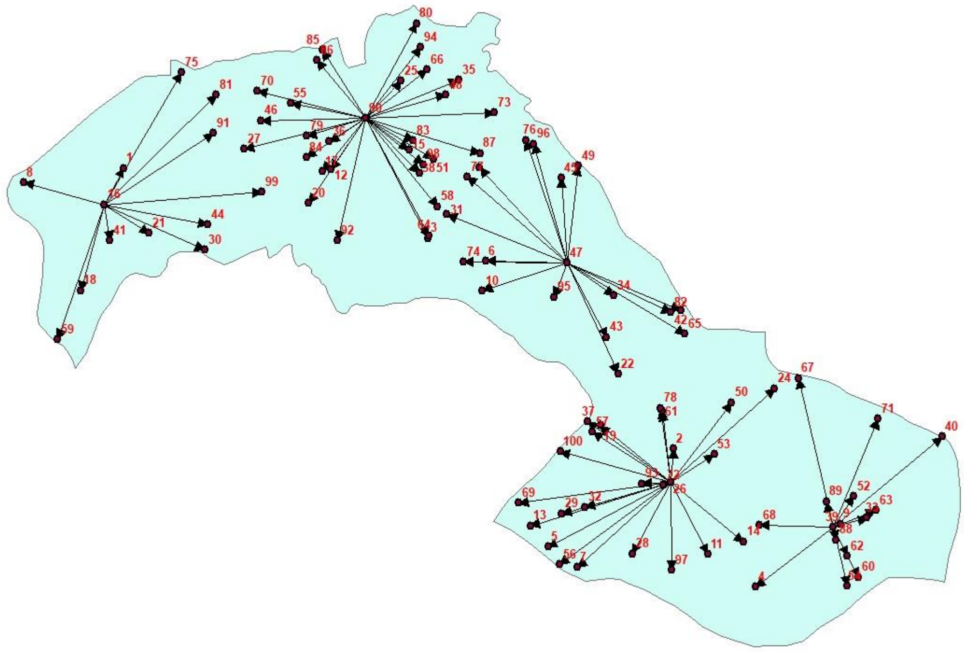

Figure 51: Solution of case 1

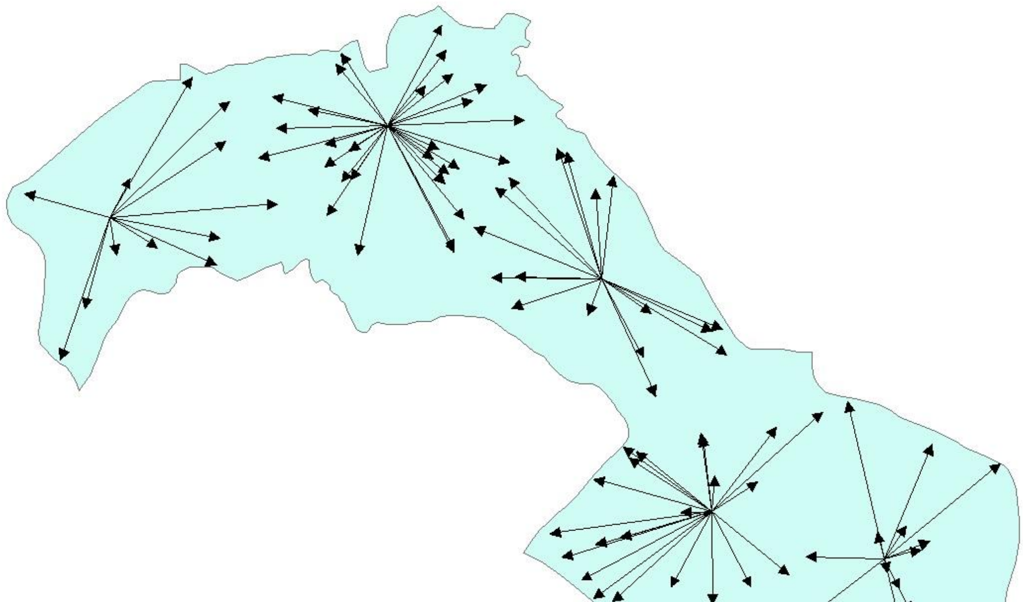

Figure 52: Solution of case 1 (Simple)

As table 4 shows all computed DL values are more than 30 minutes. However, our goal was distribute 100 order in 30 minutes. Unfornately, it isn't possible to that with data we had.

In fast food business time is very critical. Almost all customers wishes to eat their meals in hot condition. That's why, restaurant owners prefer fast distribution methods. Computed HT1 results showed that it isn't possible to satisfy 100 orders at most 30 minutes. However, HT2 may show us how many of 100 orders can distributed in 30 minutes. Moreover, any DL value may choose at HT2 algorithm since DL is a parameter in type-2 problem.

In this case study, DL values have chosen as 10 and 15 minutes in HT2 algorithm. Then, selected DL values increased to 30 minutes from 10 and 15 minutes while selected locations are kept. Also, each of the nodes weight have decided as 1. Thus, each of the nodes have become equally important.

Table 6: Type 2 objective values

Cases	**N**	**p**	**m**	**DL**	**∑W(i)*X(ij)**	**DL**	**∑W(i)*X(ij)**
1	100	5	20	10	***37***	30	***76***
2	100	5	30	10	***47***	30	***93***
3	100	8	20	10	***41***	30	***85***
4	100	8	30	10	***51***	30	***100***
5	100	5	20	15	***49***	30	***74***
6	100	5	30	15	***59***	30	***92***
7	100	8	20	15	***50***	30	***78***
8	100	8	30	15	***60***	30	***98***

Table 6 above shows that, computed objective values of case 1, 2, 3 and 4 are less than 5, 6, 7 and 8. Main reason of this is DL parameter. In other words, if DL increased computed objective values are also increased. Also, when DL values increased to 30 minutes in cases 1, 2, 3 and 4, objective values are showed increase. Similarly, when DL values increased to 30 minutes in cases 5, 6, 7 and 8, objective values are showed increase. Table 7 below shows that how motorized courier distribution in cases 1 and 5. Table 7 indicates that DL changes significantly affect allocation of motorized couriers to restaurants.

Table 7: Distribution of motorized couriers in Type 2 solutions

Cases	Restaurant Locations	Motorized Couriers
1	32	4
	39	4
	55	5
	77	5
	78	2
5	41	2
	77	5
	84	6
	89	3
	93	1
1 (DL=30)	32	2
	39	3
	55	4
	77	6
	78	5
5 (DL=30)	41	2
	77	5
	84	5
	89	3
	93	5

Figure 53 below shows case 1 solutions visually. Node 32, 39, 55, 77 and 78 have selected as restaurant locations. Motorized couriers have distributed as 4, 4, 5, 5, and 2 pieces to selected restaurant locations. Also, Figure 54 below shows case 5 solutions visually. Node 41, 77, 84, 89 and 93 have selected as restaurant locations.

Motorized couriers have distributed as 2, 5, 6, 3, and 1 pieces to selected restaurant locations.

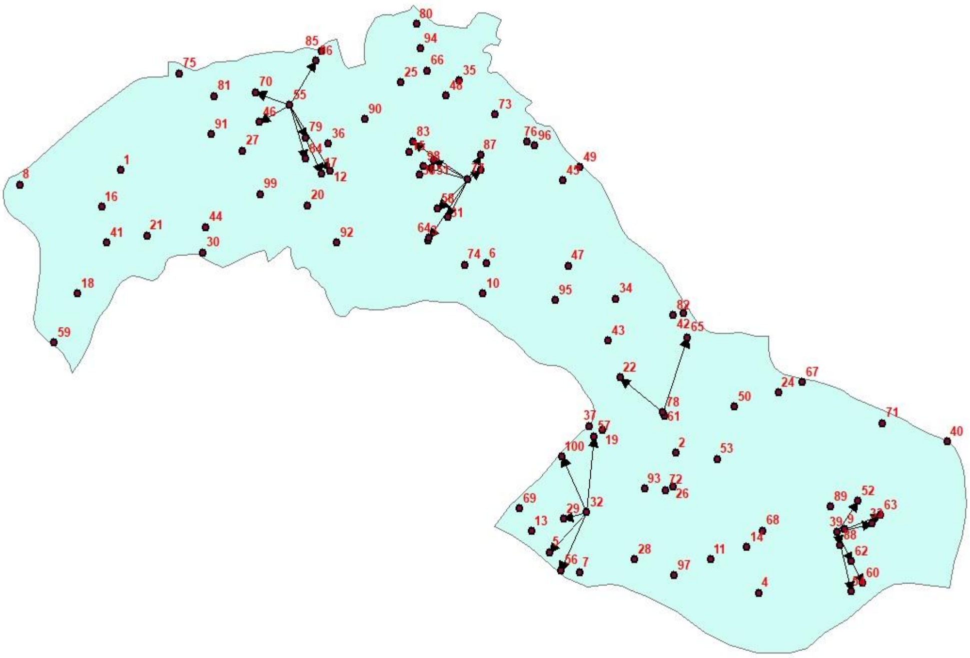

Figure 53: Case 1 solutions

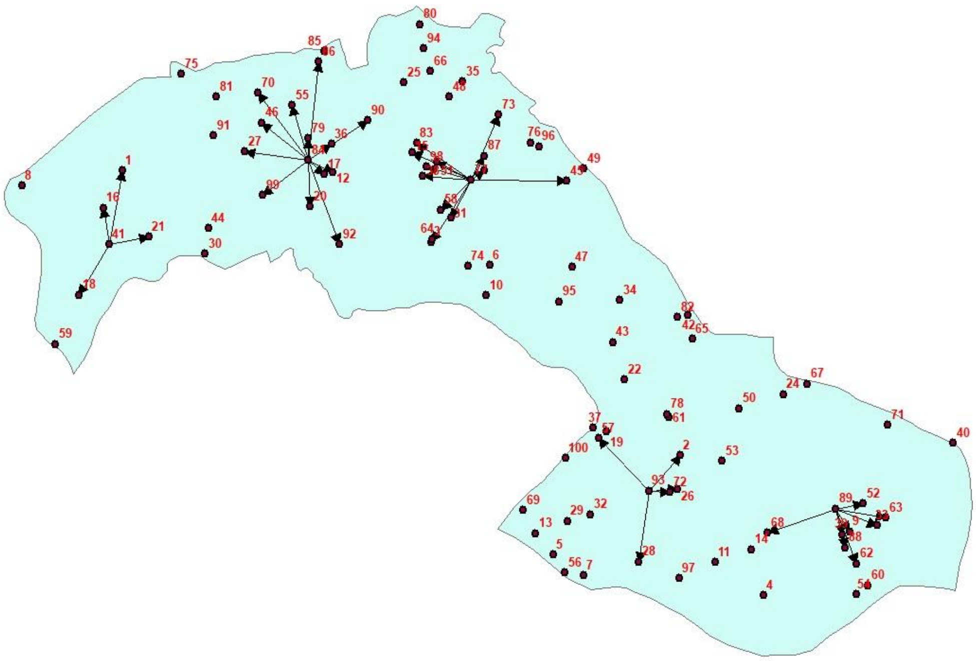

Figure 54: Case 5 solutions

Figure 55 and 56 below shows case 1 and case 5 computation results visually when DL have increased to 30 minutes. Like you may see in below figures: we've reached more client by using restaurant locations that found at DL=10 and DL=15 when DL has increased to 30 minutes.

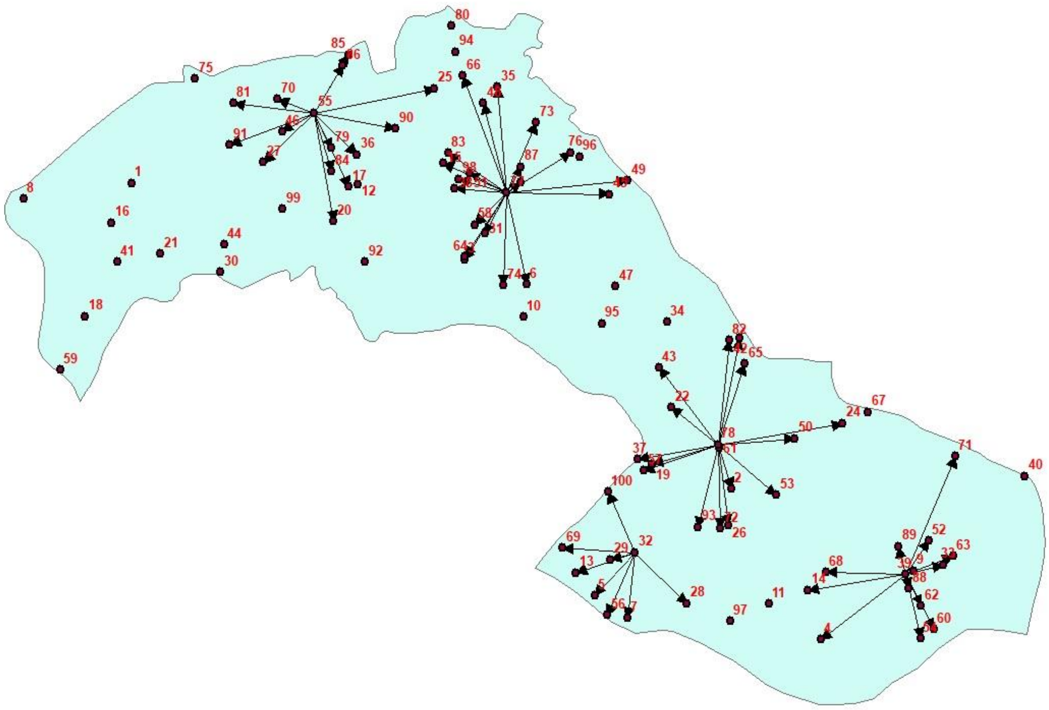

Figure 55: Case 1 solutions (DL=30)

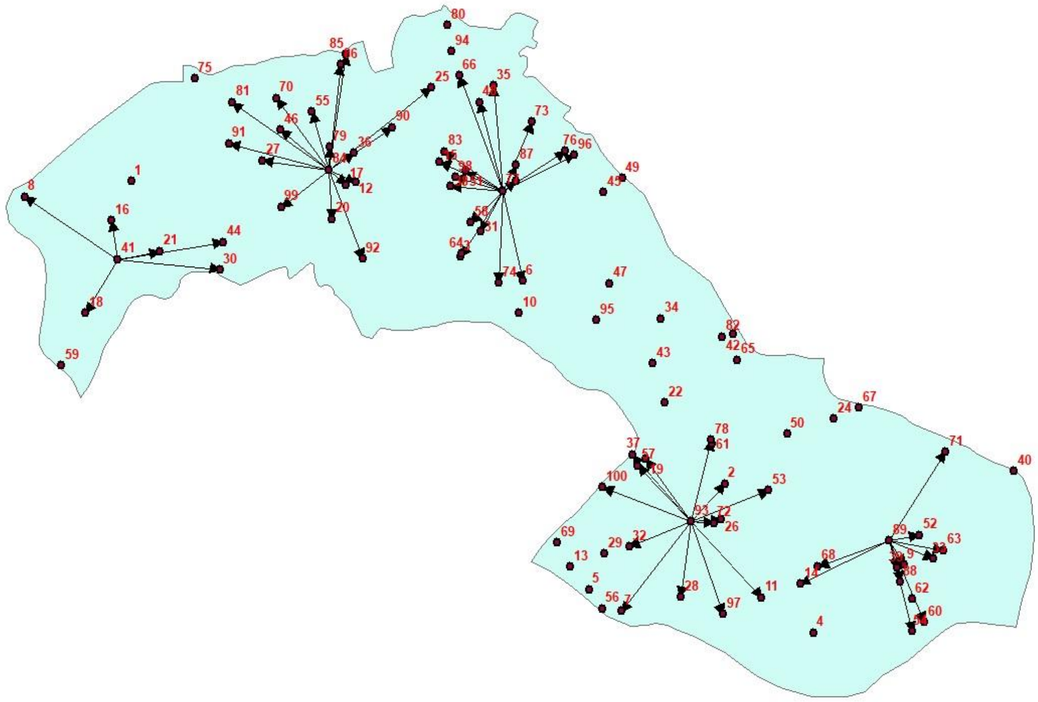

Figure 56: Case 5 solutions (DL=30)

Chapter 6

CONCLUSIONS

Two capacitated facility selection problem have been studied in this thesis. Type 1 is a version of well-known p-center problem but distribution capacities also have been considered. On the other hand, Type 2 is a version of well-known maximum covering problem but again distribution capacities have been considered. There are wide literature studies on p-center and maximum covering problems yet there is one only paper have been found which distribution capacities are considered. Delivery time is very important especially in service sector (food industry, fast-food chains, emergency service systems, fire stations etc.), moreover, it is very important on public services too such as “emergency service systems”. Delivery time is deeply related distribution capacity in these sub-sectors. This study claims that distribution capacities are equally important with distances while facility locations are decided. In order support our thesis numerous experimentations have been conducted. In other words, solutions which have found without considering distribution capacities may cause poor facility location decisions for decision makers. Both mathematical models and Heuristic algorithms have been developed In order to prove that. Heuristic algorithms are developed to show and compare computed objective values when distribution decisions are taken after facility decisions.

Heuristic algorithms have performed much faster than mathematical model yet objective function results of mathematical models have given better results than

Heuristic algorithm in same test instances. However, Heuristic algorithm results were not bad either. Type 1's mathematical model objective function results had given averagely %13 better than Heuristic algorithm. Type 2 (0.6 DL)'s mathematical model objective function results had given averagely %6 better than heuristic algorithm and, Type 2 (0.8 DL)'s mathematical model objective function results had given averagely %4 better than heuristic algorithm. Type 2 (0.8 DL) results have computed greater than Type 2 (0.6 DL). Therefore, obviously seen that DL has a significant effect on objective function in Type-2 problem. According to results, if distribution capacities have considered before facility locations decided then computed objective function values had given better results. However, heuristic algorithms solved problems very fast and obtained results close enough to the optimum solutions as well. So, if decision makers haven't got enough time to decide in real life, heuristic algorithm will be more than enough for them in order to decide.

Type-1 and Type-2 problems are more complicated than p-center and maximum covering problems since distribution capacities have been considered. P-center and maximum covering problem has solved for same test instances. According to results, huge solution time differences had been observed between p-center, maximum covering and type-1, type 2 problems. Such that for 30 nodes; average computed solution time of Type-1 is 251.77 seconds but for p-center is 0.54 seconds. Similar kind of observations can be seen for Type-2 in results section of this thesis. Thus, distribution capacities significantly affects problem's complexity.

In this study, factors which makes harder to solve Type-1 and Type-2 have been analyzed too. According to results, node amounts have been found as most significant factor. Also, facility amounts and vehicle amounts have been examined separately but there is no significant data have been collected that makes the problem harder to solve. Another finding is Type 1 problem computation time had taken more time to be solved than Type 2 problem which means that Type 1 is more difficult problem than Type 2.

In this thesis, importance of distribution capacity in facility location determination have been discussed and many valuable results have been found but there are still more parameters to consider. In future studies, fixed cost of opening a facility or buying a distribution vehicle may also be included in problems. Thus, another more realistic problem type may developed. Moreover, distribution capacities also may be considered on already exist location problems in literature. Such as, transfer point location problem, hub location problem etc.

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APPENDIX

Data of the randomly generated Type 1 test instance 10_1_3_1

N = 10;
p = 1;
m = 3;
D = [[0, 47, 73, 49, 30, 43, 29, 48, 33, 27],
[47, 0, 53, 49, 75, 89, 66, 54, 18, 36],
[73, 53, 0, 100, 86, 96, 102, 104, 65, 81],
[49, 49, 100, 0, 76, 87, 40, 6, 35, 22],
[30, 75, 86, 76, 0, 13, 43, 74, 63, 57],
[43, 89, 96, 87, 13, 0, 52, 85, 76, 69],
[29, 66, 102, 40, 43, 52, 0, 35, 48, 31],
[48, 54, 104, 6, 74, 85, 35, 0, 39, 24],
[33, 18, 65, 35, 63, 76, 48, 39, 0, 18],
[27, 36, 81, 22, 57, 69, 31, 24, 18, 0]];

Optimal solution of the randomly generated Type 1 test instance 10_1_3_1

Objective Function = 123
Solution Time = 0.375

x[1,2,10] = 1
x[2,2,10] = 1
x[3,1,10] = 1
x[4,3,10] = 1
x[5,2,10] = 1
x[6,3,10] = 1
x[7,3,10] = 1
x[8,1,10] = 1
x[9,1,10] = 1
x[10,1,10] = 1

z[1,10] = 1
z[2,10] = 1
z[3,10] = 1

y[10] = 1

Data of the randomly generated Type 2 test instance 10_1_3_1 (0,6 DL)

N = 10;
p = 1;
m = 3;
DL = 74;
W = [58, 78, 82, 42, 38, 6, 53, 60, 63, 28];
D = [[0, 47, 73, 49, 30, 43, 29, 48, 33, 27],
[47, 0, 53, 49, 75, 89, 66, 54, 18, 36],
[73, 53, 0, 100, 86, 96, 102, 104, 65, 81],
[49, 49, 100, 0, 76, 87, 40, 6, 35, 22],
[30, 75, 86, 76, 0, 13, 43, 74, 63, 57],
[43, 89, 96, 87, 13, 0, 52, 85, 76, 69],
[29, 66, 102, 40, 43, 52, 0, 35, 48, 31],
[48, 54, 104, 6, 74, 85, 35, 0, 39, 24],
[33, 18, 65, 35, 63, 76, 48, 39, 0, 18],
[27, 36, 81, 22, 57, 69, 31, 24, 18, 0]];

Data of the randomly generated Type 2 test instance 10_1_3_1 (0,8 DL)

N = 10;
p = 1;
m = 3;
DL = 99;
W = [58, 78, 82, 42, 38, 6, 53, 60, 63, 28];
D = [[0, 47, 73, 49, 30, 43, 29, 48, 33, 27],
[47, 0, 53, 49, 75, 89, 66, 54, 18, 36],
[73, 53, 0, 100, 86, 96, 102, 104, 65, 81],
[49, 49, 100, 0, 76, 87, 40, 6, 35, 22],
[30, 75, 86, 76, 0, 13, 43, 74, 63, 57],
[43, 89, 96, 87, 13, 0, 52, 85, 76, 69],
[29, 66, 102, 40, 43, 52, 0, 35, 48, 31],
[48, 54, 104, 6, 74, 85, 35, 0, 39, 24],
[33, 18, 65, 35, 63, 76, 48, 39, 0, 18],
[27, 36, 81, 22, 57, 69, 31, 24, 18, 0]];

Optimal solution of the randomly generated Type 2 test instance 10_1_3_1 (0,6 DL)

Objective Function = 411
Solution Time = 0.188

x[1,1,9] = 1
x[2,1,9] = 1
x[3,3,9] = 1
x[4,2,9] = 1
x[8,2,9] = 1
x[9,1,9] = 1
x[10,1,9] = 1

z[1,9] = 1
z[2,9] = 1
z[3,9] = 1

y[9] = 1

Optimal solution of the randomly generated Type 2 test instance 10_1_3_1 (0,8 DL)

Objective Function = 464
Solution Time = 0.312

x[1,3,10] = 1
x[2,2,10] = 1
x[3,1,10] = 1
x[4,3,10] = 1
x[7,2,10] = 1
x[8,2,10] = 1
x[9,1,10] = 1
x[10,1,10] = 1

z[1,10] = 1
z[2,10] = 1
z[3,10] = 1

y[10] = 1