DOKUZ EYLÜL UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

PLANNING OF A BICYCLE SHARING SYSTEM

by

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İZMİR

PLANNING OF A BICYCLE SHARING SYSTEM

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We have read the thesis entitled **"PLANNING OF A BICYCLE SHARING SYSTEM"** completed by **ÖZLEM ÖSKEN** under supervision of **ASSOC. PROF. DR. ALİ SERDAR TAŞAN** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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PLANNING OF A BICYCLE SHARING SYSTEM

ABSTRACT

Bicycle sharing system is a publicly available transportation system consisting of stations located in certain parts of the city. In recent year, bicycle sharing system has gained popularity in many major cities around the world. Its positive effect on air and noise pollution problem and human health issues, traffic and parking places problems of big cities are some of the reasons for this increase. Besides, there are some problems that bicycle sharing systems have to deal with. In order for these systems to be successful, the demands of the users must be met to the maximum extent. In the past work related to the subject, it seems that there are two main problems affect the bicycle sharing systems' demand and quality; the station being completely empty when users come to pick-up bicycles or a station being completely full when arriving to leave the bike.

In this study, bicycle rebalancing operations are discussed in order to solve this problem encountered by the mentioned systems. There are some variables to be determined when performing these operations. These variables are the number of bicycles that must be delivered to the stations or the number of bicycles that must be collected from the stations. Then, it will be necessary to transport these bicycles to the stations with the shortest route. For this purpose, mathematical models in the literature are examined and a new approach based on this model is proposed. An Estimation of Distribution Algorithm (EDA) is used in this approach. The proposed approach is tested with the data generated and with the data from a real BSS and results are presented.

Keywords: Bicycle sharing systems, static bicycle rebalancing problems, estimation of distribution algorithm, mathematical modeling

BİSİKLET PAYLAŞIM SİSTEMİNİN PLANLAMASI

ÖZ

Bisiklet paylaşım sistemi şehrin belirli bölgelerinde haklın kullanımına sunulmuş olan istasyonlardan oluşan bir ulaşım sistemidir. Son yıllarda bisiklet paylaşım sistemlerinin, dünya çapında büyük şehirlerdeki popülerliği artmıştır. Hava ve ses kirliliği sorununa ve insan sağlığına olumlu etkileri, büyük şehirlerdeki trafik ve park yeri problemi bu sistemlerin popülerliğinin artmasının nedenlerinden bazılarıdır. Bunun yanı sıra, bisiklet paylaşım sistemlerinin üstesinden gelmek zorunda olduğu bazı sorunlar da vardır. Bu sistemlerin başarılı olabilmesi için kullanıcıların taleplerini maksimum düzeyde karşılamaları gerekmektedir. Konu ile ilgili geçmiş çalışmalar incelendiğinde, kullanıcıların bisiklet almak için durağa geldiklerinde istasyonun tamamen boş olması veya bisiklet bırakmak için geldikleri bir istasyonun tamamen dolu olması durumlarının, bu sistemlere olan talebi ve sistemin kalitesini doğrudan etkileyen iki temel sorun olarak belirtildiği görülmektedir.

Bu çalışmada, bahsedilen sistemlerin karşılaştığı sorunun çözülmesi için gerçekleştirilen bisiklet dengeleme işlemleri ele alınmaktadır. Bu işlemler gerçekleştirilirken belirlenmesi gereken bazı değişkenler mevcuttur. Bunlar istasyonlara bırakılması veya istasyonlardan toplanması gereken bisiklet sayılarının belirlenmesidir. Daha sonra bu bisikletleri, minimum rotada istasyonlara dağıtmak gerekecektir. Bunun için literatürdeki matematiksel modeler incelenmiş ve bu modele dayanan yeni bir yaklaşım önerilmektedir. Bu yaklaşımda bir Dağılımın Tahminlemnesi Algoritması (DTA) kullanılmaktadır. Önerilen yaklaşım, oluşturulan ve bir BPS'den alınan verilerle test edilmiş ve sonuçlar sunulmaktadır.

Anahtar Kelimeler: Bisiklet paylaşım sistemleri, static bisiklet dengeleme problemleri, dağılım tahminleme algoritması, matematiksel modelleme

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CHAPTER ONE
INTRODUCTION

Bicycle sharing systems (BSSs) is a system that allows users to rent bicycles from certain stations for short trips and to return bicycles to the same or another station. Nowadays, BSSs have become one of the most important transportation systems commonly used in many countries, especially in Europe and China. With the expansion of these systems, the number of users of these systems is increasing. Bike rentals from the station they want at any time during the day and returning them to another station after a certain period of time change the amount of bikes at the stations. Thus, bicycle transport from full stations to empty stations must be carried out.

In order to keep their systems in balance, BSSs must perform a routing process after determining the number of bicycles needed by the stations. Picking up bicycles from some stations and dropping them to another stations and trying to do this process with minimum distance has been one of the most studied topics in the literature about BSSs. The subject dealt with in this study is to determine the number of bicycles needed by the stations in a BSS and to perform the distribution of these requirements at minimum distance.

Some methods are used to perform the balancing operations that mentioned above. Mathematical models and metaheuristic algorithms are mostly used among these methods. In this study, a new solution approach will be presented by using these methods to solve the problem.

In this section, the general order of this thesis is mentioned. Firstly, the general definition of BSSs is made in Chapter 2. The history and development of the BSSs around the world, general benefits of BSSs for human and environment and the current situation of those systems in the world were mentioned. Also, some studies on this subject in the literature have been mentioned. These studies were examined in three sections as strategic, tactical and operational phases.

In Chapter 3, the bicycle rebalancing problem was explained in detail. The purpose of the problem and the constraints to be taken into consideration were determined. A mathematical model in the literature according to the purpose and constraints was described and solved on an example and results were illustrated.

In Chapter 4, mathematical model was developed according to the results obtained in the previous chapter and described a model for BSS that identifies and routes the bicycle demands of the stations and plans it on a daily basis. The model is solved for an illustrative example and the results are described. Since the mathematical problem was not solved with the mathematical model as the number of stations increased, a metaheuristic algorithm was needed.

Chapter 5 describes a metaheuristic approach based on the estimation of distribution algorithm (EDA) that performs routing for BSS in order to solve the problem sets with the large number of stations mentioned in the previous chapter. This approach is solved by some data in the literature and the results are compared with the other results in the literature.

In Chapter 6, a new approach based on mathematical model and EDA is proposed to perform daily planning and routing for BSS. First, the number of bicycles required by the stations was determined using mathematical model regardless of the route. The outputs of the mathematical model were then routed in the EDA mentioned in the previous chapter.

Some datasets suitable for the problem were generated for this approach and the approach was tested using this data. This data is also solved by using the mathematical model described in Chapter 4 to compare results. In addition, the data from a real BSS were tested for the approach. The results of solving the models are described in Chapter 7. Finally in Chapter 8, the study is summarized and to concluded.

CHAPTER TWO
BICYCLE SHARING SYSTEMS

BSS is a system that provides bicycles to users for short trips. BSS has some stations at the certain locations in a city that offer users to rent a temporary bicycle. Users are enabled to rent a bicycle any station that they request, and leave it to the same station or the nearest station. Positions of the bicycles in the system change over day, therefore a balancing situation emerges. Commonly, BSSs have a database that enable to control the number of bicycles at stations, the way that bicycles move in the system, and user of the rented bicycle in electronic environment. If the system provides access to the users, they also be able to reach the number of the bicycles at the relevant station via web site or smart phone application of the bicycle sharing or kiosks at the stations. BSSs are also responsible to carry out full maintenance of the supportive tools (handlebars, tires, brakes, bells, gears, skeletons, baskets etc.) to be provided to the user. Maintenance of any components that may occur in the stations should be done at regular routine checks to avoid interruption of communication with the system. Transportation of the bicycles to the stations is carried out by means of vehicles which are suitable for carrying the bicycles and which are allocated to the system. A BSS example is shown in Figure 2.1.

Many of the BSSs in large cities have increased their capacity considerably in the short term due to the increase in demand for bicycle sharing. There are many reasons for this increase such as its positive effects on the air and noise pollution and human health, being an affordable transportation alternative for users, being independent of urban traffic, and not being concerned about vehicle waiting problem as in public transportation. The widespread use of motor vehicle traffic in cities causes many negative effects as well the fact that fossil fuels have a great deal of CO footprint, increased fossil fuel prices in recent years, and the many negative consequences of motor vehicles, and traffic congestion (Frade & Ribeiro, 2014).

Figure 2.1 Example of a BSS (Metrobike, 2019)

2.1 Bicycle Sharing Systems around the World

BSSs have become a transportation alternative that has become popular among the big cities of the world in many of its advantages. According to MetroBike LCC, at the end of 2016, 2,294,600 bicycles are available for public sharing systems and 1,900,340 of them are in China. Almost 1290 cities has bicycle sharing programs and 394 cities are planning or under construction.

Table 2.1 Bicycle sharing in some major cities (Bikesharingmap, 2019)

	May, 2017		February, 2019	
	Bikes	Stations	Bikes	Stations
Hangzhou, China	135924	5489	224620	5566
Beijing, China	60100	1453	184920	4283
Paris, France	23900	1751	31890	751
London, England	11945	772	16445	772
Barcelona, Spain	6000	420	7360	465
Washington, USA	3800	474	17155	511
Madrid, Spain	2028	165	2428	165
Tokyo, Japan	771	87	1531	124

Table 2.1 is based on data taken from the www.bikesharingmap.com site that contains the current numbers, and BSSs with no bicycle numbers are not taken into account. As seen, all the BSSs among the world have continued to grow during this period. As seen in the table above, China is clearly ahead of other countries in the use of BSS. The number of BSSs that have been active recently is about 28 in Hangzhou and 20 in Beijing.

In Paris, Velib', which is one of the most popular systems in Europe, had 20600 bicycles with 1451 stations in Paris and 3,300 bikes in 300 stations in suburbs at the end of December 2017. The system was terminated on December 31, 2017. All bicycles in the system changed with electric bicycles, and system has started to operate again under the name Velib' Metropole Bike Rentals. Those new electric bicycles called Pedelec were included in the system. Figure 2.2 shows an example of a Pedelec. The word Pedelec derives from pedal electric cycle. This type of bicycles are designed to provide electronic support when the user is pedaling to facilitate with long distance rides. Besides France, BSSs with electric bicycles have started to spread in other countries, especially in China.

Figure 2.2 Example of a pedelec (Vélo-horizon, 2019)

Another application implemented by the Velib' Metropole Bike Rentals is called *Plus+* and third application has been tried to solve the capacity problem by connecting bicycle head-to-tail with the cables to another bicycle from any full station. This application is intended to avoid the problem of drop off demand at the most used station. In this way, users will be able to leave the bicycle they rented to a full station and the problem will be solved due to the stations are completely full.

Although the rate of bicycle use in Japan is very high, the reason that the BSS usage is lower than other countries is people prefer to use their private bicycles and bicycle parking spaces are sufficient (Nakamura & Abe, 2014).

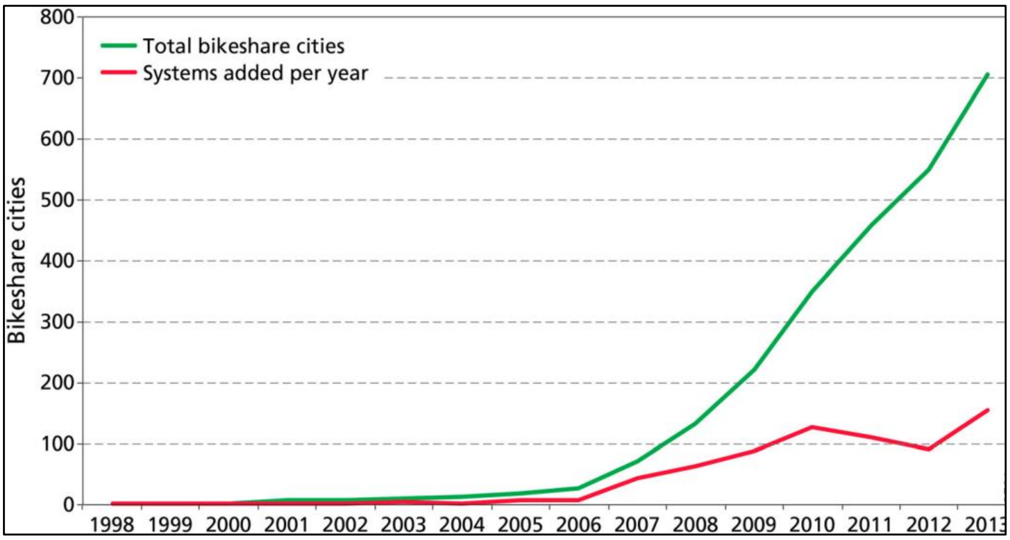


Figure 2.3 Bike sharing increase in the world (Fishman, 2015)

Increasing the number of BSS is very useful for cities and people with the reasons mentioned above and shown in Figure 2.3. On the contrary the benefits that BSS provides to users and cities, there are some problems negatively affecting the usage of BSSs. The inadequacy of cycle lanes in the cities make it difficult for cyclists to ride and more importantly, jeopardize the safety of cyclists. The slope of cities is one of the factors that negatively affect the use of bicycles.

On the other hand, according to European Commission, even though Switzerland is not a flat country, 23% of transportation is carried out by bicycle. Unpleasant weather conditions that affect transportation badly, such as heavy rain and snow, keep the user away from cycling alternatives. However, in many northern European countries like Sweden and Netherlands, users prefer to ride bicycles although a large part of the year is rainy. In Västerås, Sweden, 33%, in Cambridge, England, 27% of the transportations takes place by bicycle (European Commission, 1999).

According to the European Commission, in Europe, more than 30% of trips that made in cars cover distances of less than 3 km and 50% are less than 5 km. For the trips that last between 5 or 10 minutes, using bicycle provides transportation in a shorter time than using other transportation alternatives. At a distance of more than 1.5 km, the bicycle has become potentially weaker than other motor vehicles because the physical power of the users is necessary even if the difference in travel time between the bicycle and the car is less than 2 minutes in the city traffic (European Commission, 1999; Frade & Ribeiro, 2014).

2.2 Bicycle Sharing Systems in Turkey

In Turkey, BSSs, which has been quite late to establish the system compared to other countries, is still in the stage of growth and not fully settled. Although BSS has been established in only eight cities at present, some cities continue to work for the BSS.

Table 2.2 BSSs in Turkey (Bikesharingmap, 2019)

	February, 2019	
	Bikes	**Stations**
Istanbul	200	19
Kocaeli	120	15
Eskişehir	120	10
Izmir	500	33
Antalya	40	6
Konya	400	38
Kayseri	250	25
Ordu	200	15

Cities that have been established smart BSSs and capacity of the systems in Turkey is seen in Table 2.2. The use of the bicycle for everyday transportation being less than the other European countries is a result of Turkey's hilly and mountainous geographic position. Therefore, the importance given to bicycle sharing is also insufficient. While some of the cities have their own BSS companies, BSS that is located in Ordu and Konya, is a Germany-based system that operates in many cities in Europe called Nextbike.

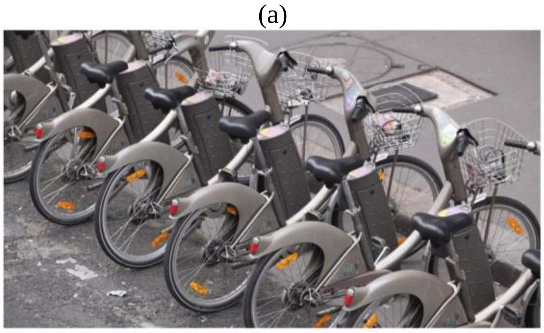
On the other hand Izmir, in terms of use BSS and cycling, is one of the most influential city in Turkey. In 2017, Izmir won European Cycling Challange, which is an urban cyclists' team competition that a month-long, with 855,000 km total cycling distance.

2.3 Historical Development of Bicycle Sharing Systems

The history of development of the BSS is divided into three generations. The first generation began in Amsterdam in 1965. The free bicycles, which were painted white, provided for public use, but it was not successful as planned (Figure 2.4 (a)).

(a)

(b)



(c)

(d)

Figure 2.4 Evolution of the BSS (a) First generation bike sharing called “witte fietzen” (wikipedia, 2019) (b) Second generation coin-based bike sharing (wikipedia, 2019) (c) Third generation card-based bike sharing (wikipedia, 2019) (d) Fourth generation bike sharing via smartphones (wikipedia, 2019)

The second generation, which is the systems that work with coin deposit, was implemented in Denmark about 25 years after the first generation. Although it is carried out by public and private organizations, as in the first generation, the situation of bikes being stolen has not been prevented (Figure 2.4 (b)). Third generation is the systems that based on the information technologies (Figure 2.4 (c)). The greatest impact on public bike users' perceived quality will be achieved by improving safety and information (Bordagaray et al., 2012).

The application that gave the opportunity to the users to be able to rent a bicycle by a smart card was first implemented at the University of Portsmouth. Due to track bicycles and its usage easily, the third generation bicycle sharing systems became a successful application and decreased bicycle damages substantially. Keeping the information of stations number of bicycles and observability of usage intensity increased service quality of the system and led it to demand-driven service. Thus, a rebalancing problem emerged that aimed to provide a balance between stations taking into account the use of bicycles.

In recent years, there are researches and studies to transition to the fourth generation which is demand-driven, dynamic and multi-modal systems (DeMaio, 2009). Users are able to find and rent bicycles via smartphone applications (Figure 2.4 (d)). Nowadays, BSSs eliminate stations and evolve dockless systems. Those systems are called free-floating bicycle system. In this system, users are able to drop off bicycles within a defined district in the city. There are no stations, docking places and kiosk machines in the system to reduce cost. Bikes are kept track by a smart management in real-time with built-in GPS (Figure 2.5).

In this type of systems, users rent bicycles through smartphones, and after the trip, they can leave bicycles at certain points. In this way, while reducing some of the costs caused by docked systems, advantage of free usage is intended to provide users. In contrast to the increase in the number of bicycles seen in Table 1, the reason for the relatively small increase in the number of stations is due to many BSSs, especially in China, have changed to the dockless system.

Figure 2.5 A dockless bike (Huffingtonpost, 2019)

2.4 Literature Review for Bicycle Sharing Systems

The literature research on the BSS shows that variable demands of users must be met and user satisfaction should be maximized in order that the system can be characterized as a successful system and favored by users. Two of the most important problems that prevent users from using the system is lack of bicycles at any station that user arrives or the station that the user wants to leave the bicycle is completely full. It is important that the BSS is reliable and stable so that the system can be seen as a preferred alternative to other transportation systems. In the previous studies, those problems expressed as bicycle balancing, repositioning or pick up /delivery problems. Generally, before the installation of BSSs, these problems are addressed within three phases, as strategic, tactical and operational.

2.4.1 Strategic Phase

In the strategic phase, the number of stations, the locations and capacities of these stations are determined in the system. Lin et al. (2013) described a nonlinear mathematical model to determine capacity of each station, bicycle lanes and number of bicycles at the stations that minimizes cost under service level and inventory constraints. Frade & Ribeiro (2015) defined a mathematical model to cover maximum user demand, decide capacity of the stations and number of the bicycles at stations under budget constraints. Faghih-Imani & Eluru (2016) stated capacity of the stations and the number of bicycles have often been overestimated to setup of several sharing systems and have developed a model to decide capacity of the stations and the number of bicycle. Caggiani et al. (2017) proposed a model that aims to optimize user satisfaction under budget constraints.

Çelebi et al. (2018) determined the best locations to establish BSS in a campus while estimated demand, number of required stations and capacity of decided stations and minimized unsatisfied demand. Conrow et al. (2018) used location-covering model to place the stations under spatial and social equity constraints.

A number of studies have focused on improving the quality of the system and providing better service to users. Kaspi et al. (2016) presented a model that detects unusable bicycle number at the stations with a probability. Hsu et al. (2018) developed a hybrid method to improve service quality and increase number of subscribers of the system. Zhang et al. (2019) used maximize coverage method to solve the location-allocation model to plan locations of electric fences for dockless BSS.

The design of the BSS requires an integrated approach for considerating transportation, inventory and facility costs as well as the service quality (Lin et al., 2013). According to Forma et al. (2015), firstly, the extent and the nature of the demand of a new BSS should be forecasted. Then, some strategic problems need to be addressed. Several researches assert the relationship between bicycle usage and stations location (Vogel et al., 2011). Positioning the stations near the demand points and public transport networks was one of the important factors in the success of the BSS (Palomares et al., 2012). Zhang et al. (2015) asserted some similarities and certain characteristic and key factors to establish a sustainable bicycle sharing. Ricci (2015) identified limitation and opportunities of bicycle sharing operations and setting up. Factors that effects users' destination preferences in bicycle sharing is also studied and modelled (Faghih-Imani & Eluru, 2015).

2.4.2 Tactical Phase

In the tactical phase, it is decided how many bikes should be in the system. Demand analysis, analysis of system movements are the critical processes in this phase. As the bicycle movements in the system constantly change throughout the day, the demand review phase is a very difficult task. Frade & Ribeiro (2014) proposed a methodology to estimate demand and state trip and topography of the city affects demand of BSSs. Chardon et al. (2015) proposed some methodologies to estimate number of daily trips based on the number of bicycles available at a station over time. Tran et al. (2015) analyzed the factors that effects bicycle sharing usage and assert that bicycle sharing usage depends on the built environment around each station. Nair et al. (2012) asserted the BSS demand is increasing in stations that located close to public transportation networks.

There are also some studies analyze the reaction of users to the BSS. Bordagaray et al. (2012) proposed a methodology that analyzes user perception level for BSSs' quality based on the use of an Ordered Logit model. Parkes et al. (2013) tried to analyze the growth of the BSSs around the world. Faghih-Imani & Eluru (2016) analyzed how the sample size affect usage and destination choice preference.

Gao & Lee (2019) combined machine learning with genetic algorithm to predict rental demand by using pre-classified historical records. Li et al. (2019) studied and analyzed trips and develop an algorithm to trip planning to increase the number of served users. Reyneud et al (2018) analyzed bicycle availability at a BSS and estimated available bicycles at specific times of the day.

2.4.3 Operational Phase

In the literature, rebalancing of BSSs are divided into static bicycle rebalancing problems (SBRP) and dynamic bicycle rebalancing problem (DBRP). In static systems, a fixed number of bicycles is initially determined for each station. The system tries to reposition the bikes according to the number defined at this beginning.

2.4.3.1 Static Bicycle Rebalancing Problems

Raviv et al. (2013) defined two formulation for SBRP formulations. First formulation is referred to as the arc-indexed with the objective function is to minimize total cost of the system and travel time, under inventory, capacity of vehicles and stations constraints. Second formulation is referred to as time-indexed based on discretizing the time available for repositioning. Time-indexed formulation allows vehicles to visit multiple time at stations and stay to synchronize transshipments. In order to solve the formulations two-phase solution method is developed and tested with instances up to 104 stations and 2 vehicles. Results are shown that arc-indexed formulation reaches better solutions than time-indexed formulation. Authors also remark the characteristics that affect quality of the solution.

Forma et al. (2015) propose a 3-step heuristic model based on the arc-indexed formulation by Raviv et al. (2013) that minimizes the number of unserved demand and travelling distance, clustering stations and routing vehicles to rebalancing. First step creates station clusters by using a specialized saving heuristic according to the geographic location and the initial inventory. Second step routes the vehicles for repositioning by the clusters and decides inventory of bicycles to be loaded or unloaded at each station. Then, the last step solves the repositioning problem. This step uses the routing decisions obtained in previous step as input and inventory decisions for all stations are made. The last two steps are formulated as mixed integer linear programming (MILP) with the goal that minimizes a weighted sum of the expected number of unserved users. The method was tested on instances of up to 200 stations and 3 repositioning vehicles.

Ho & Szeto (2014) considered mathematical formulation proposed by Raviv et al. (2013) under single vehicle assumption, pick-up and drop-off stations are defined similar to Caggiani & Ottomanelli (2012), and Ting & Liao (2013). Three set of instances are used to test to this study. The first instance is 30 to 100 stations with a vehicles capacitated with 20 bicycles. The second instance is 100 to 400 stations with vehicles capacitated with 10 to 40 bicycles. The last instance is 200 to 400 stations with vehicle capacitated with 20 bicycles. While solving the problem, an iterated Tabu Search (TS) heuristic provides very short computing times is used.

Ho & Szeto (2016) revise the arc-indexed formulation for multi vehicle bicycle rebalancing problem presented by Raviv et al. (2013) by adding station characteristic constraints to the model. To solve multi-vehicle bike-repositioning problem, a hybrid large neighborhood search (LNS) is presented. The heuristic is evaluated on three sets of instances with 518 stations and 5 vehicles. Authors compared results with the 3-step math heuristic proposed by Forma et al. (2015) stated that proposed heuristic obtain better solutions than 3-step heuristic.

Szeto et al. (2016) propose a new heuristic that obtain good solutions of a static bicycle rebalancing problem. Arc- index formulation proposed by Raviv et al. (2013) is developed. A chemical reaction optimization (CRO) is proposed to determine vehicle routes, the loading and unloading quantities at each visited station. Heuristic is tested with 300 stations and it is indicated that the proposed CRO provides high-quality solutions with short computing times.

Schuinjbrock et al. (2016) determined service levels at each station as well as vehicle routes to rebalance the inventory. Due to user behaviors being non-stationary, Markov Chain formulation is used to determine inventory level at bicycle station with lower and upper bounds. A MILP inspired by the mathematical model in Raviv et al. (2013) was presented with the objective that minimizes the total routing time or user dissatisfaction. Model is solved with two heuristic, Clustered MILP and Clustered MILP with cuts. In addition, a constraint-programming model is developed that its objective is to find a feasible solution while rebalancing the system as soon as possible. Both methods are tested with the instance of 28 stations and vehicles capacitated with 10 to 20 bicycles. Authors determined that clustered MILP with Cuts heuristic performed better than the constraint programming formulation while the number of vehicles increases.

Dell'Amico et al. (2014) present four MILP formulations with the objective of minimizing total cost. First formulation is based on multiple travelling salesman problem (TSP). For second formulation, the balance of the flows and lower and upper bounds on the flows constraints added to the first formulation. Sub-tour elimination constraint developed by Hernández-Pérez & Salazar-González (2004) is replaced classical sub-tour elimination constraint from the first formulation. Fourth formulation is based on two-commodity flow model originally presented by Baldacci et al. This formulation requires adding a copy of the depot to the graph. Routes of the vehicles start at the initial depot and after visiting customers, end their route in the final depot. Branch-and-cut algorithms are developed to solve the formulations with real world instances ranging from 13 to 116 stations. Authors then decided that the third formulation is having better outcomes. Dell'Amico et al. (2016) study with the same problem. Third formulation in Dell'Amico et al. (2014) is used and solved with destroy and repair metaheuristic algorithm. Authors state that solutions found by this algorithm have shorter computing times for the smaller instances and better upper bounds for the larger instances when solutions are compared to solutions with found by branch-and-cut algorithm in Dell'Amico et al. (2014). Real world instances are expanded to 564 stations.

Gaspero et al. (2015) present two constraint programming and two strategies for balancing bike sharing systems problem. First strategy is to optimize the objective function (cost); second strategy is to build a feasible solution fast without considering the cost. Two constrains programming are defined routing and step respectively. Routing is classical vehicle routing problem. Step is to find a route with a planning horizon. A LNS approach is proposed to experience for a sample size of 40 to 240 stations and determined that LNS approach is more effective on larger instances.

Kloimüllner et al (2015) proposed cluster first- route second approach for solving bicycle rebalancing operations. They use logic-based Benders decomposition to solve an assignment problem as master problem which decides which stations have to be serviced by which vehicle and TSP as sub-problems. They test the algorithm with instances up to 60 stations and state that proposed method is not always found within the time limit for larger instances.

Erdoğan et al. (2014) develop a formulation for static bicycle rebalancing problem with demand intervals. First, fixed route subproblem without and with handling cost is considered. Then a MILP based on minimum cost network flow formulation is developed. Two exact algorithms for the static repositioning with demand intervals, a standard branch-and-cut algorithm and a Benders decomposition based branch-and-cut algorithm are developed. Those algorithms determine pickup and delivery quantities with fixing vehicle route and simultaneously with the vehicle route respectively. The model is tested with 30 to 50 stations with both algorithms and results are shown that Benders based algorithm provides shorter computation times and can solve more instances.

Li et al. (2016) consider rebalancing operations with multiple types of bicycles. They develop a MILP to minimize the total cost includes vehicle travel cost, the total penalties of unmet demand, and the total substitution and occupancy penalty. A hybrid genetic algorithm (GA) that given by Vidal et al. (2012) is proposed to solve the problem and an embedded greedy heuristic is used to determine the number of loading or unloading bikes by types, algorithms are tested with 10 to 180 stations that generated by Rainer-Harbach et al. (2013) and as result, authors decided that hybrid GA yields high-quality solutions with short running times.

Bulhões et al. (2017) define a mathematical model that minimizes the cost of a bike sharing system vehicles, proposed a branch- and-cut algorithm to obtain lower bound for objective function value and an iterated local search that performs efficient move evaluations. Algorithms computationally experienced with 10 to 200 stations that obtained for the real world based instances Dell’Amico et al. (2014) and Rainer-Harbach et al. (2015).

Pal & Zhang (2017) study on a free-floating bicycle sharing system model. A MILP with the objective of makespan minimization is presented for rebalancing problem. Hybrid of nested LNS and variable neighborhood descent (VND) heuristics is developed and tested with 20 to 450 stations and 10 to 1000 bicycle vehicle capacity and results are compared with exact algorithms from literature.

Chemla et al. (2013) developed an exact mathematical model that based on the constant upper bound of visits assumption with the objective function that minimizes the visited stations. Two relaxations are presented to obtain lower bound of the optimal solution and solved by a branch-and-cut algorithm. Upper bound of the optimal value is computed by TS algorithm. Proposed algorithms are solved on the instance with 10 to 1000 bicycle capacities and 20 to 100 stations.

Erdoğan et al. (2015) defined an integer programming which is simplified version of second relaxation of static bike rebalancing problem by Chemla et al. (2013) that objective is to minimize total travel cost under vehicle routing constraints. Algorithm for separating the combinatorial Benders' cuts to check the feasibility, and a modification of the separation algorithm for non-preemptive static bicycle rebalancing problems are proposed and tested instances with up to 60 stations and results are compared with results found by Chemla et al. (2013).

Cruz et al. (2017) studied the bicycle sharing rebalancing problem with a single vehicle. The objective is to find minimum cost route that meets the demand of all stations. An iterated local search heuristic is proposed that based on Chemla et al. (2013) and Erdoğan et al. (2015). The algorithm was tested on 20 to 100 stations and results are compared with Chemla et al. (2013) and Erdoğan et al. (2015).

Angelouais et al. (2014) developed an alternative approach that determines vehicle routes with visiting stations in regular intervals and amount of bicycles that must pick up or deliver at the station. One for TSP and the other for flow assignment, two mathematical models were used. First, vehicle routes are determined with the objective that minimizes the total travel time for the set of routes. Second, routes are supplied as input to the flow assignment model that determined flow of bicycles. Those mathematical models are solved with an algorithm that finds shortest set of routes and testes with 30 stations and it is shown that improved algorithm balances the number of bicycles entering and leaving stations.

Alvares-Valdes et al. (2015) tried to optimize service quality level, unsatisfied demand, which means empty stations or full docks, for any time period in the future is forecasted. Forecasted unsatisfied demands found in the previous stage is used to calculate the target number of bicycles per station. After determining target number of bicycles, repositioning routes of vehicles are constructed. They also deal with the damaged bicycles at stations to collect and take it back while dropping bicycles to stations. Presented algorithm is experimented using an instance of 28 stations with vehicles capacitated with 10 to 20 bicycle.

Kadri et al (2016) developed a mathematical model that minimizes the sum of weighted arrival times to stations to solve the rebalancing problem. Due to importance of the bounds for optimal solution, three relaxations for lower bound and three heuristic for upper bound are discussed to develop lower and upper bounds quality. Instances with 10 to 100 stations are used to solve the problem but proposed branch and bound algorithm is able to solve up to 30 stations.

Unlike other studies, Dell'Amico et al. (2018) have addressed the demand of the system as probabilistic. In five different methods they developed, they described the demand as random variables and performed the routing process based on some scenarios. BSS with probabilistic demand problem solved by using methods such as deterministic equivalent program, L-Shaped methods, and branch-and-cut. Heuristic algorithms also developed by combining constructive procedures based on novel correlation between different scenarios. Algorithms were tested on newly collected realistic instances up to 80 stations.

2.4.3.2 Dynamic Bicycle Rebalancing Problems

Repositioning in dynamic systems continues parallel to the use of bikes by users. In other words, when bicycles are repositioned by system operators on demand, users continue to pick up and deliver bicycles. In dynamic systems, these pick up-deliver operations are tracked, expected number of user demand is forecasted, the number of bicycles to be required for the station is decided and the vehicle routing is performed. Caggiani & Ottomanelli (2012) presented a simulation model that minimizes the costs while keeping users satisfaction high for dynamic bicycle rebalancing with a fuzzy decision support system. Neural networks method is used to forecast future demand bicycles. To obtain vehicle routes, a TSP is considered and minimization problem is formulated as nonlinear integer programming. The solution algorithm based on a Branch and Bound is tested with five stations. Again Caggiani & Ottomanelli (2013) conducted another simulation model determines optimal vehicle route and number of bicycles load and unload in dynamic case.

Zhang et al. (2017) proposed a mathematical model for dynamic repositioning that determines inventory level, user arrival, bicycle repositioning and vehicle routing, and user dissatisfaction. To forecast expected user dissatisfaction and expected inventory level, estimation model that proposed by Raviv & Kolka (2013) was used. Objective function minimizes the total costs and the expected user dissatisfaction. A heuristic algorithm is developed to solve the problem with up to 200 stations very efficiently.

Contardo et al. (2012) presented an arc-flow formulation that minimizes unmet demand on space-time network and a heuristic procedure to solve dynamic bicycle sharing rebalancing problem and develop a heuristic method with based on two decomposition procedures. First, Dantzig-Wolfe decomposition used to solve the problem and second, Benders decomposition is applied with the information that reached from first decomposition. Heuristic tested on instance with 25 to 100 stations.

Brinkmann, et al. (2015) developed long and short-term strategies for stochastic and dynamic inventory routing problem with the objective that minimizes the number of latest serving time of a station violations for BSSs. Kloimüllner et al. (2014) considered the dynamic rebalancing systems with the objective is to minimize unfulfilled demands. Certain metaheuristic approaches are extended and tested with instances 30 to 90 stations.

CHAPTER THREE
REPOSITIONING PROBLEM IN STATIC BICYCLE SHARING SYSTEMS

3.1 Problem Definition

Stations of the BSSs should be located in certain locations of the city, every station should have enough dock and enough bicycles on those docks to meet the users demand. Users can rent bikes from the stops they want, and return these bikes to the stops they want. It is undesirable for BSS not to have bicycles in a station that users prefer to rent a bicycle and that the station where the users want to return the bike is full. Therefore, a rebalancing operation must be performed. It was mentioned in the previous sections that the rebalancing process for BSS was carried out in two ways as static and dynamic. Static rebalancing was discussed in this study.

The SBRP aims to determine the number of bicycles to be taken from stations with excess bicycle and the number of bicycles at the stations that require bicycle while finding a route that will carry those bicycles with a minimum distance to the required stations.

3.2 Mathematical Model of the Static Bicycle Routing Problems

The mathematical formulation mentioned below is based on integer linear programming formulation for the SBRP introduced by Raviv et al (2013). BSS consists of n stations and a depot that supply bicycles to the stations. Set of stations is refered to as N, and set of stations included depot is N_0 . The capacity of stations i $(0,..N)$ is T_i, initial number of bicycles at the station is s_i^0. Set of the transportation vehicles is V and capacity of the vehicles is k_v. Each station has a demand d_i, this demand value can be either positive or negative. If $d_i > 0$, then i is a pick-up node and bicycles should be loaded to the vehicle. If $d_i < 0$, then i is a delivery node and bicycles should be dropped to the station. The cost of arc (i,j) is represent as $C_{i,j}$. Objective function and constraints presented by Raviv et al. (2013) are adopted for the simplicity and purpose of this study.

3.2.1 Sets, Parameters and Decision Variables

Sets:

- N set of stations, $i=0,,N$
- V set of vehicles, $v=1,,V$

Parameters:

- T_i the capacity of station i
- C_{ij} cost of carrying bicycles from station i to station j
- d_i the number of bicycles pick-up or drop off to the stations i
- k_v capacity of vehicle v
- $s^0{}_i$ initial inventory level of station i
- M upper bound on the number of arcs in a vehicle's tour

Decision Variables:

- x_{ijv} binary variable, equals 1 if station j is visited after station i with vehicle v, 0 otherwise
- f_{ijv} the number of bicycles carried from station i to station j at the with vehicle v
- $Y^l{}_{iv}$ the number of bicycles loaded to vehicle v from station i
- $Y^u{}_{iv}$ the number of bicycles uploaded from vehicle v to station i
- q_{iv} auxiliary variables used for sub-tour elimination constraints
- S_i inventory level of station i after repositioning operation

3.2.2 Mathematical Formulation

$$minimize \quad \sum_{i}\sum_{j}\sum_{v} C_{ij} * x_{ijv} \tag{3.1}$$

Subject to

$$S_i \ = \ s_i^0 \ + \ d_i - \sum_{v \in V} Y_{iv}^l - \ Y_{iv}^u \qquad \forall i \in N \tag{3.2}$$

$$\sum_{i \in N, i \neq j} x_{ijv} \leq 1 \qquad \forall \ j \in N, v \in V \tag{3.3}$$

$$\sum_{i \in N, i \neq j} x_{ijv} \neq \sum_{i \in N, i \neq j} x_{jiv} \qquad \forall j \in N_{0,}, v \in V \tag{3.4}$$

$$Y_{iv}^l - \ Y_{ivv}^u = \sum_{j \in N, i \neq j} f_{ijv} - \sum_{j \in N, i \neq j} f_{jiv} \qquad \forall i \in N_{0,} v \in V \tag{3.5}$$

$$\sum_{v \in V} Y_{iv}^l \ \leq \ T_i \qquad \forall i \ \in N \tag{3.6}$$

$$\sum_{v \in V} Y_{iv}^u \ \leq T_i - \ S_i^0 \qquad \forall i \ \in N \tag{3.7}$$

$$\sum_{j \in N} x_{0jv} \ \geq \ 1 \qquad \forall v \in V \tag{3.8}$$

$$f_{ijv} \leq k_v * x_{ijv} \qquad \forall i, j \in N_{0,} i \neq j, v \in V \tag{3.9}$$

$$Y_{iv}^l - \ Y_{ivv}^u \geq \sum_{j \in N_0} x_{ijv} \qquad \forall i \in N_{0,} v \in V \tag{3.10}$$

$$q_{jv} \leq q_{iv} + 1 \ - M * (1 - x_{ijv}) \qquad \forall i, j \in N_{0,} i \neq j, v \in V \tag{3.11}$$

$$x_{ijv} \in 0{,}1 \qquad \forall i, j \in N_{0,} v \in V \tag{3.12}$$

$$f_{ijv} \geq 0 \qquad \forall i, j \in N_{0,} v \in V \tag{3.13}$$

$$Y_{iv}^{U} \& Y_{iv}^{l} \geq 0 \qquad \forall i \in N_{0,} v \in V \qquad (3.14)$$

$$q_{iv} \geq 0 \qquad \forall i, \in N_{0,} v \in V \qquad (3.15)$$

Objective function (3.1) minimizes the total traveled distance. Constraint (3.2) gives the inventory level after the repositioning operation. Constraint (3.3) ensures that each station can be visited at most once. Constraints (3.4) and (3.5) represent the conservation of flow and conservation of inventory respectively. Constraints (3.6) and (3.7) are restriction the number of bicycles on capacity and availability. Constraint (3.8) ensures that every vehicle must start its route from depot. Constraint (3.9) limits the number of bicycles according to vehicle capacity. Constraint (3.10) avoids visiting a station that no loading or unloading operation occurs. Constraint (3.11) is the sub-tour elimination constraint and constraints (3.12)-(3.15) is the integrality of variables.

3.3 Illustrative Example for Mathematical Formulation

The model described above is solved for a small problem. In the small problem addressed, system with 10 stations and 1 depot is assumed. The inventory level of stations does not change at the time of routing as the system is closed to users. The initial inventory level in the depot was determined by taking into account all the bicycles in the system. It is assumed that the demands of the stations are deterministic and known. This problem is solved using the Lingo 14.0 program.

3.3.1 Data of the Illustrative Example

The example problem is mentioned above, which has 10 stations and 1 depot. Each station has capacity with 20 bicycles and initial inventory with 10 bicycles. There are two vehicles for transportation process and the capacity of the vehicles are 15 bicycles. Negative values are delivery values that should be unloaded from vehicle and positive values are pick-up values that should be loaded to vehicle.

Table 3.1 Demand of the stations

Stations	Depot	1	2	3	4	5	6	7	8	9	10
Demand	0	-2	-17	6	-3	1	15	-11	1	17	16

Demands of the stations are given in Table 3.1. The stations are shown in Figure 3.1. The distance data between these stations has been taken in the literature for the TSP.

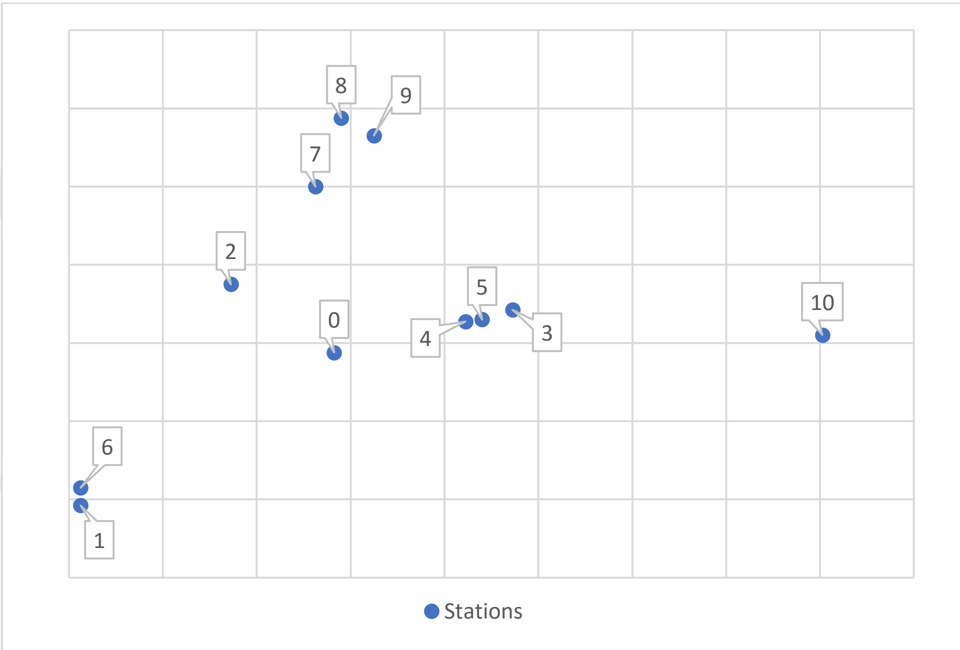


Figure 3.1 Stations

3.3.2 Results of the Illustrative Example

After the model was solved in Lingo program optimally, the value of the objective function was found to be 3899 meters and computational time was 3.31 seconds. Not all stations were included in the route, only five stations were routed for pickup or delivery operations and only one vehicle is used for routing operation. The route found by the model is shown in Figure 3.2 with bicycles that picked up and dropped off.

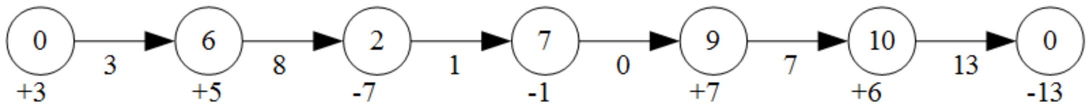


Figure 3.2 Result of the model

In order to carry out the routing process in this problem, the number of bicycles demanded by the stations should be known. It was also assumed that the number of bicycles at the stations did not change at the time of routing. In the next section, this model was developed and became a model that determines the number of bicycles needed by the stations and made planning and routing on a daily basis.

CHAPTER FOUR
PLANNING AND ROUTING BICYCLE SHARING SYSTEMS ON A DAILY BASIS

4.1 Problem Definition

In the previous chapter, a mathematical model was given to perform the routing process for SBRP. In this chapter, the model is developed to make both planning and routing. An imaginary BSS was contemplated and some assumptions were made. These assumptions are described below.

4.1.1 Assumptions

- In this system, there is a certain number of stations and a depot.
- The number of bicycles demanded by the users and returned in the stations are significantly smaller than the depot capacity.
- The number of bicycles that users demanded and returned is known.
- Users may demand bicycles from stations or return bicycles they have rented previously.
- The bicycle demands of the stations can be provided from the depot or any suitable stations.
- These values are given for each hour with 24 time periods total.
- Inventory level is controlled hourly. Bicycles returned to the station are added to the instant inventory, while bicycles demanded from the station are reduced from instant inventory.
- The capacity and feasibility of the stations are checked for each hour according to the user movements and inventory levels. If necessary, pick-up and drop-off operations are performed.
- Routing is required at the shortest distance for the resulting pick-up or drop-off operations.

- There is a single vehicle for transportation process of that picks-up and drops-off the bicycles.
- The total routing time occurs within the scheduled time period and does not exceed one hour.

Thus, the bicycle demands of the stations and the time of those demands are planned, and they are routed at minimum distance. The mathematical model that performs this is shown below.

4.2 Mathematical Model

This mathematical model is based on SBRP described by Raviv et al. (2013). Model determines the routes of transportation vehicle and the number of bicycles to pick up or deliver to stations. Objective function of this model is minimize total travelled distance. Set of stations $N = \{0,..,N\}$ consists depot $(i=0)$ and bicycle stations $(i=1,..N)$, and set of time $T = \{1,..T\}$ consists time periods.

4.2.1 Sets, Parameters and Decision Variables

Sets:

- N set of stations, $i,j=0,,N$
- T set of time periods, $t=1,,T$

Parameters:

- Q_i capacity of station i
- C_{ij} cost of carrying bicycles from station i to station j

- *Dem_{it}* the number of bicycles taken by the users from the station *i* at the time period *t*
- *Ret_{it}* the number of bicycles dropped off by the users to the station *i* at the time period *t*
- *Inv^0_i* initial inventory level at the station *i*

Decision Variables:

- *Inv_{it}* inventory level of station *i* at the time period *t*
- *P_{it}* the number of bicycles picked up from the station *i* at the time period *t*
- *D_{it}* the number of bicycles delivered to the station *i* at the time period *t*
- *x_{ijt}* binary variable, equals 1 if station *j* is visited after station *i*, 0 otherwise
- *z_{ijt}* the number of bicycles carried from station *i* to station *j* at the time period *t*

4.2.2 Mathematical Formulation

$$minimize \quad \sum_i \sum_j \sum_t C_{ij} * x_{ijt} \tag{4.1}$$

Subject to

$$Inv_{it} = Inv_{it-1} - Dem_{it} + Ret_{it} - P_{it} + D_{it} \qquad \forall i \in N, t \in T \tag{4.2}$$

$$Inv_{i1} = Inv_i^0 - Dem_{i1} + Ret_{i1} - P_{i1} + D_{i1} \qquad \forall i \in N, t \in T \tag{4.3}$$

$$\sum_{j \in N, j \neq i} z_{ijt} = \sum_{j \in N, j \neq i} z_{jit} + P_{it} - D_{it} \qquad \forall i \in N, t \in T \tag{4.4}$$

$$z_{ijt} \leq x_{ijt} * V \qquad \forall i \in N, t \in T \tag{4.5}$$

$$\sum_{i \in N} P_{it} = \sum_{i \in N} D_{jt} \qquad \forall i \in N, t \in T \tag{4.6}$$

$$\sum_{j \in N, j \neq i} x_{ijt} \leq 1 \qquad \forall i \in N, t \in T \tag{4.7}$$

$$\sum_{j \in N, j \neq i} x_{ijt} = \sum_{j \in N, j \neq i} x_{jit} \qquad \forall i \in N, t \in T \tag{4.8}$$

$$g_{jt} \geq 1 + g_{it} - M * \left(1 - x_{ijt}\right) \qquad \forall i, j \in N, i \neq j, t \in T \tag{4.9}$$

$$Inv_{it} \geq 0 \qquad \forall i \in N, t \in T \tag{4.10}$$

$$P_{it} \geq 0 \qquad \forall i \in N, t \in T \tag{4.11}$$

$$D_{it} \geq 0 \qquad \forall i \in N, t \in T \tag{4.12}$$

$$Inv_{it} \leq Q_i \qquad \forall i \in N, t \in T \tag{4.13}$$

$$z_{ijt} \geq 0, integer \qquad \forall i, j \in N, i \neq j, t \in T \tag{4.14}$$

$$g_{it} \geq 0 \qquad \forall i \in N, t \in T \tag{4.15}$$

$$x_{ijt} \in 0,1 \qquad \forall i, j \in N, i \neq j, t \in T \tag{4.16}$$

Objective function (4.1) aims to minimize total travelled distance. Constraint (4.2) balances inventory levels in every station at each time period. Constraint (4.3) is constraint (4.2) but for first time period and previous inventory level is given as initial inventory level. Constraint (4.4) is flow of bicycles through transportation vehicles. Constraint (4.5) is capacity constraint for transportation vehicle. Constraint (4.6) is to balance number of bicycles that picked up and delivered to stations for each time period. Constraint (4.7) ensures that each station visited at most once. Constraint (4.8) is flow of conservation constraint. Constraint (4.9) is sub-tour elimination constraint. Constraints (4.10), (4.11), (4.12), (4.14) and (4.15) is non negativity constraints. Constraint (4.13) avoids inventory levels for each station exceed capacity. Constraint (4.15) is binary constraint.

4.3 Illustrative Example for Mathematical Formulation

The model described above is solved for the same small problem from Chapter 3. Again, system with 10 stations and 1 depot is assumed. For the simplicity of the model and the ease of solution, only five time periods were taken. The inventory level of stations changes hourly. The initial inventory level in the depot was determined by taking into account all the bicycles in the system. It is assumed that the demands of the stations are deterministic and known. This problem is also solved using the Lingo 14.0 program.

4.3.1 Data of the Illustrative Example

The example problem is mentioned above, which has 10 stations and 1 depot. Each station has capacity with 20 bicycles and initial inventory with 10 bicycles. The vehicle capacity has been taken as 15 bicycles due to the single vehicle assumption. The demand and return values were created for 10 stations with 5 time periods according to uniform distribution. Small example of the created data for demand and return values in dataset 1 are given in Table 4.1 and Table 4.2.

Table 4.1 Example for demands of dataset 1 for 10 station and 5 time period

Time	1	2	3	4	5
Depot	0	0	0	0	0
1	3	4	10	4	8
2	8	1	6	5	9
3	10	7	0	8	2
4	6	1	4	3	7
5	0	10	10	8	1
6	2	4	3	3	9
7	9	5	2	6	1
8	9	9	4	1	10
9	7	4	9	6	8
10	3	3	3	6	6

Table 4.2 Example for returns of dataset 1 for 10 station and 5 time period

Time	1	2	3	4	5
Depot	0	0	0	0	0
1	6	3	8	9	0
2	10	9	3	7	10
3	10	5	4	7	2
4	9	5	1	2	2
5	4	6	6	8	0
6	1	0	5	1	6
7	0	7	4	5	0
8	5	0	2	9	8
9	8	1	1	4	4
10	3	3	5	8	1

The values in Table 4.1 are the values that users demand from the station at that time period, while the values in Table 4.2 are the values return by the users to the station.

4.3.2 Result of the Illustrative Example

The model was solved in the Lingo program optimally, the value of the objective function was found to be 1244 meters and computational time was 3.41 seconds. Only one route was needed during 5 periods. The route found by the model is shown in Figure 4.1 with bicycles that picked up and dropped off.

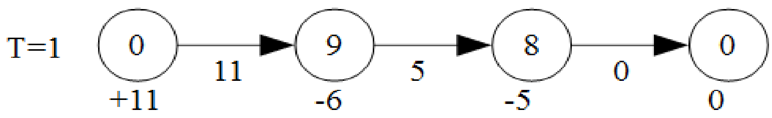


Figure 4.1 Results of the model

As the number of stations and the time period increased, the mathematical model was insufficient. Therefore, a new approach was developed by combining a mathematical model and a heuristic algorithm. The heuristic algorithm that was considered for this approach was tested. This algorithm is described in detail in Chapter 5.

CHAPTER FIVE
ESTIMATION OF DISTRIBUTION ALGORITHM BASED APPROACH FOR STATIC BICYCLE ROUTING PROBLEM

As the number of stations increases, SBRP becomes NP-hard and it is necessary to use some heuristic approaches to solve the SBRP. Therefore, this section defines the estimation of distribution algorithm (EDA) to solve SBRP. The algorithm used to solve the routing problem with BSS data from the literature and the results were compared with the other results in the literature.

5.1 Estimation of Distribution Algorithm

5.1.1 General definition of Estimation of Distribution Algorithm

Estimation of Distribution Algorithm (EDA), also called probabilistic model-building genetic algorithm, is an evolutionary algorithm introduced by Mühlenbein, & Paaß (1996). EDA is an algorithm that advances iteratively and creates new offspring in each iteration.

Flow chart of general EDA is shown in Figure 5.1. In EDA, initial population is generated according to certain rules, but mostly generated from uniform distribution. Depending on the problem, a fitness function is determined to keep the best solutions. The fitness value of each individual is calculated and a subset of the population is selected by the selection operator, such as truncation or tournament selection, according to solutions that have desired fitness values (Pelikan, et al, 2012). A certain number of solutions are produced in first iteration, and these solutions are assigned a value with the fitness function. Solutions with the best fitness value are kept with a certain threshold, while solutions with low fitness value are eliminated.

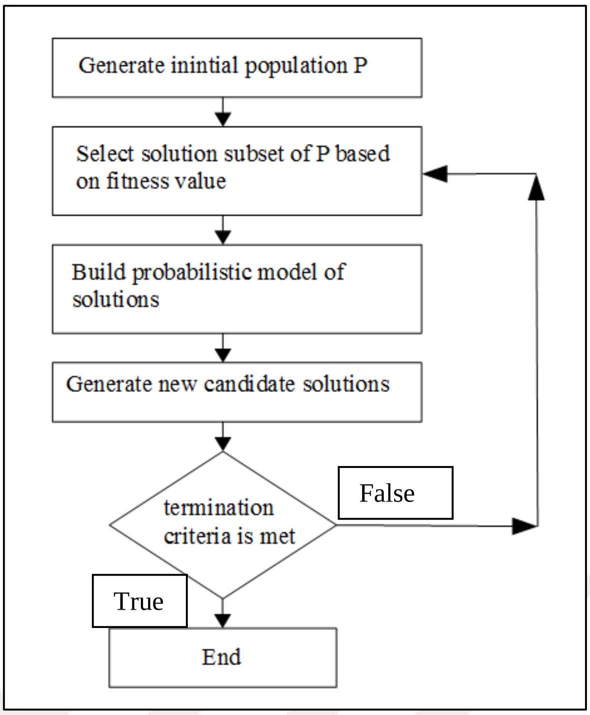


Figure 5.1 Flow chart of general EDA

Unlike other approaches, offspring populations are generated with probability values instead of crossover and mutation operators (Larranaga & Lozano, 2002). A probability distribution is generated from the best solutions and new generation solutions are generated according to this distribution. Thus, statistically improved new offspring would have produced. Fitness values of the new population are calculated in the next iteration. The probability values are recalculated and solution values are developed in each iteration which is usually referred to as one generation of the EDA (Hauschild & Pelikan, 2011). General pseudocode of EDA defined by Hauschild, & Pelikan (2011) is as follows:

- Set g= 0
- generate initial population P(g)
- **while** (termination criteria is not met) **do**
    - calculate fitness of population P(g)

    - select promising solutions S(g) from P(g)
    - build a probabilistic model M(g) from S(g)
    - sample M(g) to generate new candidate solutions O(g) and incorporate O(g) into P(g)
    - g= g + 1
- **end while**

5.1.2 Past Studies about Estimation of Distribution Algorithm

In the literature, EDA is successfully applied to a wide variety of combinatorial optimization problems. It is seen that EDA is frequently used in scheduling problems. Qian et al. (2017) used EDA for m-machine flow-shop scheduling problem. Similarly, Jarboui et al. (2009) and Wang et al. (2015) minimized the total flow time in flow-shop scheduling with using EDA.

Pan & Ruiz (2012) applied EDA for lot-streaming flow shop scheduling problem. Hao et al. (2013) and Liu et al. (2015) used EDA for job-shop scheduling. Wang & Fang (2012) defined the multi-mode and resource-constrained project scheduling problem with EDA (MMRCPSP) and Zheng & Wang (2015) studied MMRCPSP with low-carbon production scheduling using EDA.

EDA has also been effective in other areas. Jiang et al. (2006) studied nuclear reactor fuel management optimization with EDA. Ou-Yang et al. (2013) used EDA for single row facility layout problem. EDA was used as a hybrid model with a local search in some studies because of complexity by Exposito-Izquierdo et al. (2013) and Wang et al. (2015).

EDA also used in multi-objective problems. Sun et al. (2017) and Jiang et al. (2018) used EDA for multi-objective optimization problems, and Zhou et al. (2013) studied multi-objective TSPs using EDA.

5.2 Estimation of Distribution Algorithm Based Approach for Static Bicycle Routing Problem

The EDA approach was adapted for SBRP. Each population was defined as a SBRP solution, which is a route that starts with the depot and ends with the depot. Each station has a demand that can be either positive or negative. If demand of the station is positive, then this station is a pick-up node and bicycles should be loaded to the vehicle. If demand of the station is negative, then this station is a delivery node and bicycles should be dropped to the station. The demand of each station and the distance matrix between stations are entered as inputs.

At the beginning of the algorithm, initial population is generated randomly. At each iteration, distance values of routes are calculated and the routes are sorted by distance values from small to large. Routes with the shortest distance with 50% threshold value are transferred to the next iteration and others are eliminated. A probability distribution of selected routes is calculated and new routes are produced from that distribution. Since the routes are created to start from the depot, the node with the highest probability is selected and added to the route. In this way, the node that is close to it after each node continues to be selected. When the route is complete, the new results are added under the selected routes and the next iteration starts.

A feasibility check is required when selecting the best routes. It has mentioned before pick-up and drop-off operations occur in SBRP. Stations should be arranged to be feasible by taking into consideration the vehicle capacity. 2-opt algorithm was added to the approach to provide better results and to avoid local optimality. Pseudocode of EDA for SBRP is as follows:

- Generate initial population randomly, G(0)
- **for** *i*=1,2...,*IterationNumber* do
    - calculate objective function values of candidate routes
    - select routes *S(i)*, that have minimum distance value with threshold value 50%

- calculate probability of selected population *P(i)*
- generate new candidate routes *R(i)* and combine with *S(i)* as *G(i+1)*
- **if** *i* is divisible by 50
    - perform 2-opt algorithm to the population to evolve solutions
- **end if**
- **end for**

5.2.1 Objective Function of Proposed Estimation of Distribution Algorithm

For the proposed EDA, certain calculations were performed at the objective function stage. It is assumed that the vehicle leaves depot empty at the beginning. The demand of the next node on the route is checked. If there is a need for bicycle (positive demand), the initial load value of the vehicle is increased by this demand. If the bicycle is to be taken to other stations (negative demand), the initial load of the vehicle does not change, but is added to the current load of the vehicle. In this way, the initial and current capacity of the vehicle are calculated and the capacity is checked. When the sum of the current load of the vehicle and the negative demand of next point exceeds the vehicle capacity, the route is completed for that vehicle and an empty vehicle is assigned for the remaining stations. Similarly, if the current load of the vehicle cannot meet the demand of the next point and the initial load of the vehicle has exceeded the vehicle capacity, the route is completed for that vehicle and an empty vehicle is assigned for the remaining stations.

5.2.2 2-opt Algorithm

2-opt is a local search operation that examines the different possibilities by disconnecting and relinking the two nodes from route. This search algorithm is developed for solving TSPs (Lin, 1965).

In this proposed approach, 2-opt is included the process at regular intervals in order to improve solution quality. In this procedure, two edges from the tour are deleted, and reconnected as different tour. If new created path has shorter distance value, this new path is replaced with the existing path. Figure 5.2 shows an example of a possible solution obtained by 2-opt.

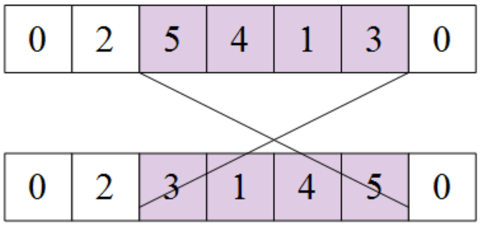


Figure 5.2 A possible solution of 2-opt algoritm

5.3 Computational Study for Estimation of Distribution Algorithm based Static Bicycle Routing Problem

The algorithm was coded in Matlab 2017a program and tested with the set of instances used by Dell'Amico et al. (2014), which were collected and arranged from 22 BSSs across some cities. This set of instances consists of 13 to 564 stations with in three different vehicle capacities. The obtained results were compared with the results in Dell'Amico et al. (2014) and Dell'Amico et al. (2016). These instances were analyzed in 3 sections as small, medium and large instances.

5.3.1 Small Instances

The number of stations between 13 and 28 were grouped as small instances. 12 out of 32 cities were included in this grouping. It is specified by Dell'amico (2014) that 10-capacity vehicle was not used for some cities due to having larger demands of some stations than vehicle capacity. Obtained results of the small instances are given in Table 5.1. Dell'Amico et al. (2014) and Dell'Amico et al. (2016) and the results of the proposed EDA were compared and the values found to be the same as their best value were marked as bold.

Table 5.1 Result of the Small Instances

	V	Q	Dell'Amico et al. (2014) Best Feasible Solution	Dell'Amico et al. (2014) Time	Dell'Amico et al. (2016) Best Feasible Solution	Dell'Amico et al. (2016) Time	Proposed EDA Best Feasible Solution	Proposed EDA Time	GAP%
Bari	13	30	14600	0.02	14600	0.000001	**14600**	0.1005	0.0000
Bari	13	20	15700	0.02	15700	0.000001	**15700**	0.1320	0.0000
Bari	13	10	20600	0.03	20600	0.000001	**20600**	0.2098	0.0000
Reggio Emilia	14	30	16900	0.02	16900	0.000001	**16900**	0.1257	0.0000
Reggio Emilia	14	20	23200	0.03	23200	0.000001	23800	0.1488	2.5862
Reggio Emilia	14	10	32500	0.05	32500	0.01	**32500**	0.4210	0.0000
Bergamo	15	30	12600	0.03	12600	0.01	**12600**	0.4498	0.0000
Bergamo	15	20	12700	0	12700	0.01	**12700**	0.5635	0.0000
Bergamo	15	12	13500	0.11	13500	0.000001	**13500**	0.6311	0.0000
Parma	15	30	29000	0.02	29000	0.000001	**29000**	0.5206	0.0000
Parma	15	20	29000	0.02	29000	0.000001	**29000**	0.5406	0.0000
Parma	15	10	32500	0.05	32500	0.000001	**32500**	4.8399	0.0000
Treviso	18	30	29259	0.05	29259	0.04	**29259**	3.9045	0.0000
Treviso	18	20	29259	0.03	29259	0.04	**29259**	3.8781	0.0000
Treviso	18	10	31443	0.09	31443	0.08	**31444**	4.2202	0.0032
La Spezia	20	30	20746	0.03	20746	0.03	**20746**	3.6801	0.0000
La Spezia	20	20	20746	0.03	20746	0.03	**20746**	3.7752	0.0000
La Spezia	20	10	22811	0.09	22811	0.12	**22811**	6.1054	0.0000
Buenos Aires	21	30	76999	0.37	76999	0.03	**76999**	9.8583	0.0000
Buenos Aires	21	20	91619	16.8	91619	4.2	**91619**	19.8633	0.0000
Ottawa	21	30	16202	0.02	16202	0.000001	**16202**	3.8449	0.0000
Ottawa	21	20	16202	0.02	16202	0.000001	**16202**	3.7063	0.0000
Ottawa	21	10	17576	0.11	17576	0.02	**17576**	4.3897	0.0000
San Antonio	23	30	22982	0.08	22982	0.000001	23105	4.6773	0.5352
San Antonio	23	20	24007	0.09	24007	0.05	**24007**	5.5235	0.0000
San Antonio	23	10	40149	1.06	40149	0.37	**40149**	22.809	0.0000

Table 5.1 continues

	V	Q	Dell'Amico et al. (2014)		Dell'Amico et al. (2016)		Proposed EDA		GAP%
			Best Feasible Solution	Time	Best Feasible Solution	Time	Best Feasible Solution	Time	
Brescia	27	30	30300	0.06	30300	0.07	**30300**	6.0445	0.0000
Brescia	27	20	31100	0.2	31100	0.09	31200	5.2263	0.3215
Brescia	27	11	35200	1.37	35200	0.39	36400	6.3769	3.4091
Roma	28	30	61900	0.84	61900	0.36	62000	5.6356	0.1616
Roma	28	20	66600	1.72	66670	3.46	67000	6.6418	0.4950
Roma	28	18	68300	0.58	68300	0.000001	69400	9.3310	1.6105
Madison	28	30	29246	0.02	29246	0.04	**29246**	4.1064	0.0000
Madison	28	20	29839	0.05	29839	0.04	**29839**	4.8280	0.0000
Madison	28	10	33848	0.53	33848	0.2	**33848**	4.6183	0.0000

The problems were solved with the proposed EDA and 28 of the 35 results are the same as from Dell'Amico et al. (2014) and Dell'Amico et al. (2016). The percentage gap between the other results is generally less than 5%. In addition, the percentage gap is less than 1% for four of the results.

In terms of solution times, Dell'Amico et al. (2014) and Dell'Amico et al. (2016) appear to be faster than the proposed EDA. This is because EDA is an iterations-based approach and even if algorithm has found the best results, it has consumed time to complete iterations.

5.3.2 Medium Instances

The number of stations between 41 and 116 were grouped as medium instances. 10 out of 32 cities were included in this grouping. Again, 10-capacity vehicle was not used for some cities and changed to another value with respect to maximum demand of the city. Obtained results of the small instances are given in Table 5.2. Dell'Amico et al. (2014) and Dell'Amico et al. (2016) and the results of the proposed EDA were compared and the values found to be the same as their best value were marked as bold.

Table 5.2 Results of the Medium Instances

			Dell'Amico (2014)		Dell'Amico(2016)		Proposed EDA		GAP%
	V	Q	Best Feasible Solution	Time	Best Feasible Solution	Time	Best Feasible Solution	Time	
Guadalajara	41	30	57476	0.22	57476	2.14	**57476**	25.0893	0.000
Guadalajara	41	20	59493	0.34	59493	1.48	59894	22.4752	0.674
Guadalajara	41	11	64981	1.79	64981	2.41	**64981**	35.5648	0.000
Dublin	45	30	33548	6.05	33548	2.29	34657	30.0587	3.306
Dublin	45	20	39786	76.72	39786	3.73	41140	26.0248	3.403
Dublin	45	11	54392	610.8	54392	5.28	57061	49.7941	4.907
Denver	51	30	51583	0.67	51583	0.48	52123	26.1965	1.047
Denver	51	20	53465	25.33	53465	24.68	53666	20.5696	0.376
Denver	51	10	67459	231.52	67459	102.99	68286	28.1141	1.226
Rio de Janeiro	55	30	122547	65.57	122547	198.66	127397	23.9006	3.958
Rio de Janeiro	55	20	156140	3600	155517	304.13	163204	31.5273	4.943
Rio de Janeiro	55	10	259049	3600	257147	241.12	260872	66.2367	1.449
Boston	59	30	65669	28.14	65669	16.16	66138	30.0329	0.714
Boston	59	20	71879	473.84	71916	178.16	73167	38.4294	1.740
Boston	59	16	75065	3600	75085	280.5	78180	43.5774	4.122
Torino	75	30	47634	13.79	47634	246.44	49158	25.0697	3.199
Torino	75	20	50204	859.69	50438	251.83	53690	39.2423	6.448
Torino	75	10	64797	3600	61717	303.85	64337	67.7536	4.245
Toronto	80	30	41549	3600	41390	201.49	43988	24.5485	6.277
Toronto	80	20	47898	3600	46631	269.37	47863	42.4982	2.642
Toronto	80	12	60763	3600	58539	321.39	60024	38.3159	2.537
Miami	82	30	156104	3600	154038	335.05	156658	33.8184	1.701
Miami	82	20	229237	3600	214250	265.13	216867	58.5425	1.221
Miami	82	10	415762	3600	397921	300.28	408533	66.1815	2.667
Ciudad de Mexico	90	30	88227	3600	72279	231.91	83062	73.9473	14.917
Ciudad de Mexico	90	20	116418	3600	94319	254.22	103268	196.1597	9.488
Ciudad de Mexico	90	17	109418	3600	103658	359.59	113133	224.3161	9.141
Minneapolis	116	30	137843	3600	138467	754.28	150911	620.2988	8.990
Minneapolis	116	20	186449	3600	166150	1003.72	178337	1318.044	7.3590
Minneapolis	116	10	298886	3600	262936	946.37	275028	2621.1	4.5988

The problems were solved with the proposed EDA and two of the 30 results are the same as from Dell'Amico et al. (2014) and Dell'Amico et al. (2016). The percentage gap between the other results is generally less than 15% for all results. In addition, percentage gap is less than 1% for three of results, less than 5% for 18 of the results. Although the proposed EDA found better than the results in Dell'Amico et al. (2014) for nine of the problems, it does not approach the results in Dell'Amico et al. (2016).

In terms of solution times, it is observed that EDA's performance was found to be faster than the other two studies. This is because EDA is an iterations-based approach. The values in Table 5.2 are the results when the number of iterations of the algorithm is reached. The results were very close to the two other studies mentioned above and these results were obtained faster.

5.3.3 Large Instances

The number of stations between 150 and 564 were grouped as large instances. 10 out of 32 cities were included in this grouping. 10-capacity vehicle was not used for almost every city. Obtained results of the small instances are given in Table 5.3.

Table 5.3 Results of the Large Instances

			Dell’Amico(2016)		Proposed EDA		GAP%
	V	Q	Best Feasible Solution	Time	Best Feasible Solution	Time	
Brisbane	150	30	115120	742.81	147533	875.87	28.1558
Brisbane	150	20	146313	957.83	176160	2054.79	20.3994
Brisbane	150	17	160015	966.44	185887	3293.91	16.1685
Milano	184	30	167493	871.18	223030	2945.01	33.1578
Milano	184	20	218249	823.76	271755	3465.17	24.5160
Milano	184	18	234423	1048.32	288271	3550.04	22.9704
Lille	200	30	176976	666.67	226580	2009.15	28.0287
Lille	200	20	213090	280.09	265459	2389.77	24.5760
Toulouse	240	30	188995	1147.86	293220	3602.75	55.1470
Toulouse	240	20	228674	1398.52	336910	4617.32	47.3320

Table 5.3 continues

	V	Q	Dell'Amico(2016) Best Feasible Solution	Dell'Amico(2016) Time	Proposed EDA Best Feasible Solution	Proposed EDA Time	GAP%
Toulouse	240	13	307874	868.98	409531	6421.96	33.0190
Seville	258	30	225076	898.4	355209	3816.43	57.8174
Seville	258	20	279990	1054.31	413263	5003.39	47.5992
Valencia	276	30	287854	789.54	442189	4268.17	53.6157
Valencia	276	20	367201	1064.4	506793	5479.12	38.0151
Bruxelles	304	30	311097	851.97	528126	2597.65	69.7625
Bruxelles	304	20	376387	835.66	589922	2865.31	56.7328
Bruxelles	304	16	424432	1038.33	647633	3178.24	52.5882
Lyon	336	30	360009	879.61	628992	3606.12	74.7156
Lyon	336	20	433959	1136.03	714402	4562.21	64.6243
Barcelona	410	30	543929	458.27	890486	7663.07	63.7136
Barcelona	410	20	771507	1538.57	1060702	9762.96	37.4844
Barcelona	410	19	800622	1411.27	1089384	10093.2	36.0672
London	564	30	699571	1572.97	1337019	3774.19	91.1198
London	564	20	718026	1447.33	1339061	3773.93	86.4920

When the results found for large instances are examined, it is seen that the performance of the EDA is not good and needs to be improved as the number of stations increases.

5.4. Summary

The EDA-based metaheuristic approach developed for SBRP was tested using some problem instances from the literature. When the obtained results are examined, this approach can give effective results in the routing of BSSs with a certain number of stations. However, when the number of stations of the BSS increases, the approach is insufficient. Thus, proposed algorithm is suitable for the routing of small and medium sized BSSs but not suitable for the routing of larger sized BSSs.

CHAPTER SIX

PLANNING AND ROUTING BICYCLE SHARING SYSTEM WITH ESTIMATION OF DISTRIBUTION ALGORITHM BASED APPROACH

6.1 Proposed Approach

It was mentioned in Chapter 4 that mathematical models are not be able to solve the routing problem for BSS as the number of stations increased. Therefore, a new solution approach was developed. In this chapter, a new method was introduced by combining the mathematical model described in Chapter 4 with the EDA based routing approach described in chapter 5.

6.1.1 Mathematical Model Part of Proposed Approach

The constraints of the mathematical model related to routing, like sub-tour elimination and flow constraints, were removed to simplify the model. Thus, the model determines only the number of bicycles that is picked up from or delivered to stations and time period for routing. The output values obtained from the solution of the model are entered as inputs for demand data into the proposed EDA approach.

6.1.1.1 Sets, Parameters and Decision Variables

Sets:

- N set of stations, $i,j=0,,N$
- T set of time periods, $t=1,,T$

Parameters:

- Q_i capacity of station i
- C_{ij} cost of carrying bicycles from station i to station j
- Dem_{it} the number of bicycles taken by the users from the station i at the time period t
- Ret_{it} the number of bicycles dropped off by the users to the station i at the time period t
- Inv^0_i initial inventory level at the station i

Decision Variables:

- Y^p_{it} binary variable, equals 1 if bicycles picked up from the station i at the time period t, 0 otherwise
- Y^d_{it} binary variable, equals 1 if bicycles delivered to the station i at the time period t, 0 otherwise
- Y_{it} binary variable, equals 1 if station i is visited at the time period t, 0 otherwise
- e_t binary variable, equals 1 if route is assigned at time period t, 0 otherwise

6.1.1.2 Mathematical Model

$$minimize \quad \sum_i \sum_t Y_{it} + \sum_t e_t \tag{6.1}$$

Subject to

$$Inv_{it} = Inv_{it-1} - Dem_{it} + Ret_{it} - P_{it} + D_{it} \qquad \forall i \in N, t \in T \tag{6.2}$$

$$Inv_{i1} = Inv_i^0 - Dem_{i1} + Ret_{i1} - P_{i1} + D_{i1} \qquad \forall i \in N, t \in T \tag{6.3}$$

$$\sum_{j \in N, j \neq i} z_{ijt} = \sum_{j \in N, j \neq i} z_{jit} + P_{it} - D_{it} \qquad \forall i \in N, t \in T \tag{6.4}$$

$$\sum_{i \in N} P_{it} = \sum_{i \in N} D_{jt} \qquad \forall i \in N, t \in T \tag{6.5}$$

$$P_{it} \leq Y_{it}^{p} * V \qquad \forall i \in N, t \in T \tag{6.6}$$

$$D_{it} \leq Y_{it}^{d} * V \qquad \forall i \in N, t \in T \tag{6.7}$$

$$Inv_{it} \geq 0 \qquad \forall i \in N, t \in T \tag{6.8}$$

$$P_{it} \geq 0 \qquad \forall i \in N, t \in T \tag{6.9}$$

$$D_{it} \geq 0 \qquad \forall i \in N, t \in T \tag{6.10}$$

$$Inv_{it} \leq Q_i \qquad \forall i \in N, t \in T \tag{6.11}$$

$$Y_{it}^{p} \leq Y_{it} \qquad \forall i \in N, t \in T \tag{6.12}$$

$$Y_{it}^{d} \leq Y_{it} \qquad \forall i \in N, t \in T \tag{6.13}$$

$$e_t \geq Y_{it} \qquad \forall i \in N, t \in T \tag{6.14}$$

$$Y_{it}^{p} \in 0{,}1 \qquad \forall i \in N, t \in T \tag{6.15}$$

$$Y_{it}^{d} \in 0{,}1 \qquad \forall i \in N, t \in T \tag{6.16}$$

$$Y_{it} \in 0{,}1 \qquad \forall i \in N, t \in T \tag{6.17}$$

$$e_t \in 0{,}1 \qquad \forall t \in T \tag{6.18}$$

Objective function (6.1) is defined as the sum of number of visited stations and total time period for which the routing is to be performed. Constraints (6.2) balances inventory levels in every station at each time period. (6.3) is constraint (6.2) but for first time period and previous inventory level is given as initial inventory level. (6.4) is flow of bicycles. Constraint (6.5) is to balance number of bicycles that picked up and delivered to stations for each time period. Constraints (6.6) and (6.7) ensure that the number of bicycles loaded or unloaded to the vehicle does not exceed vehicle capacity. Constraints (6.8), (6.9) and (6.10) is non-negativity constraints. Constraint (6.11) avoids inventory levels for each station exceed capacity. Constraint (6.12) and (6.13) controls visited stations. Constraint (6.14) ensures to assign time period if any station is visited at that time period. Constraints (6.15), (6.16), (6.17) and (6.18) are binary constraint.

6.1.2 Illustrative Example for Mathematical Formulation

The same data that was solved in the mathematical model in Chapter 4 used to test the developed approach. The demand and return values were entered as input for 10 stations with 5 time periods. Again, the data shown in Table 4.1 and Table 4.2 were solved by using the Lingo 14 optimization program in 0.49 seconds. The result of the mathematical model part of the developed approach is shown in Table 6.1.

Table 6.1 Result of the mathematical part of developed approach

Selected Stations	Pick-up Values	Drop-off Values	Time Period
Depot	11		1^{st}
8		5	1^{st}
9		6	1^{st}

According to the results, it is seen that the bicycle demands of the 8^{th} and 9^{th} stations are met from the depot. There has been a need for routing for only one time period. The EDA-based approach defined in Chapter 5 was adapted to route the obtained results with the shortest-distance.

6.1.3 Estimation of Distribution Algorithm Based Routing Part of Proposed Approach

The pickup and delivery values found by mathematical model were grouped to each result within their own time period and were taken as input for EDA. The pick-up values were written as positive demand and the drop-off values were written as negative demand. In order to carry out the loading process in accordance with the predetermined vehicle capacity, it was written as an input to the EDA. Previously, this algorithm is broadly described in Chapter 5.

6.1.3.1 Infeasibility Problem of Routing

Some results found in the Lingo model section of the developed approach may not be feasible in the EDA section. For a numerical example, assume that the values obtained from the Lingo model of the approach are as follows:

- 13 bicycles must be picked up from depot,
- 15 bicycles must be picked up from station 4,
- 10 bicycles must be delivered to stations 1,
- 6 bicycles must be delivered to station 3
- 12 bicycles must be delivered to station 7.
- Vehicle capacity is 15.

Although the total number of bicycles loaded into the vehicle and the total number of bicycles unloaded from the vehicle are equal, a feasible route cannot be obtained. Therefore, an algorithm was added to the approach. This algorithm is given below.

- The station with the biggest absolute value is selected.
- If the demand value of the selected station is even, half of that value is taken as the new demand value, if the demand value is odd, bigger one of the

nearest two integers to the half of the demand is taken as the new demand of the station.

- A dummy station having the same characteristics as that station is created and the remaining part of the demand is transferred to this dummy station.
- The station will be visited twice and infeasibility will be eliminated.
- If any feasible route cannot be found, algorithm is repeated.

The values given above are routed with the new algorithm. Result is shown in Figure 6.1.

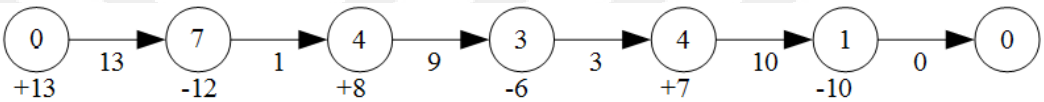


Figure 6.1 A feasible solution for given example

6.1.4 Illustrative Example for Routing with Estimation of Distribution Algorithm Based Approach

The recommended EDA was run for the results in Table 6.1 and the shortest route obtained is shown in Figure 6.2. Total travelled distance was found 1244 meters and computational time was 0.15 seconds.

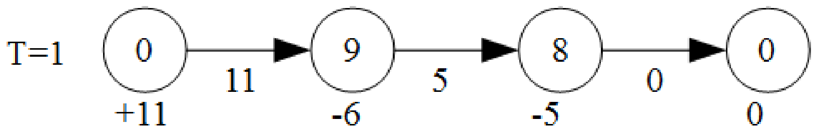


Figure 6.2 Results of the proposed EDA

The developed approach found the same result as the mathematical model mentioned in Chapter 4 for this example, but much faster with a total time of 0.64 seconds.

The results of the developed approach for 5 and 24 time periods will be explained in Chapter 7. In order to compare the results, the same data was also solved in the mathematical model in Chapter 4. The results are described in detail in Chapter 7.

CHAPTER SEVEN
COMPUTATIONAL STUDY FOR PROPOSED APPROACH

7.1 Generated Data for created Bicycle Sharing System

In order to examine problem with different demand and return values, 10 different datasets are generated with uniform distribution. The demand and return values were created for 40 stations with 24 time periods according to uniform distribution. In order to examine problem with different demand and return values, 10 different datasets are created with uniform distribution. Demand of the stations has equal probability for each hour of the day.

It was assumed that the daily average demand would be 5 bicycles for each station because the initial inventory of the stations was taken as 10 bicycles and stations' capacity was 20 bicycles. Datasets 1,2,3 and 4 are considered as average demand problems with the average daily demand and return of each station is 5 bicycles. Datasets 5,6 and 7 are considered as above average demand problems with the average daily demand and return of each station is 7 bicycles. Datasets 8,9 and 10 are considered as below average demand with the average daily demand and return of each station is 3 bicycles.

All stations discussed in the problem are shown in Figure 7.1. The distance data between these stations has been taken in the literature for the TSP.

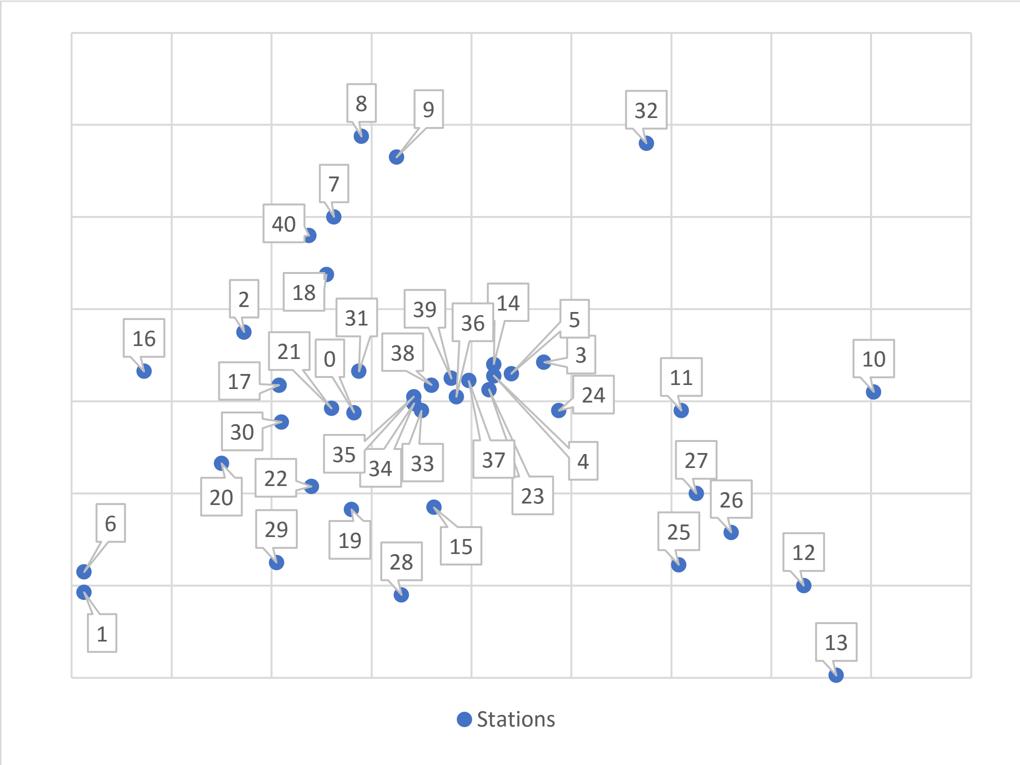


Figure 7.1 Stations

7.2 Comparison of Results

The data were solved by mathematical model and by proposed approach, and then the results were compared. Firstly, each data was handled for the first 5 time periods in terms of comparability. The result values shown in the tables are based on total distances in meter and all computational times are written in seconds.

7.2.1 Results for 5 Time Period

It was mentioned that the problems in the generated datasets would be handled as 10, 20, 30, and 40 stations. Two approaches were first examined as 10 stations and 5 time periods. The results of the proposed approach that are the same with or better than the results of the mathematical model, are marked as bold.

7.2.1.1 Results for 10 Stations

In Table 7.1, results for 10 stations are shown. The mathematical model found all the results to be optimal. The graphical representation of the results is given in Figure 7.1. The proposed approach achieved the same results with optimal results in nine of 10 problems. Only the result for the 3rd dataset is 9% higher than the optimal value. However, the mathematical model found this value after running for approximately 6 minutes.

Table 7.1 Results for 10 stations

	Mathematical Model		**Proposed Approach**				
Dataset	Optimal Solution	Time	Best Result	Lingo time	Matlab time	Total Time	Gap %
1	1244	3.41	**1244**	0.49	0.15	0.64	0
2	1607	7.39	**1607**	0.57	0.15	0.72	0
3	2675	331.32	2917	1.05	0.29	1.34	9
4	2630	92.16	**2630**	0.67	0.3	0.97	0
5	1377	2.56	**1377**	0.60	0.33	0.93	0
6	1347	6.3	**1347**	0.91	0.22	1.13	0
7	652	1.01	**652**	0.39	0.14	0.53	0
8	2082	8.19	**2082**	0.56	0.1	0.66	0
9	2624	19.58	**2624**	0.64	0.2	0.84	0
10	2056	6.59	**2056**	0.62	0.19	0.81	0

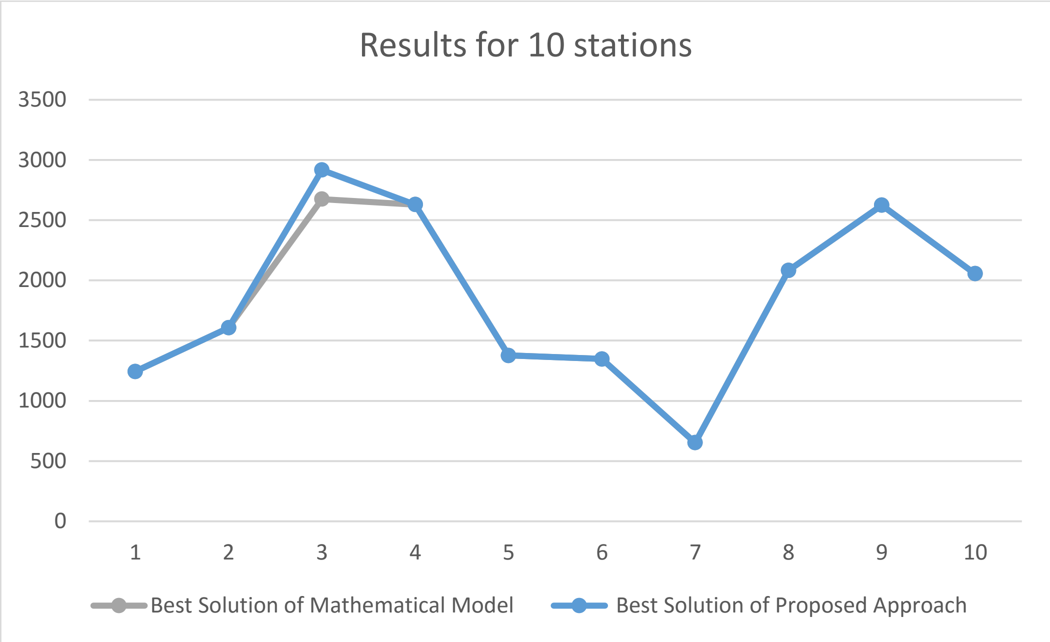


Figure 7.1 Graphical representation of results for 10 stations

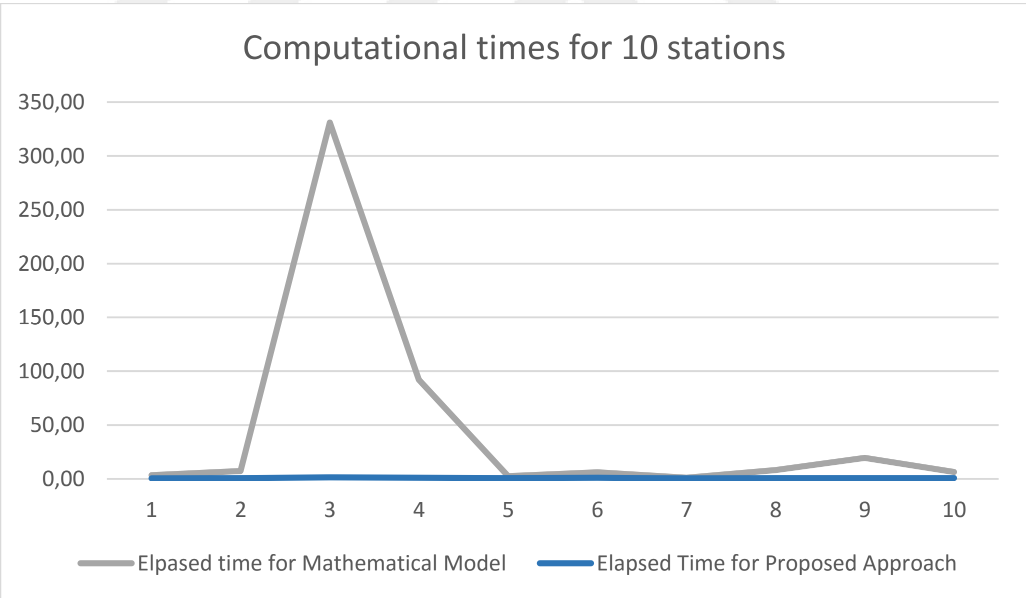


Figure 7.2 Computational times of results for 10 stations

The proposed approach achieves those results in less than 2 seconds for all datasets. Comparison of solution times is shown in Figure 7.2.

7.2.1.2 Results for 20 Stations

In Table 7.2, results for 20 stations are shown. The mathematical model was run for 24 hours and the best value at the end of that period was obtained as a result. For 6 of the 10 problem sets, the two methods found the same result. In 2 problem sets, the mathematical model found the result lower with a difference of less than 15% than the proposed approach. The proposed approach found better result with 3% than the mathematical model in the 3rd problem, which was the only dataset that could not find the optimal result in the 10-station version. The graphical representation of the results is given in Figure 7.3.

Table 7.2 Results for 20 stations

	Mathematical Model		**Proposed Approach**				
Dataset	Best Result	Time	Best Result	Lingo time	Matlab time	Total time	Gap %
1	3100	86400	3362	1.16	1.41	2.57	8
2	3493	86400	3984	1.22	1.67	2.89	14
3	4683	86400	**4562**	1.94	0.89	2.83	-3
4	3665	86400	**3665**	1.44	1.6	3.04	0
5	2575	86400	2666	1.05	1.12	2.17	4
6	2039	86400	**2039**	1.69	1.88	3.57	0
7	2799	86400	**2799**	1.05	1.92	2.97	0
8	3045	86400	**3045**	1.17	1.83	3.00	0
9	2766	86400	**2766**	1.14	1.15	2.29	0
10	3332	86400	**3332**	1.91	1.29	3.20	0

In Table 7.2, results for 20 stations are shown. The mathematical model was run for 24 hours and the best value at the end of that period was obtained as a result. For 6 of the 10 problem sets, the two methods found the same result. In 2 problem sets, the mathematical model found the result lower with a difference of less than 15% than the proposed approach. The proposed approach found better result with 3% than the mathematical model in the 3rd problem, which was the only dataset that could not find

the optimal result in the 10-station version. The graphical representation of the results is given in Figure 7.3

In terms of computational time, the mathematical model found those results by running for 24 hours, despite the fact that the proposed approach found them less than 4 seconds for all datasets.

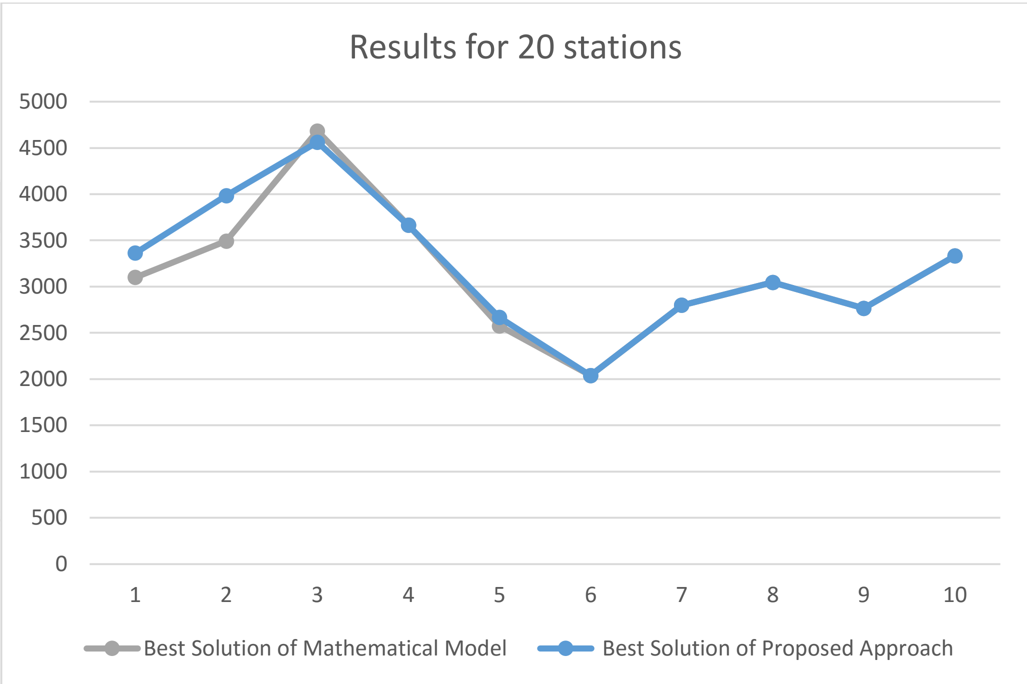


Figure 7.3 Graphical representation of results for 20 stations

7.2.1.3 Results for 30 Stations

In Table 7.3, results for 30 stations are shown. The mathematical model was run for 24 hours and the best value at the end of that period was obtained as a result. It is seen that two approaches have the same result in 2 datasets. In 4 dataset, the proposed approach found better results than the mathematical model. For the third dataset, the proposed approach found better result with than the mathematical model. The graphical representation of the results is given in Figure 7.4. The proposed approach found all these results in less than 5 seconds, but the mathematical model was run for 24 hours.

Table 7.3 Results for 30 stations

	Mathematical Model		Proposed Approach				
Dataset	Best Result	Time	Best Result	Lingo time	Matlab time	Total Time	Gap %
1	3473	86400	3552	1.31	1.05	2.36	2
2	3859	86400	**3683**	1.84	0.79	2.63	-5
3	6558	86400	**5205**	2.80	1.64	4.44	-1
4	3641	86400	3840	2.75	1.99	4.74	5
5	3120	86400	**3076**	2.08	2.01	4.09	-1
6	3063	86400	**3063**	2.23	0.69	2.92	0
7	3188	86400	3355	2.97	0.77	3.74	5
8	3121	86400	3164	2.14	2.16	4.30	1
9	2914	86400	**2909**	1.70	1.04	2.74	0
10	4383	86400	**3820**	2.33	1.75	4.08	-13

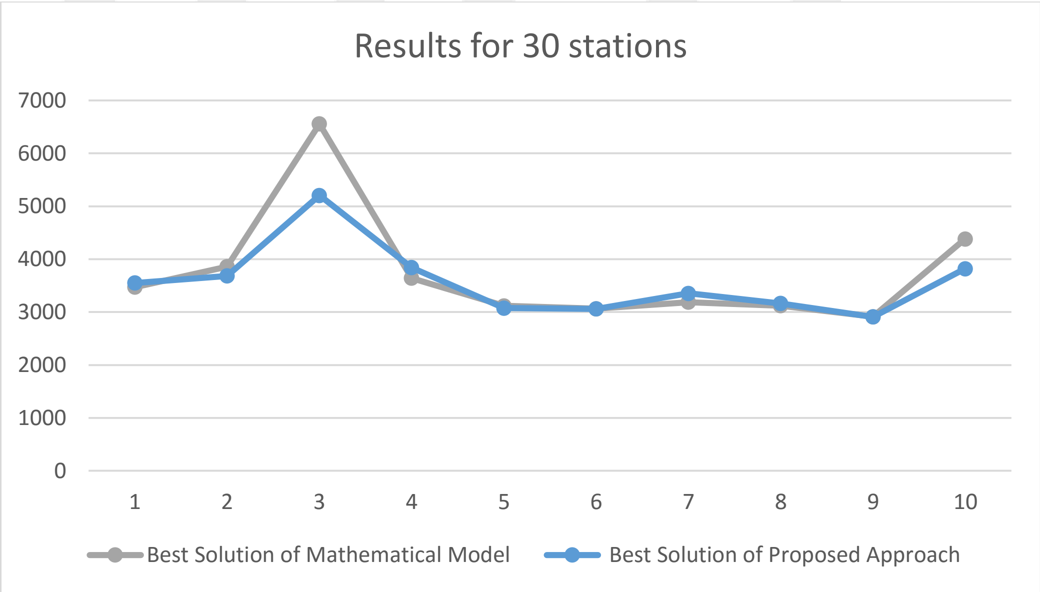


Figure 7.4 Graphical representation of results for 30 stations

7.2.1.4 Results for 40 Stations

In Table 7.4, results for 40 stations are shown. The mathematical model was run for 24 hours and the best value at the end of that period was obtained as a result. The proposed approach seems to achieve better results in 8 out of 10 data sets. With the increase in the number of stations, the proposed approach finds better results in a shorter time than the mathematical model. The graphical representation of the results is given in Figure 7.5.

Table 7.4 Results for 40 stations

	Mathematical Model		**Proposed Approach**				
Dataset	Best Result	Time	Best Result	Lingo time	Matlab time	Total Time	Gap %
1	4855	86400	**4530**	4.59	1.8	6.39	-7
2	4672	86400	**4080**	4.39	2.53	6.92	-13
3	7126	86400	8792	4.75	2.74	7.49	23
4	5261	86400	5480	2.89	1.04	3.93	4
5	4885	86400	**3557**	2.83	2.07	4.90	-27
6	4431	86400	**3272**	3.92	1.71	5.63	-26
7	3429	86400	**3272**	3.94	1.71	5.65	-5
8	5416	86400	**3643**	3.31	1.48	4.79	-33
9	3088	86400	**3028**	2.47	1.73	4.20	-2
10	4796	86400	**4486**	3.42	1.68	5.10	-6

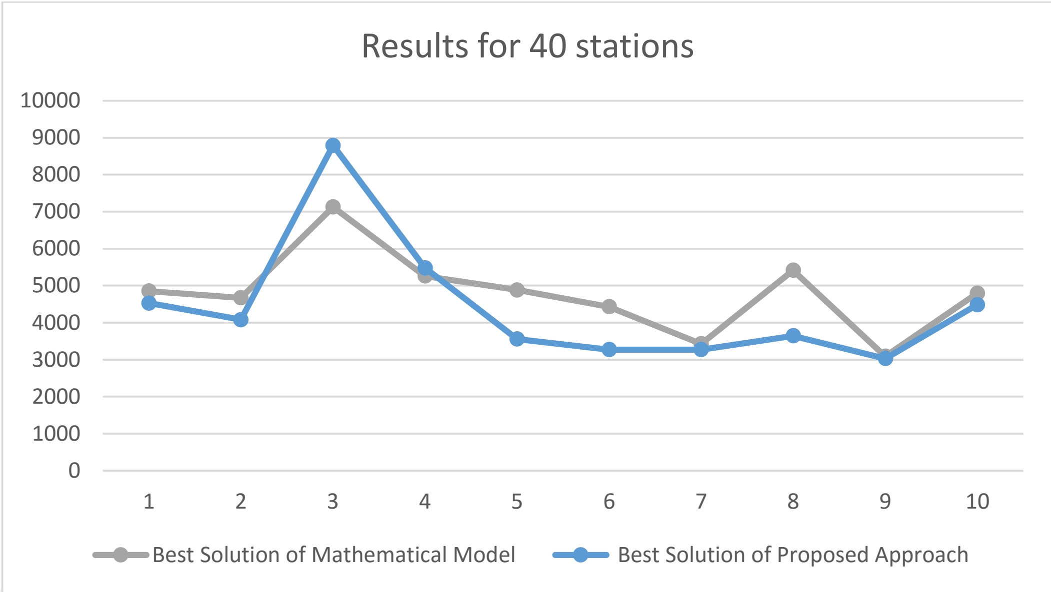


Figure 7.5 Graphical representation of results for 40 stations

7.2.2 Results for 24 Time Periods

At this stage, the main point of the problem was examined, which is planning and routing on a daily basis. The data were taken as 24 time periods. As in the previous section, 10 dataset were solved with mathematical model and proposed approach, for 10.20,30 and 40 stations respectively. The results of the proposed approach that are the same with or better than the results of the mathematical model, are marked as bold.

7.2.2.1 Results for 10 Stations with 24 Time Periods

In Table 7.5, results for 10 stations with 24 time periods are shown. The mathematical model was run for 24 hours and the best value at the end of that period was obtained as a result. The graphical representation of the results is given in Figure 7.6. The reason why the proposed approach does not find better than the mathematical model for 10 stations with 24 time periods is the increasing need for routing. The grouping of 10 stations without considering the distance between them in different time periods causes the distance taken in each route to be increased.

Table 7.5 Results of 10 stations with 24 time periods

Dataset	Mathematical Model		Proposed Approach				
	Best Result	Time	Best Result	Lingo time	Matlab time	Total Time	Gap %
1	13191	86400	14379	7.72	0.60	8.32	9.01
2	13276	86400	15008	10.11	1.09	11.20	13.05
3	10439	86400	12426	27.62	2.63	30.25	19.03
4	13652	86400	15985	100.3	4.77	105.07	17.09
5	7542	86400	7766	7.52	1.43	8.95	2.97
6	8709	86400	11000	14.33	0.69	15.02	26.31
7	11038	86400	12365	18.16	0.91	19.07	12.02
8	9507	86400	10426	100.15	0.52	100.67	9.67
9	8285	86400	8552	10.83	1.91	12.74	3.22
10	6903	86400	7637	101.14	1.31	102.45	10.63

The visited stations found by the mathematical model are the same stations that found by the planning part of the proposed approach, but they are grouped to different time periods depending on vehicle capacity and inventory level, regardless of distance. The difference between the results is due to this reason.

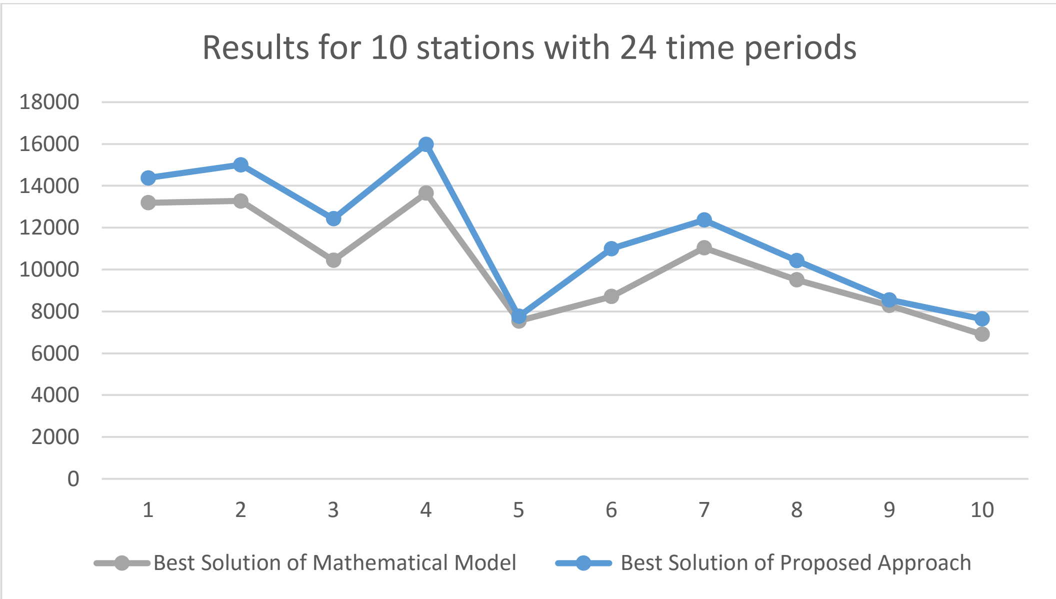


Figure 7.6 Graphical representation of results for 10 stations with 24 time periods

7.2.2.2 Results for 20 Stations with 24 Time Periods

In Table 7.6, results for 20 stations with 24 time periods are shown. The mathematical model was run for 24 hours and the best value at the end of that period was obtained as a result. The graphical representation of the results is given in Figure 7.7. For the second dataset, the mathematical model was unable to obtain a feasible result. As the number of stations increases, it is observed that the grouping without looking at the distance problem mentioned before is losing its importance. In four of the 10 datasets, the proposed approach achieved better results than the mathematical model. However, the proposed approach achieved these results in less than 3 minutes.

Table 7.6 Results for 20 stations with 24 time periods

	Mathematical Model		**Proposed Approach**				
Dataset	Best Result	Time	Best Result	Lingo time	Matlab time	Total Time	Gap %
1	28483	86400	**27639**	28.23	2.24	30.47	-2.96
2	-	86400	**26817**	102.26	4.07	106.33	-
3	24806	86400	25560	74.66	3.11	77.77	3.04
4	22455	86400	25135	185.06	5.29	190.35	11.935
5	14999	86400	16631	29.09	2.99	32.08	10.881
6	14062	86400	16157	101.28	2.41	103.69	14.898
7	21775	86400	**21451**	101.77	2.23	104.00	-1.49
8	19578	86400	**18200**	164.92	2.53	167.45	-7.04
9	12339	86400	14049	101.49	2.09	103.58	13.858
10	12469	86400	13587	101.4	1.63	103.03	08.966

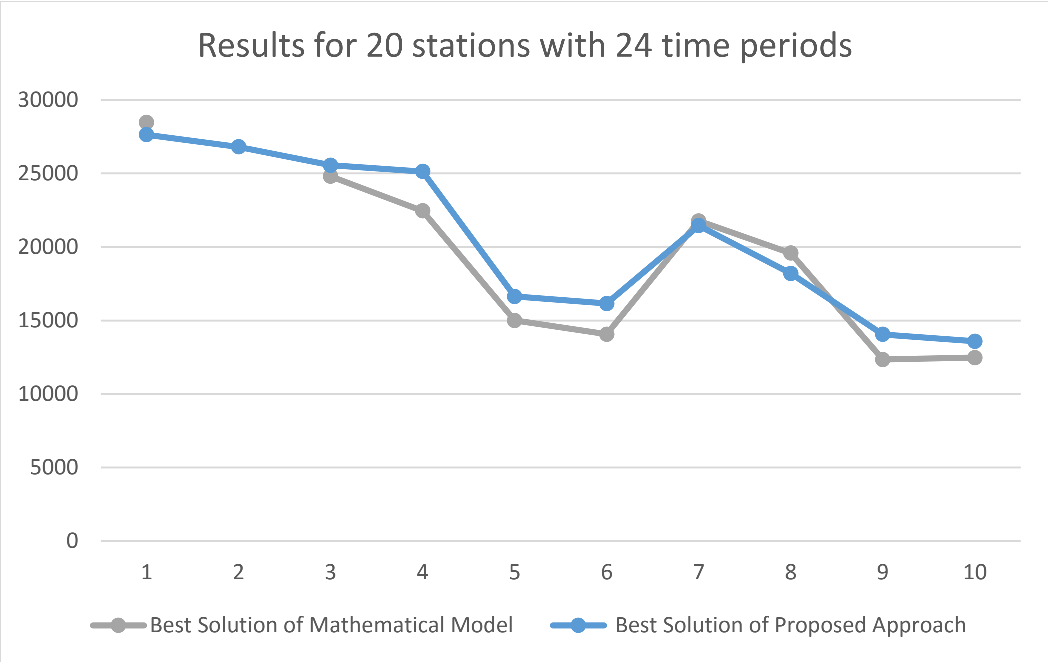


Figure 7.7 Graphical representation of results for 20 stations with 24 time periods

7.2.2.3 Results for 30 Stations with 24 Time Periods

In Table 7.7, results for 30 stations with 24 time periods are shown. The mathematical model was run for 48 hours and the best value at the end of that period was obtained as a result.

Table 7.7 Results for 30 stations with 24 time periods

	Mathematical Model		**Proposed Approach**				
Dataset	Best Result	Time	Best Result	Lingo time	Matlab time	Total Time	Gap %
1	-	172800	**32816**	102.41	5.64	108.05	-
2	95847	172800	**25931**	151.17	4.10	155.27	-72.95
3	-	172800	**35029**	123.45	5.78	129.23	-
4	-	172800	**32228**	217.93	6.54	224.47	-
5	-	172800	**34784**	101.75	6.88	108.63	-
6	24829	172800	**23173**	350.75	3.56	354.31	-06.67
7	35454	172800	**27515**	214.35	2.31	216.66	-22.39

Table 7.7 continues

	Mathematical Model		Proposed Approach				
Dataset	Best Result	Time	Best Result	Lingo time	Matlab time	Total Time	Gap %
8	33114	172800	**22168**	324.9	3.07	327.97	-33.06
9	32777	172800	**21116**	178.68	2.43	181.11	-35.58
10	29561	172800	**22335**	239.96	5.86	245.82	-24.44

With the increase in the number of stations, the proposed approach found better results than the mathematical model. The mathematical model was not able to get a feasible solution in 4 of the datasets. The developed approach achieved all these results within maximum of 6 minutes. The graphical representation of the results is given in Figure 7.8.

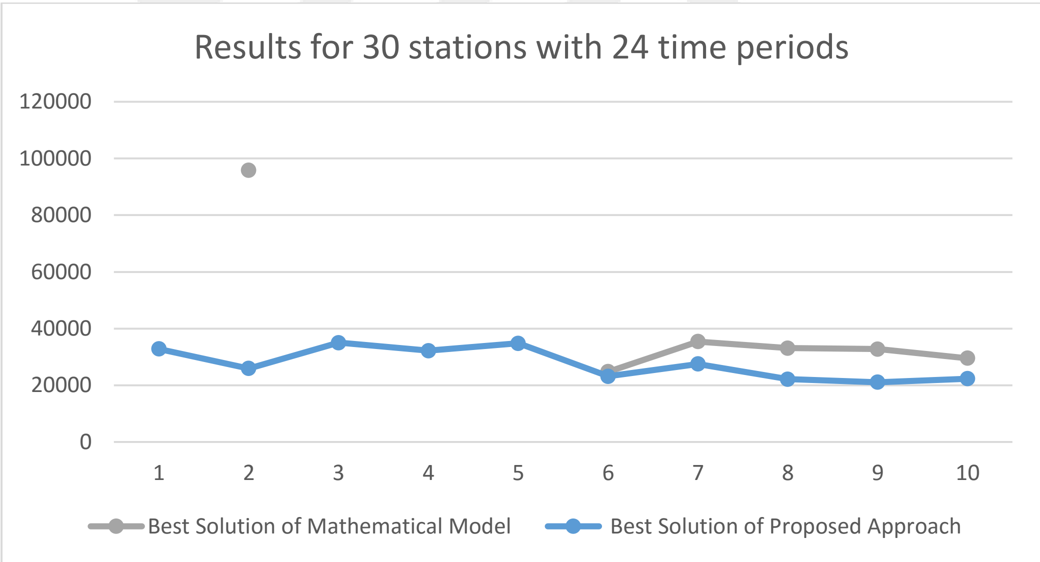


Figure 7.8 Graphical representation of results for 30 stations with 24 time periods

7.2.2.4 Results for 40 Stations with 24 Time Periods

In Table 7.8, results for 40 stations with 24 time periods are shown. The mathematical model was run for 48 hours and feasible result was not obtained for all datasets. The proposed approach found all results within maximum 8 minutes.

Table 7.8 Results for 40 stations with 24 time periods

	Mathematical Model		**Proposed Approach**			
Dataset	Best Result	Time	Best Result	Lingo time	Matlab time	Total Time
1	-	172800	**37071**	204.25	10.81	215.06
2	-	172800	**36030**	238.48	9.46	247.94
3	-	172800	**33847**	130.11	9.02	139.13
4	-	172800	**35206**	463.38	8.52	471.90
5	-	172800	**20676**	402.99	5.48	408.47
6	-	172800	**23647**	164.52	4.87	169.39
7	-	172800	**27545**	262.77	6.94	269.71
8	-	172800	**24713**	178.14	7.29	185.43
9	-	172800	**24112**	294.49	15.15	309.64
10	-	172800	**22675**	171.68	10.89	182.57

Again, the results of the 9th dataset were chosen to illustrate the routes found by the two models. However, a different representation was chosen because the two models were routed in different time periods and many routes were made during the day. The routes found by the mathematical model are given in Table 7.8 and the routes found by the proposed approach are given in Table 7.9.

Table 7.8 Routes found by mathematical model

	10 Stations	20 Stations	30 Stations
00:00			
01:00	0→5→10→3→4→7→2→1→0	0→4→14→9→8→7→2→16→17→0	0→9→7→2→7→0
02:00			0→19→15→4→12→10→27→25→26→24→4→3→0
03:00			0→2→16→17→0
04:00			0→17→15→4→14→19→12→22→30→29→3→5→23→21→2→0
05:00		0→15→12→10→13→5→4→1	0→30→1→28→12→13→26→27→19→4→14→3→21→17→0
06:00			0→15→24→4→4→23→5→0
07:00		0→9→7→18→2→17→0	
08:00		0→5→3→10→11→4→14→15→19→0	0→5→24→11→2→26→13→27→15→19→7→18→8→2→0
09:00	0→4→5→10→9→8→7→0	0→1→20→16→2→0	
10:00			0→30→21→22→29→28→27→24→11→0→26→15→19→0
11:00			
12:00			0→30→0
13:00		0→1→13→5→0	0→21→17→1→6→20→19→24→12→25→26→27→3→15→28→22→4→5→14→23→0
14:00	0→1→0		0→4→24→27→11→14→0
15:00			0→16→20→21→0
16:00			
17:00			
18:00			
19:00			0→16→30→0
20:00			
21:00			
22:00			
23:00			

Table 7.9 Routes found by proposed approach

	10 Stations	20 Stations	30 Stations	40 Stations
00:00				0→23→5→0→27→15→4→14→36→16→31→7→2→17→0
01:00			0→4→15→22→25→27→14→23→9→7→17→0	
02:00	0→2→7→8→4→0→5→0	0→4→14→10→5→15→8→7→18→2→16→19→0		
03:00				
04:00			0→17→20→26→10→5→21→16→0	
05:00				
06:00		0→19→7→17→0		0→35→14→39→9→18→17→21→30→31→26→25→32→10→19→29→20→22→0
07:00			0→29→17→4→14→27→3→19→0	
08:00	0→→3→10→5→4→1→0	0→9→3→13→1→15→5→10→14→4→16→0		0→37→5→4→3→27→28→13→1→15→34→7→0
09:00			0→28→13→10→5→7→16→1→27→30→0	
10:00				
11:00				
12:00				0→38→35→34→27→28→16→8→31→0
13:00	0→9→1→0			
14:00				
15:00			0→28→25→29→1→8→18→21→0	
16:00				0→39→32→21→1→29→25→0
17:00		0→20→1→0		
18:00				
19:00				
20:00				
21:00				
22:00				
23:00				

7.3 Summary of the Results for Generated Data

To summarize this study in general, the increase in the number of stations while making a daily routing plan causes the mathematical model not to find a feasible result, but the proposed approach leads to better results. Because, the problem of grouping to time periods regardless of distance for the smaller BSSs has lost importance as the number of stations increases. Thus, it can be concluded that the proposed approach has better results than the mathematical model in medium size BSS.

7.4 Computation for Real World Data

One week of usage data was obtained from Bisim, a BSS operating in Izmir, to test the proposed approach with actual data. Received data shows the number of bicycles entering and leaving the station. Bisim has 30 stations and a depot. The capacity of the transport vehicle is taken as 20 bicycles. The received data was translated into hourly demand to be suitable for the problem addressed. Since the data was weekly, there were 168 time periods in total.

It is aimed to take the routing plan for 7 days of the week. The received data starts at 00:00 on Monday and ends at midnight on Sunday. The inventory level at the end of each 24 period will be the initial inventory value of the next period. Since the number of stations in the received data is 30, the planning period is set to 6 hours and the models are set to run 4 times each day to make daily planning more effective. Each six-hour period was run in a set and the inventory level after the operation was entered as input for the next set. Thus, 28 sets have been run so that each day will be four sets.

The results are shown in Table 7.10. The distances are in meters and the times are recorded in seconds. For each set, mathematical model was run for an hour. Because there are more than one routing in some sets, the difference between the results of the two approaches may be high. We see this issue on Wednesday, 11^{th} set and 12^{th} set.

Table 7.10 Results for Bisim problem

		Mathematical Model		Proposed Approach				
Days	Set	Distance	Time	Distance	Lingo time	Matlab time	Total Time	Gap %
Monday	1	0	3600	**0**	0.85	**0**	0.85	**0**
	2	22.4	3600	**22.4**	0.92	**0.0226**	0.9426	**0**
	3	68.8	3600	**51.2**	1.13	**0.0063**	1.1363	**-25.5814**
	4	43.2	3600	**43.2**	1.21	**0.0083**	1.2183	**0**
Daily total distance		134.4		**116.8**				**-13.0952**
Tuesday	5	16	3600	**16**	0.97	**0.0011**	0.9711	**0**
	6	44.8	3600	**41.6**	1.37	**0.0064**	1.3764	**-7.14286**
	7	41.6	3600	**41.6**	2.25	**0.0087**	2.2587	**0**
	8	60.8	3600	**43.2**	2.23	**0.0096**	2.2396	**-28.9474**
Daily total distance		163.2		**142.4**				**-12.7451**
Wednesday	9	41.6	3600	**41.6**	0.92	**0.0015**	0.9215	**0**
	10	40	3600	41.6	1.51	**0.0033**	1.5133	4
	11	46.4	3600	104.00	1.37	**0.0048**	1.3748	124.138
	12	294.4	3600	**86.40**	1.83	**0.0122**	1.8422	**-70.6522**
Daily total distance		422.4		**273.6**				**-35.2273**
Thursday	13	44.8	3600	**22.4**	0.92	**0.0022**	0.9222	**-50**
	14	41.6	3600	48.4	1.51	**0.0032**	1.5132	16.3462
	15	47.2	3600	56	1.37	**0.0109**	1.3809	18.6441
	16	105.6	3600	**105.6**	1.83	**0.0125**	1.8425	**0**
Daily total distance		239.2		**232.4**				**-2.84281**
Friday	17	41.6	3600	**41.6**	0.95	**0.0020**	0.9520	**0**
	18	51.2	3600	**46.4**	1.13	**0.0022**	1.1322	**-9.375**
	19	48	3600	**46.4**	1.23	**0.0079**	1.2379	**-3.33333**
	20	89.6	3600	92.8	1.67	**0.0188**	1.6888	3.57143
Daily total distance		230.4		**227.2**				**-1.38889**
Saturday	21	41.6	3600	**41.6**	0.96	**0.0012**	0.9612	**0**
	22	105.6	3600	**48**	1.39	**0.0055**	1.3955	**-54.5455**
	23	156.8	3600	**105.6**	1.5	**0.0056**	1.5056	**-32.6531**
	24	198.4	3600	**144**	2.08	**0.0581**	2.1381	**-27.4194**
Daily total distance		502.4		**339.2**				**-32.4841**
Sunday	25	41.6	3600	51.2	1.45	**0.0039**	1.4539	23.0769
	26	46.4	3600	48	1.51	**0.0145**	1.5245	3.44828
	27	89.6	3600	123.2	1.31	**0.0161**	1.3261	37.5
	28	236.8	3600	**169.6**	2.25	**0.0086**	2.2586	**-28.3784**
Daily total distance		414.4		**392**				**-5.40541**
TOTAL DISTANCE		2106.4		**1723.6**				**-18.1732**

Table 7.11 Routes found by mathematical model

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
00:00							
01:00		0→1→3→5→10→0	0→26→0	0→5→7→8→19→22→28→15→14→10→6→4→0	0→1→2→3→4→5→6→7→9→11→12→26→25→0	0→24→25→26→23→22→18→16→11→10→9→8→7→0	0→3→9→11→13→19→22→23→26→24→21→16→15→14→10→6→5→4→1→0
02:00							
03:00							
04:00							
05:00							
06:00							
07:00		0→4→23→26→24→21→19→17→14→13→12→10→6→8→5→3→2→0	0→22→25→0	0→2→3→5→10→15→16→14→0	0→13→25→26→27→24→29→28→22→12→10→8→0	0→1→4→23→28→26→11→9→2→0	
08:00						0→3→0	
09:00						0→5→0	
10:00							0→5→17→26→29→13→15→9→0
11:00	0→2→3→10→11→13→14→9→7→6→5→4→0			0→10→9→7→4→0		0→30→3→1→0	
12:00							

Table 7.11 continues

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
13:00	0→4→6→10→14→11→15→16→26→25→23→0	0→1→10→12→14→15→25→26→24→13→11→0	0→14→24→25→27→28→29→26→20→19→16→13→12→11→10→8→7→5→4→1→0	0→3→6→9→10→12→13→14→1→0	0→1→3→29→30→27→26→25→24→20→17→16→14→13→12→11→9→8→7→4→2→0	0→5→14→15→17→20→29→28→16→26→23→11→10→12→9→6→4→3→1→0	0→1→3→5→8→11→13→24→26→29→27→25→15→6→0
14:00	0→1→3→6→10→12→9→11→7→4→0			0→2→5→6→7→8→28→27→26→23→21→19→17→3→0		0→1→2→26→5→3→0	
15:00							0→2→15→14→16→18→20→22→21→24→25→4→3→1→0
16:00							
17:00						0→1→2→4→21→30→26→27→0	
18:00							
19:00	0→7→22→23→27→26→20→8→0	0→5→8→10→12→15→19→20→24→25→28→29→27→26→6→2→1→0	0→4→5→6→7→23→22→20→19→18→16→15→12→10→2→8→9→11→13→14→17→19→21→25→28→27→30→29→27→26→1→0	0→1→5→6→7→17→21→22→23→25→29→20→10→9→4→3→2→0	0→1→5→10→13→14→20→26→24→23→22→19→18→16→12→9→8→6→3→2→0	0→26→25→24→23→27→28→3→4→0	0→1→2→24→21→20→27→26→11→19→7→0

Tablo 7.11 continues

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
20:00			0→1→3→7→8→11→12→13→14→16→15→10→9→6→5→17→19→21→23→25→29→28→27→25→30→24→20→22→18→4→2→0		0→1→4→7→8→9→26→24→28→6→0	0→2→11→27→20→19→18→15→16→14→13→10→5→3→0	0→9→23→15→25→10→26→16→4→6→7→2→1→0
21:00			0→9→11→14→15→18→29→27→26→24→22→23→28→20→30→21→20→19→17→16→13→12→8→10→2→1→0	0→2→6→10→14→26→27→24→21→4→3→0		0→1→2→21→19→16→15→11→10→23→26→0	
22:00		0→7→6→5→4→1→3→0				0→18→23→27→26→25→24→21→17→11→5→3→2→0	0→10→9→7→4→2→3→13→19→26→1→6→8→14→0
23:00			0→24→23→25→22→21→20→16→13→14→15→17→18→19→1→2→2→4→5→11→12→10→8→9→7→6→0	0→4→10→9→5→0			0→6→10→9→5→0

The mathematical model found 2 routes in the 11th set, while the proposed approach found 2 routes in the 12th set. However, while looking at the total distance traveled on a daily basis, it can be said that the proposed approach has found better results. Considering the total distance traveled for weekly, the difference between the results of the two approaches is more than 18%. Furthermore, in terms of solution times, the proposed approach finds results in much shorter time than the mathematical model.

The routes found by the mathematical model are given in Table 7.11 and the routes found by the proposed approach are given in Table 7.12.

Table 7.12 Routes found by proposed approach

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
00:00							
01:00		0→7→10→4→0	0→26→0	0→5→9→14→10→0	0→25→26→0	0→7→26→22→10→9→0	0→4→8→9→3→12→21→26→16→10→0
02:00							
03:00							
04:00							
05:00							
06:00							
07:00			0→1→22→25→26→6→0	0→16→9→6→0			
08:00		0→26→23→16→10→7→6→0				0→1→3→4→5→9→30→28→12→0	
09:00					0→8→10→29→25→0		0→5→9→12→26→29→30→27→15→10→0
10:00				0→10→14→9→0			
11:00	0→14→10→0						
12:00							
13:00	0→6→23→26→10→16→14→10→0	0→6→7→12→15→22→23→25→26→16→4→0	0→6→12→1→13→15→25→0	0→3→10→23→30→14→9→1→6→4→0		0→14→23→29→21→3→12→0	0→15→8→5→1→25→20→16→27→29→0
14:00			0→1→22→29→27→0		0→1→8→19→29→26→25→20→12→0	0→6→16→17→27→28→26→20→0	

Table 7.12 continues

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
15:00							0→1→25→0
16:00							
17:00						0→10→30→26→0	
18:00							
19:00		0→3→4→15→23→27→26→25→22→8→5→1→0	0→4→5→14→16→23→29→25→19→9→3→0	0→5→20→30→25→23→6→1→0	0→5→26→25→19→8→10→0	0→4→9→16→20→25→26→27→15→12→6→5→1→0	0→9→19→20→21→23→27→1→0
20:00	0→14→16→22→27→23→0				0→6→7→26→27→30→22→20→14→1→0	0→23→10→0	
21:00			0→6→10→25→0	0→26→14→9→8→0		0→10→0	0→10→30→26→0
22:00						0→1→26→30→0	0→10→26→0
23:00				0→10→0			0→23→10→0

While looking at the results for real life data, it is seen that the results of the proposed approach are more preferable. Because the number of routes that created for the daily plan is lesser and total traveled distance is shorter.

CHAPTER EIGHT
CONCLUSION

8.1 Summary

Since BSSs have attracted the attention of users in recent years, it is important to respond to the needs of the system and provide user satisfaction. In order to meet the needs of the system and provide user satisfaction, the number of bicycles in the stations should be well adjusted. For this purpose, a bicycle transport and supply operation is performed in the system in the opposite direction of the bicycle flow occurred by the users. In order to ensure this flow, bicycle demands should be estimated according to the rental movements of the users and the distribution of these bicycles should be provided by taking the shortest route.

In this thesis, an approach has been proposed for BSSs to the plan of bicycle demands on a daily basis, decide on the time period that the route will take place, and route with minimum distance, under the assumption that bicycle usage data is known. The datasets for BSS were developed and the proposed approach with these data was tested. First of all, SBRP was defined and the related mathematical model was presented. After the model was tested with a small numerical example for SBRP, the model was developed to the main problem.

The main issue in this study is to reveal the daily plan to balance the inventory level by the assumption of knowing the number of bicycles demanded by the users from the system and returned to the system. A new model was presented for this purpose. In this model, it was aimed to determine the demands of the stations and to make the routing process based on time periods by changing the inventory levels in terms of time periods. This mathematical model is insufficient with the increase in the number of stations of the BSS, so a new approach is proposed. In this approach, bicycle needs of stations and time periods for routing operation were determined with a mathematical model and EDA was used for routing with minimum distance considering demand values.

With the generated data, the mathematical model and the proposed approach were solved and the results were compared. For simplicity, data with 10, 20, 30 and 40 stations were examined for 5 time periods. Then, the same data was resolved for 24 time periods and the results were evaluated.

It can be said that the proposed approach has achieved good results due to the fact that achieving much faster results and the mathematical model cannot find a feasible result with increased number of stations. When the number of stations increased to 30, the mathematical model did not find good results, and although it runned two days for 40 stations, could not find any results for the 10 datasets.

The same operations were performed for weekly data from a real BSS. The system examined for a 4 sets with 6-hour periods per day revealed a better routing plan with the proposed approach on a weekly basis. In the proposed approach, the total distance traveled is shorter and the total number of routes is lesser.

8.2 Future Works

In this study, unlike the studies mentioned in the literature research, time periods were used to create a daily route plan and the focus was on determining the time of day and the number of bicycles to be carried.

As the assumption is made that the number of bicycles that the users will rent from the stations and return to the stations is known in the system, this study is considered as totally deterministic. This assumption cannot be achieved in real life. For further studies, these data can be handled as probabilistic. In addition, due to the static routing problem in this study, it is possible to perform dynamic routing in future studies.

It was mentioned that there are studies for systems with different types of bicycles. Routing can be performed for these systems with assumptions that there are different demands for different types of bicycles within certain time periods.

In order to be closer to real-life systems, a study can be carried out the possibility of damage and repair of bicycles in addition to demand data.

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