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A Multi-Periodic Optimization Modeling Approach for the Establishment of a Bike Sharing Network: a Case Study of the City of Athens

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***Abstract*— This study introduces a novel mathematical formulation that addresses the strategic design of a bicycle sharing network. The developed pure integer linear program takes into consideration data such as the potential future demand patterns during the day, the bike's popularity in a city, the desired proximity of the stations and the available budget for such a network. With these input data, it optimizes the location of bike stations, the number of their parking slots and the distribution of the bicycle fleet over them in order to meet as much demand as possible and to offer the best service to the users. The estimated demand for the network is split into "Demand for Pick-Ups" and "Demand for Drop-offs" during the 24 hours of the day, which are discretized into time intervals. The proposed approach is implemented on the very center of the city of Athens, Greece.**

***Index Terms*— bike sharing, integer, mathematical model, multi-periodic**

I. INTRODUCTION

Bike sharing networks have received increasing attention during the last decades and especially in the 21st century as a no-emission option in order to improve the first/last mile connection to other modes of transportation, thus facilitating the mobility in a densely populated city. The bike sharing network consists of docking stations, bicycles and information technology (IT) interfaces that have been recently introduced to improve the quality offered to the users.

There have been three generations of bike sharing programs over the past half century [1] with the 3rd one emerging in 1996 at Portsmouth University (Bikeabout). However, it was not until 2005 that this generation flourished with the launch of Velo'v with 1500 bikes in Lyon. Two years later, Paris launched Velib' and Barcelona launched Bicing, which are two of the most successful networks nowadays. Nowadays, there are 678 programs in operation and 186 in planning or under construction all over the world (Metrobike, December 2013).

This expanding trend of bike sharing networks necessitates their better planning and design in order that they are successful. The goal of this paper is to propose a novel mathematical formulation to design such networks incorporating the hourly demand estimation, the fixed costs of infrastructure, the proximity and density of stations, as well as their size. Given a set of candidate locations of stations and with a predefined available construction budget the model decides the number and the location of the stations, how large they will be and how many bikes should they have at the beginning of the day in order to meet the assumed demand.

The remainder of the paper is organized as follows. Section II provides a brief literature review of the main approaches that have been proposed to solve similar problems. Section III presents the developed novel mathematical model. In section IV the case-study for the center of Athens is described followed by the results of the implementation of the model on it. Finally, in section V there is a commentary on the proposed model, its broader application and potential areas of future work.

II. LITERATURE REWIEW

Shu et al. (2010) [2] proposed practical models for the design and management of a bicycle-sharing network given the location of the stations. A stochastic network flow model is introduced in order to predict the flow of bicycles within the network and to estimate the number of trips supported by the system, the suitable number of bicycles to be deployed and the number of docks needed in each station examining the viability of periodic re-distribution of bicycles as well. In the herein research the number of the stations is not predefined, as in [2], but part of the design problem and the demand of each candidate location is deterministic. Finally, the present work addresses the design of such networks and not their management, so no re-distribution aspects are taken into consideration.

Lin et al. (2011) [3] developed a pure integer non-linear program for the strategic design of a bike sharing network. Given a set of origins, destinations, candidate bicycle stations and the travel demands from origins to destinations with specific demand processes, it optimizes the location of the stations and bicycle lanes and the required inventory

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level for sharing bicycles at each station to meet demand. The herein model is a pure integer linear program where no origin-destination flows are assumed, but every location is characterized by time-discretized demand for pick-ups and drop-offs during a single day. This approach is considered to give improved and less complicated simulation of the network's future usage. Additionally, the bike sharing network is dealt with independently and so the establishment of bicycle lanes is not in the scope of the present research.

Sayarshad et al. (2011) [4] introduce a multi-periodic optimization formulation to determine the minimum required bike fleet size that minimizes simultaneously unmet demand, unutilized bikes and the need to transport empty bikes between rental stations. The herein model, also, uses multi-periodic formulation without re-distribution concerns because it addresses only the network design problem and not its usage, as in [4].

Martinez et al. (2012) [5] present a heuristic, encompassing a mixed integer linear program, which optimizes the location of bike stations and the fleet dimension, while measuring the required bicycle re-distribution activities. It considers a mixed fleet of regular and electric bikes and several fare collection methods of the system. The present research considers only regular bikes assuming that electric ones are yet to come in such a network. Moreover, it includes no fare policy as this may be decided after the establishment of the bike sharing network.

García-Palomares et al. (2012) [6] use Geographical Information System (GIS) to calculate the spatial distribution of the potential demand for trips, locate stations using location-allocation models, determine station capacity and define the characteristics of the demand for stations. In the herein project the GIS is not used as access to a respective software could not be granted. The demand data are derived by the recorded usage data of already implemented similar bike sharing networks.

III. Model Formulation

A. Problem Definition

Given a set of candidate locations of bike stations and the time-dependent demand for bikes at these locations during an average day it is necessary to know where to place the bike stations and how many parking slots and bikes should each one have. The available budget of a city for the construction of the whole bike sharing system is predefined and so are the costs of a single bike, a single parking slot and a single station. The walking time between the locations is another parameter of the problem used to manipulate the proximity of the constructed stations.

As regards demand in each location, it is split into "Demand for Pick-Ups", i.e. how many users would like to take a bike from a station, and "Demand for Drop-Offs", i.e. how many riders would like to leave a bike into a station. The 24 hours of the day are discretized into time intervals of one hour, during which different numbers of users come to a station either to pick up or drop off a bicycle.

B. Mathematical Model

The model includes the following subscripts and sets, input parameters and decision variables:

Subscripts and Sets:

$i, k \in N$: the candidate locations of bicycle stations

$t, p \in T$: the time intervals in a single day

Input Parameters:

$\overline{CB}$: cost of purchasing a single bicycle,

$\overline{CS}$: cost of establishing a bike station (without any parking slots),

$\overline{CTH}$: cost of constructing a single parking slot into an established station,

$\overline{APE_{ik}}$: walking time from location i to location k (in minutes),

$\overline{\text{maxper}}$: maximum walking time (in minutes) between two candidate locations, of which the one has an established station and the other one does not have a station. This parameter is introduced in order to manipulate the proximity of the finally proposed stations to be established,

$\overline{BDG}$: total available budget for the establishment of the whole bike sharing network,

$\overline{DF_{it}}$: "Demand for Pick-Ups" from location i during time interval t,

$\overline{DE_{it}}$: "Demand for Drop-Offs" at location i during time interval t,

$\overline{DD_p}$: a parameter that equals 1 if the "Demand for Drop-Offs" is more than the "Demand for Pick-Ups" until time interval p and 0 otherwise,

$\overline{Z\min}$: minimum number of parking slots a station could have,

$\overline{Z\max}$: maximum number of parking slots a station could have,

$\overline{perde}$: percentage of the demand that is transferred from a location where a station is not established to an established station. It is assumed that if a station is not established at a location, part of its demand is lost ($1-\overline{perde}$). This parameter is a measure of the citizens' inclination to bike-riding,

$\overline{CDT}$: penalty cost per unit of demand and per minute of walking time, if a customer has to walk from his/her location with no established station to the nearby station,

$\overline{CDEMAND}$: penalty cost for a unit of unmet demand,

$\overline{M}$: a very large number,

$\overline{m}$: a very small number,

Decision Variables

X_k : binary variable that equals 1 if a station is established at location k and 0 otherwise,

Z_{ik}: binary variable that equals 1 if candidate location i is served by the established station at location k and 0 otherwise,

DN_k : general integer variable that equals the number of constructed bicycle parking slots at station k,

BN_{kt} : general integer variable that equals the number of

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bicycles that are available at station k at the beginning of time interval t,

BF_{kt} : general integer variable that equals the number of bicycles that could leave station k during time interval t, where BN_{kt} bicycles are available,

BE_{kt} : general integer variable that equals the number of bicycles that could arrive at station k during time interval t, where DN_k parking slots are established and BN_{kt} bicycles are available,

$UDBinF_{kt}$: binary variable that equals 1 if a station k cannot serve some “Demand for Pick-Ups” at time interval t and 0 otherwise (not enough available bicycles),

$UDBinE_{kt}$: binary variable that equals 1 if a station k cannot serve some “Demand for Drop-Offs” at time interval t and 0 otherwise (not enough available parking slots),

In Fig. 1 the thorough consideration of the problem is explained. N locations i are predefined together with their “Demand for Pick-Ups” (i.e. $\overline{DF}_{it}$) and “Demand for Drop-Offs” (i.e. $\overline{DE}_{it}$) at all time intervals during an average day. It is a matter of optimization how many bike stations will be established and where, so that every location has a nearby station. The locations k, where stations are established, is a subset of the locations i.

The demand patterns of each candidate location express the will of the location’s citizens to use the network if a station were finally established there. In case a station is not established at a specific location (not all locations will have a station), the location’s citizens will have to walk to the

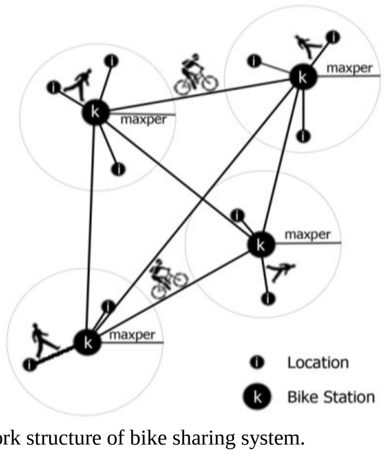

Fig. 1. Network structure of bike sharing system.

nearest established station, which is $\overline{\text{maxper}}$ walking time away, in order to use the network. In this way, it is assumed that location i is served by station k, i.e. Z_{ik} =1. The percentage of the citizens that are willing to do this is expressed by the parameter $\overline{perde}$. This parameter is assumed to be a measure of the bike’s popularity in a specific city. For example, if the citizens are keen riders, they would be willing to walk from their location to the nearest station so as to pick up a bike and use the network ($\overline{perde} \to 1$). However, if the bike is not a very popular means of transport in a city, then only few of the demand of a location with no station would be transferred to the nearest one ($\overline{perde} \to 0$). The rest of the demand is not served supposing that this part of citizens will not take a bike due to the distance of the station k from their location i.

Objective Function

The objective function of the model is a minimization of three terms:

$$
\begin{aligned}
MINIMIZE: \overline{CDT} * \overline{perde} * \sum_i \sum_k \sum_t (\overline{DF}_{it} + \overline{DE}_{it}) * Z_{ik} * \overline{APE}_{ik} + \\
+\overline{CDEMAND} * (\sum_t \sum_k \overline{DF}_{kt} - BF_{kt}) + \\
+\overline{CDEMAND} * (\sum_t \sum_k \overline{DE}_{kt} - BE_{kt})
\end{aligned} \tag{1}
$$

The first term expresses the amount of demand that is transferred from a location i to its allocated station k, which are a specific walking time away from one another.

The second and the third term of the objective function are introduced in order to minimize the unmet demand.

The goal of the model is not only to meet as much demand as possible (second and third term), but also to provide best service to the users. For this reason, the first term is introduced so that only few customers from location i with no station (i.e. $\overline{perde} * (\overline{DF}_{it} + \overline{DE}_{it})$) will have to walk for a minimum time (i.e. $\overline{APE}_{ik}$) to station k (i.e. Z_{ik}). Otherwise, without this term the model proposes a solution where high-demand locations are served by not so close low-demand stations.

The three terms are multiplied with a parameter in order to be expressed in the same unit (€). Thus, the units of $\overline{CDT}$ are (€/customer/minute) and those of $\overline{CDEMAND}$ are (€/customer). The second and the third term are multiplied by the same penalty unit cost $\overline{CDEMAND}$ meaning that no different weight is given to either the “Demand for Pick-Ups” or the “Demand for Drop-Offs”.

Constraints

The mathematical model is subject to the following constraints:

$$\overline{CB} * \sum_k BN_{kt_0} + \overline{CS} * \sum_k X_k + \overline{CTH} * \sum_k DN_k \le \overline{BDG} \tag{2}$$

$$X_k * \overline{Z\min} \le DN_k \le X_k * \overline{Z\max}, \forall k \tag{3}$$

$$BN_{kt} \le DN_k, \forall k, t \tag{4}$$

$$\sum_k BN_{kt} \le \sum_k BN_{kt_0}, \forall t \tag{5}$$

$$BN_{kt+1} = BN_{kt} + BE_{kt} - BF_{kt}, \forall k, t \tag{6}$$

$$Z_{ik} \le X_k, \forall i, k \tag{7}$$

$$X_k \le Z_{kk}, \forall k \tag{8}$$

$$\sum_k Z_{ik} = 1, \forall i \tag{9}$$

$$Z_{ik} \le \frac{\overline{\text{maxper}}}{\overline{APE}_{ik}}, \forall i, k, i \ne k \tag{10}$$

$$BF_{kt} \le BN_{kt}, \forall k, t \tag{11}$$

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$$BE_{kt} \le DN_k - BN_{kt}, \forall k,t \tag{12}$$

$$BF_{kt} \le \overline{DF}_{kt} + (\sum_{i \ne k} Z_{ik} * \overline{DF}_{it} * \overline{perde}), \forall k,t \tag{13}$$

$$BE_{kt} \le \overline{DE}_{kt} + (\sum_{i \ne k} Z_{ik} * \overline{DE}_{it} * \overline{perde}), \forall k,t \tag{14}$$

$$\begin{aligned} &\left[\overline{DF}_{kt} + (\sum_{i \ne k} Z_{ik} * \overline{DF}_{it} * \overline{perde}) - BN_{kt}\right] * \overline{m} \le \mathrm{UDBinF}_{kt} \le \\ &\le 1 + \left[\overline{DF}_{kt} + (\sum_{i \ne k} Z_{ik} * \overline{DF}_{it} * \overline{perde}) - BN_{kt}\right] * \overline{m}, \forall k,t \end{aligned} \tag{15}$$

$$\begin{aligned} &\left[\overline{DE}_{kt} + (\sum_{i \ne k} Z_{ik} * \overline{DE}_{it} * \overline{perde}) - (DN_k - BN_{kt})\right] * \overline{m} \le \mathrm{UDBinE}_{kt} \le \\ &\le 1 + \left[\overline{DE}_{kt} + (\sum_{i \ne k} Z_{ik} * \overline{DE}_{it} * \overline{perde}) - (DN_k - BN_{kt})\right] * \overline{m}, \forall k,t \end{aligned} \tag{16}$$

$$\begin{aligned} &\overline{DF}_{kt} + (\sum_{i \ne k} Z_{ik} * \overline{DF}_{it} * \overline{perde}) - \overline{M} * UDBinF_{kt} \le BF_{kt} \le \\ &\le \overline{DF}_{kt} + (\sum_{i \ne k} Z_{ik} * \overline{DF}_{it} * \overline{perde}) + \overline{M} * UDBinF_{kt}, \forall k,t \end{aligned} \tag{17}$$

$$\begin{aligned} &BN_{kt} - \overline{M} * (1 - UDBinF_{kt}) \le BF_{kt} \le BN_{kt} + \overline{M} * (1 - UDBinF_{kt}), \\ &\forall k,t \end{aligned} \tag{18}$$

$$\begin{aligned} &\overline{DE}_{kt} + (\sum_{i \ne k} Z_{ik} * \overline{DE}_{it} * \overline{perde}) - \overline{M} * (UDBinE_{kt} + \overline{DD}_t) \le BE_{kt} \le \\ &\le \overline{DE}_{kt} + (\sum_{i \ne k} Z_{ik} * \overline{DE}_{it} * \overline{perde}) + \overline{M} * (UDBinE_{kt} + \overline{DD}_t), \forall k,t \end{aligned} \tag{19}$$

$$\begin{aligned} &(DN_k - BN_{kt}) - \overline{M} * (1 - UDBinE_{kt} + \overline{DD}_t) \le BE_{kt} \le \\ &\le (DN_k - BN_{kt}) + \overline{M} * (1 - UDBinE_{kt} + \overline{DD}_t), \forall k,t \end{aligned} \tag{20}$$

$$X_k = \{0,1\}, \forall k \tag{21}$$

$$Z_{ik} = \{0,1\}, \forall i,k \tag{22}$$

$$\mathrm{UDBinF}_{kt} = \{0,1\}, \forall k,t \tag{23}$$

$$\mathrm{UDBinE}_{kt} = \{0,1\}, \forall k,t \tag{24}$$

$$DN_k \ge 0, \forall k \quad \text{general integer} \tag{25}$$

$$BN_{kt} \ge 0, \forall k,t \quad \text{general integer} \tag{26}$$

$$BE_{kt} \ge 0, \forall k,t \quad \text{general integer} \tag{27}$$

$$BF_{kt} \ge 0, \forall k,t \quad \text{general integer} \tag{28}$$

Constraint (2) warrants that the total cost for the establishment of all stations, the construction of all parking slots in them and the purchase of all bikes does not exceed the available budget. Constraint (3) ensures that the bicycle parking slots (i.e. DN_k) at each constructed station are between the permissible minimum and maximum value (i.e. $\overline{Z\min}$ and $\overline{Z\max}$). Constraint (4) ensures that at all time intervals, each station cannot have more bikes than the number of its parking slots.

Constraint (5) means that at all time intervals the total number of bicycles at all stations will not exceed the total number of bicycles at the first time interval. This constraint is introduced because the first time interval is assumed to be 4-5am, so at 4am all bikes are considered to be parked into the stations and no user keeps a bike away. During the day a user can keep a bike for more than the duration of the time interval (e.g. one hour) and return it to a station at a later time interval. So in a given time interval t due to more "Demand for Pick-Ups" than "Demand for Drop-Offs" the total number of available bikes at all stations will be less than the initial number. Afterwards, in a later time interval t'>t due to more "Demand for Drop-Offs" than "Demand for Pick-Ups" the available bikes at all stations will be more than those in time interval t, but not greater than the total number of bikes in t_0. This constraint also ensures that the model does not add bikes to the network during the day, i.e. the bike sharing network is a closed network.

Constraint (6) expresses that the number of bicycles at station k at the beginning of time interval t+1 is equal to the ones it had at the beginning of time interval t plus the bikes that arrive minus the ones that leave during time interval t.

Constraint (7) guarantees that a location i cannot be served by location k, if a station is not built in location k. Constraint (8) warrants that if a station is constructed at location k this location will be served by its own station. Constraint (9) ensures that each location i may be served by exactly one bike station k. Constraint (10) expresses that a constructed station k can serve only locations which are located within a maximum walking time away from it.

Constraint (11) guarantees that at every time interval the bicycles that can leave the station can be no more than the available ones. Constraint (12) ensures that at every time interval the bikes that can come to a station can be no more than the free parking slots. Constraint (13) expresses that at every time interval the bikes that can leave a station can be no more than the demand for pick-ups of this station plus a percentage of the demand of all other locations this station serves. Constraint (14) expresses the same as the previous one, but for the demand for drop-offs.

Constraints (15) and (16) force the variables $UDBinF_{kt}$ and $UDBinE_{kt}$ to be 1 if a station k cannot serve some "Demand for Pick-Ups" or "Demand for Drop-Offs" respectively during time interval t and 0 otherwise.

Constraints (17) and (18) guarantee that if there is unsatisfied "Demand for Pick-Ups", all available bikes will leave the station and if there is no unsatisfied "Demand for Pick-Ups", the whole demand will be met.

Constraints (19) and (20) guarantee that if there is unsatisfied "Demand for Drop-Offs", all bikes will fill the available slots and if there is no unsatisfied "Demand for Drop-Offs", the whole demand will be met. These two constraints are relaxed if the "Demand for Drop-Offs" is more than the "Demand for Pick-Ups" until time interval p (i.e. $\overline{DD}_p = 1$), which is a deformation of the assumed demand (until time interval t the total number of users that want to drop off a bike at all stations cannot be more than the ones that have already picked up one). The bike sharing network is a closed network and with this parameter at these two constraints the model is not obliged to meet the whole "Demand for Drop-Offs" at the time intervals at which this deformation happens.

Finally the constraints (21), (22), (23), (24), and (25), (26), (27), (28) are the integrality and the non-negativity

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constraints, respectively.

At this point it is necessary to explain how the model decides the number of a station's parking slots (i.e. DN_k) and its bikes at first time interval (i.e. BN_{kt_0}). Giving a value at these two variables it determines the values of $UDBinF_{kt}$ and $UDBinE_{kt}$ (constraints (15) and (16)). The latter variables determine the values of the bikes that will leave or come to the station k at the first time interval (i.e. BF_{kt_0} and BE_{kt_0}, constraints (17) to (20)). The last ones determine the available bikes of the station k at the beginning of the next time interval t_1 (i.e. BN_{kt_1}, constraint (6)) and so goes on. Heading to minimize unmet demand the model proposes those values of DN_k and BN_{kt_0} at each station that will result into having the suitable number of available bikes and free parking slots in the following time intervals given the station's different distribution of demand during the day.

IV. Athens Case-Study

A. Data settings

Generally, it should be noticed that the goal of this research is to develop a globally applicable modeling approach for the design of the bike sharing network and not the estimation of demand.

However, so as to estimate the potential demand of a bike sharing network for the city of Athens, the three existing in the literature papers were analyzed and one of them was taken into consideration. Froehlich et al. (2009) [7] provide spatiotemporal analysis of the bicycle station usage in Barcelona's shared bicycling network, called *Bicing*. Lathia et al. (2012) [8] analyze the usage data of the London *Barclay Cycle Hire* network. Finally, Etienne et al. (2012) [9] propose a model to form clusters of the stations of the *Velib'* network of Paris based on their usage data.

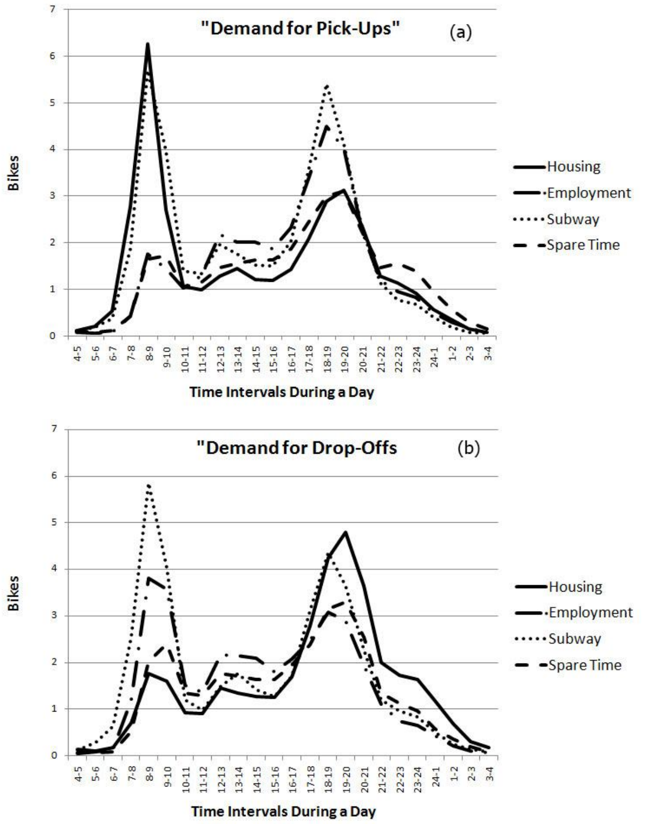

Fig. 2. a) The hourly "Demand for Pick-Ups" of each cluster during a weekday in Athens, b) The hourly "Demand for Drop-Offs" of each cluster during a weekday in Athens.

The last one was considered more helpful due to the ampler way it describes stations' dynamics. In converting the usage data of the *Velib'* network in whole Paris into potential demand of a future bike sharing network in the 1st Municipal District of Athens, the authors took into consideration several factors, such as population density, [10] and [11], stations' proximity to the city center and urban characteristics.

The candidate locations in the problem of Athens are categorized into four clusters depending on their location. Fig. 2 depicts the mean demand values of each one of the four clusters of stations during the weekdays in Athens.

Based on the urban design and the transportation network characteristics of the center of Athens, the authors of this paper chose 50 candidate locations where bike sharing stations could be established. These 50 locations were categorized into the previously described 4 clusters and each one was given a scaling factor of 0.25 (depicts a low-activity location) to 2 (depicts a high-activity location).

TABLE I
DATA

Parameter	Value
CB	500€
CS	12,000€
CTH	900€
BDG	1,000,000€
maxper	7 minutes
Zmin	8 parking slots
Zmax	70 parking slots
CDT	1€/customer/minute
CDEMAND	30€/ lost customer

The values of the rest of the input parameters for the case study of Athens are shown in Table I.

B. Results

The problem was formulated as a pure integer linear problem and was solved using CPLEX optimizer through a C++ code. The code was implemented on a laptop computer (Intel 2.67 GHz Core i5 and 4GB of RAM).

In this paragraph, the results of 2 solved cases of the problem will be presented. In the first one it is considered that the bike is a very popular means of transport among the Athenians ($\overline{perde} = 1$) and in the second one that it is not so popular ($\overline{perde} = 0.5$). Whether the first or the second scenario is actually the case is something to be decided by a social survey in the center of Athens, which is not in the scope of this paper. All other parameters are the same for both cases.

Fig. 3 and 4 depict the proposed established bike stations in case 1 and 2 respectively. The shape of each dot corresponds to the station's cluster, whereas its size represents the number of parking slots each station should have.

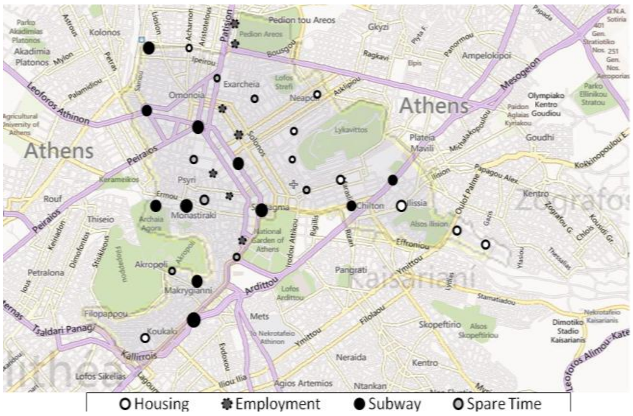

Fig. 3 The established stations of the solution of the 1st case categorized in clusters and with their size. (Reference: http://www.bing.com/maps/)

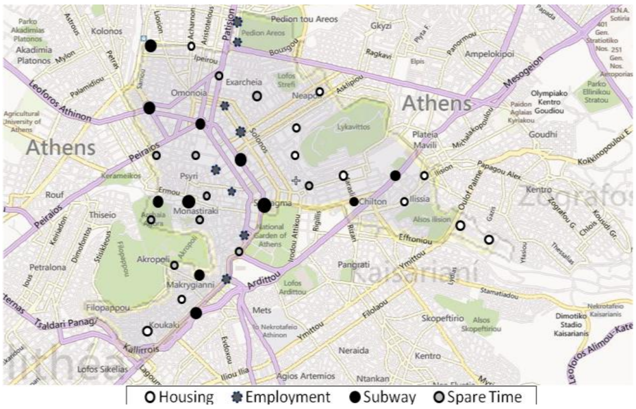

Fig. 4 The established stations of the solution of the 2st case categorized in clusters and with their size. (Reference: http://www.bing.com/maps/)

In the first case the total number of docking stations is 34 and the number of parking slots is 517 making a mean value of 517/34=15.2 slots per station. The total number of bikes in the network is 253 and their distribution over the established stations at the first time interval of the day shows that stations of the cluster "Housing" are nearly full of bikes in order to meet the increased "Demand for Pick-Ups" during the morning peak. On the other hand, the stations of the cluster "Employment" do not have many bikes. This results in having more free parking slots in order to meet the increased "Demand for Drop-Offs" during the morning peak.

In the second case the established stations are 40 with a total number of 461 parking slots. This makes a mean value of 461/40=11.525 slots per station. The purchased bikes are 210. The same notice as regards the bike distribution over the stations at the first time interval can be made in this case as well.

Comparing the results of the two cases, it should be mentioned that there is a difference between them in the number and the size of the established stations. In the first case the locations with no established station transfer their whole demand to the nearby station ($\overline{perde} = 1$). So the model proposes fewer but larger stations to meet the added demand by nearby locations. In the second case wherever the model does not established a station and serves the specific location from a nearby station, it "loses" 50% of its demand ($1 - \overline{perde} = 1 - 0.5 = 50\%$). For this reason, the second solution proposes more stations than the first one having less money to build enough parking slots and thus making them smaller.

V. Conclusion

It is crucial that the bike sharing networks are designed according to the demand they are to meet in the future. The knowledge gained from the already implemented networks can and should be used for the design of future ones. In this paper the authors modified the usage data from the *Velib'* network of Paris so as to predict demand in Athens and design a suitable bike sharing network to meet that demand.

However, the value of this paper lies rather on the mathematical formulation itself than on its implementation. The mathematical formulation allows the user to alter different parameters of the future bike sharing network (such as the demand patterns, $\overline{maxper}$, $\overline{perde}$, the budget etc.) and take a solution of how this network should be. In this paper a sensitivity analysis over one parameter ($\overline{perde}$) was provided to show the changes on the solution. The values of these parameters need to be drawn from a social survey of the under-study region and then inserted into the mathematical model to get an optimal design of a bike sharing network.

Moreover, different "runs" of the developed code can be made to get a solution, where the available budget is changed or the demand profiles approximate the seasonal differences (winter-summer) or the week differences (weekdays-weekend). The different solutions taken can then be combined in order to get a better network design. This combination might be a matter of a future work.

References

[1] P. DeMaio, "Bike sharing: History, Impacts, Models of Provision, and Future," *Journal of Public Transportation*, vol. 12, No 4, 2009, pp. 41-56.

[2] J. Shu, M. Chou, Q. Liu, C-P Teo and I-L Wang, "Bicycle-Sharing System: Deployment, Utilization and the Value of Re-distribution," *National University of Singapore*, 2010.

[3] J-R Lin and T-H. Yang, "Strategic design of public bicycle sharing systems with service level constraints," *Transportation Research Part E*, vol. 47, 2011, pp. 284-294.

[4] H. Sayarsad, S. Tavassoli and F. Zhao, "A multi periodic optimization formulation for bike planning and bike utilization," *Applied Mathematical Modelling*, vol.36, 2011, pp. 4944-4951.

[5] M. L. Martinez, L. Caetano, T. Eiro and F. Cruz, "An optimization algorithm to establish the location of stations of a mixed fleet biking system: an application to the city of Lisbon," *Procedia- Social and Behavioral Sciences*, vol. 54, 2012, pp. 513-524.

[6] C. J. Garcia-Palomares, J. Gutierrez and M. Latorre, "Optimizing the location of stations in bike sharing programs: A GIS approach," *Applied Geography*, vol. 35, 2012, pp. 235-246.

[7] J. Froehlich, J. Neumann and N. Oliver, "Sensing and Predicting the Pulse of the City through Shared Bicycling," *Proceedings of the 21st International Joint Conference on Artificial intelligence*, USA, 2009, pp. 1420–1426.

[8] N. Lathia, S. Ahmed and L. Capra, "Measuring the impact of opening the London shared bicycle scheme to casual users," *Transportation Research Part C*, vol. 22, 2011, pp. 88-102.

[9] C. Etienne and L. Oukhellou, "Model-based count series clustering for Bike sharing system usage mining, a case study with the Velib' system of Paris," *Transportation Research-Part C Emerging Technologies*, vol. 22, 2012, pp. 88.

[10] Institut National de la Statistique et des Études Économiques. Présentation de la région Ile-de-France. http://www.insee.fr/fr/regions/idf/default.asp?page=faitsetchiffres/presentation/presentation.htm. Accessed Nov. 1, 2013.

[11] Hellenic Statistical Authority (EL.STAT). Population. http://www.statistics.gr/portal/page/portal/ESYE/PAGE-themes?p_param=A1602. Accessed Nov. 1, 2013.

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