A METAHEURISTIC APPROACH FOR THE REPOSITIONING PROBLEM IN BIKE SHARING SYSTEMS (BSS): A STUDY CASE IN TOLUCA, MEXICO

UN ENFOQUE META-HEURÍSTICO PARA EL PROBLEMA DE REPOSICIONAMIENTO EN LOS SISTEMAS DE BICICLETA PÚBLICA (SBP): UNA CASO DE ESTUDIO EN TOLUCA, MÉXICO

Javier Garcia-Gutierrez
UAEMéx, School of Engineering, Graduate Department
jgarciag@uaemex.mx
Tel: 722 214 0855. Cerro de Coatepec s/n, Ciudad Universitaria, CP. 50100, Toluca, Estado de México. México

Manuel González de la Rosa
Toluca Institute of Technology, Industrial Engineering Department
gtg515i@hotmail.com
Tel. 722 208 7200. Av. Tecnológico s/n. Colonia Agrícola Bellavista, C.P. 52149, Metepec, Estado de México, México.

Javier Romero-Torres
UAEMéx, Nezahualcóyotl Professional Academic Unit, Engineering Transportation Department
jromero@uaemex.mx
Tel: 55 51126373. Av. Bordo de Xochiaca s/n, Col. Benito Juárez, CP. 57000, Nezahualcóyotl, Estado de México. México

Abstract
The impact of Bike Sharing Systems (BSS) in the world had experienced such success that nowadays most iconic cities in the world have adopted its own system. The particular characteristics of the user's mobility in every city have not allowed developing a generalized procedure to operate the systems. Moreover, the lack of symmetry in the mobility patterns, and the dynamic users' behavior lead to eventually "unbalance" the system, this is, to a lack of bikes at stations, and therefore bikes have to be repositioned to stations where effective demand is present, and there is no unified or scientifically supported methodology. In this paper we deal with a study case in Toluca city (Huizi system), in which the entity in charge of current operational activities wants to design a procedure scientifically based to perform repositioning daily activities at the minimum operational cost guarantying the availability of bikes for the users (service level). Due to operational requirements, this bi-objective problem was formulated using a dynamic scope and stated as a combinatorial optimization model and finally solved using a multi-objective evolutionary algorithm.

Keywords: Bikesharing systems; dynamic repositioning; stations balancing; multi-objective evolutionary algorithm (MOEA); NSGA-II.

Resumen

El impacto de los Sistemas de Bicicletas Públicas (SBP) en el mundo ha experimentado tal éxito que hoy en día, las ciudades más icónicas del mundo han adoptado su propio sistema. Las características particulares de la movilidad de los usuarios en cada ciudad no ha permitido desarrollar un procedimiento generalizado para operar los sistemas. Más aun, la falta de simetría en los patrones de movilidad, y el comportamiento dinámico de los usuarios llevan eventualmente a un desbalanceo de los sistemas, esto es, a una falta de bicicletas en las estaciones, y por lo tanto las bicicletas tienen que ser reposicionadas en estaciones donde la demanda efectiva está presente, y no hay una metodología unificada o científica. En este artículo, nos enfrentamos a un caso de estudio en la ciudad de Toluca (sistema Huizi), en el cual, la entidad a cargo de las actividades operacionales actuales desea diseñar un procedimiento científicamente basado para desempeñar las actividades diarias de reposicionamiento a un costo mínimo operacional garantizando la disponibilidad de bicicletas para el usuario (nivel de servicio). Debido a requerimientos operacionales, este problema bi-objetivo fue formulado utilizando un enfoque dinámico y declarado como un modelo de optimización combinatorio y finalmente resuelto utilizando un algoritmo evolutivo multi-objetivo.

Palabras clave: Sistemas de bicicletas públicas; reposicionamiento dinámico; balanceo de estaciones; algoritmo evolutivo multi-objetivo (AEMO); NSGA-II.

Introduction

A Bike Sharing System (BSS) is an urban transportation mode intended to help daily commuters in the completion of the last mile travels from home to work and back, or for short urban travels within a central business district, offering in this way a faster, cheaper, healthier and environmentally friendly option compared to motorized transportation modes. BSSs operate as follows: a registered user picks up a public bicycle at any station where they are available, using it for a predefined amount of time, depending on her/his rate plan, and turns it back to another (or even the same) station of the system. Nowadays, 4th generation of BSSs allows automation on bike check-in/out processes and information collection.

In early 2016, the number of worldwide implementations had almost reached a thousand systems (Metrobike LLC, 2016). Just in the last three years (from 2012 to 2015) they had almost doubled the number of systems and bikes, this is, from 549 to 948 systems, and from around 550,000 bikes to more than 1'250,000 bikes. These numbers endorses the importance of the BSSs in important and iconic cities of Europe, East Asia and North America (DeMaio, 2008), and it is being considered the transportation mode with the highest growth rate in the history (Shaheen, et al., 2012).

The success of a BSS implementation depends of the ability to optimally design the system in terms of the location, capacity and number of stations as well as the availability of the bike fleet according to the dynamic and unbalanced demand. Among the several problems that the scientific community has paid attention to, we can mention the following: demand forecasting, network design, system dimensioning, and user’s perceived level of service, among several others. Recently, these topics have been more easily met since more recent BSS technology (4th and 5th generation) can provide real time information that is indeed useful for planning and operation purposes.

The BSS repositioning problem have capture the attention in the last years due to the challenge that implies the resolution of a complex dynamic problem of operational nature that depends on endogenous and exogenous factors (Zhao et al., 2015). The importance of this problem resides in the increasing number of BSS implementations in the world and for the high marginal costs related to the repositioning activities.

The repositioning problem comes from the following circumstances: the BSS are mainly used for last mile travels or short travels in a specific moment of the day, leading to an unbalanced distribution of the bikes in the spatial and temporal dimensions and increasing the probability that a user who wants to check in the system might find a station without any bike, or on the other hand, not finding a free rack to affix the bicycle when checking out. In such cases the user might choice to walk to the next station or use another transportation mode to reach her/his destination. To avoid this, the BSS operator redistributes the bikes using (generally) motorized vehicles from full to empty stations trying to position bikes where demand are already taking place. Among the causes that lead to bike disequilibrium are the following (Vogel et al., 2011):

- Streets with slopes that discourage returns.
- Lack of bike infrastructure that allows accessibility to certain places.
- Edge effect on bike station on the limits of the system (since they generally have lower utilization).
- High or low spatial demand during the day (such as transshipments or activity points).
- High or low temporal demand during the day (such as rush hours).
- Excessive homogeneity on the type of use, or even marked preponderance of one over the other.

The bikes repositioning might represent the most delicate points on the BSS operation since it implies the significant operational costs, and since, it is mostly made using motorized vehicles (fossil fuels) sometimes the environmental pollution generated is comparable to the one it was intended to avoid with its implementation (Büttner et al., 2011). Finally, the lack of an efficient repositioning is translated into: reduction in the system capacity, conditioning the daily user and even to discourage her/him from using the system in the future. In this sense, from the managerial perspective, in order to reduce the current operational costs as well as to increment the system capacity, it is necessary to relocate the bikes at the stations efficiently. In the technical literature, repositioning schemes for shared vehicles are categorized as: user based and operator based (Allouche et al, 1999; Barth and Todd 2001; Kek et al., 2006; Vogel and Mattfeld, 2010). In the first, users are encouraged to return the bikes unsaturated stations to preserve the balance of bicycles between stations. In the second approach, repositioning is made by the operation entity staff. User-based repositioning might be feasible for medium-term operations whereas repositioning made by the operator is effective for short periods of time. Nevertheless, in any sense, such scopes might generally fit to the actual needs of every study case.

Mathematically, the repositioning problem for BSS had been originally managed in the literature as a derivation of the routing with pickup and delivery problem (PDP). More recently, it has been adopted the denomination of the Bike Sharing Pickup and Delivery problem (BSPDP) as a particularization of the original PDP (Caggiani and Ottomanelli, 2012). When relocation is carried out at night when the demand of bicycles is negligible it is denominated static repositioning, otherwise, when movements are made during the day due to high variations on the levels of demand it is called dynamic repositioning.

Most of the literature approaches deal with the BS-static PDP (Forma et al., 2010, 2015; Benchimol et al., 2011; Shu et al., 2010; Chemla et al., 2011; Contrado et al., 2012; Ho and Szeto, 2014). On the dynamic view, in general, the BS-PDP is worked without focusing on repositioning patterns and time periods (Vogel and Mattfeld, 2010). Some research suggest a fixed time interval repositioning (Nair and Miller-Hooks, 2011; Sayarshad et al, 2012), and some other suggest repositioning of vehicles moving randomly from saturated to empty stations (Fricker and Gast, 2012; Angeloudis et al., 2012). Among several work related to the dynamic repositioning problem we found Caggiani and Ottomanelli (2012), Contardo et al. (2012), Rainer-Harbach (2013), Raviv et al. (2013), Schuijbroek et al. (2013). One of the most recent papers about dynamic repositioning in BSS is the one presented by Regue and Recker (2014) in which a proactive approach is applied to model the forecast of bikes inventory at stations, and solve it by using an optimization model. The approach presented here resembles the idea of determining the probability of bike demand at every station for each period.

In Mexico, to date, there are three BSS located at Mexico City, Guadalajara y Toluca respectively (Ecobici, MiBici and Huizi). All of them are currently operated by different type of entities, and moreover, under different business models that might explain the difference in current operational issues. Nevertheless, in the three of them, the repositioning problem is a common problem even though their current technology allows gathering daily operational information. From personal interviews had with the operational entities of the three systems, for repositioning purposes, the methodologies implemented consists on basic rules coming from empirical experimentation and therefore there is no unified or scientifically supported methodology.

In this paper we deal with a study case in the city of Toluca (Huizi system) in Mexico, in which the entity in charge of current operational activities (the Directorate of Environment and Public Services of Toluca Municipality) wants to design a procedure scientifically based to perform repositioning daily activities at the minimum operational cost guarantying the availability of bikes for the users (service level).

This paper presents the design of a methodology to solve the BSS problem under a dynamic scope starting from a bi-objective combinatorial formulation and solved adopting a multi-objective evolutionary algorithm (MOEA) for fast-solving. Due to the characteristics of the operational processes involved in the daily repositioning activities, it is asked the problem to be quickly solved several times a day without any feedback of any decision maker, this is, decision maker preferences are not really a concern.

Methodology for BSS bike repositioning model

In this present work the problem is faced under the following conditions.

1. Demand information is known. This assumption would even be true for all 4th generation BSSs in Mexico since such data is available and it is disaggregated spatially and temporarily, so that it is possible to characterize it in terms of the hour, weekday, month and season of the year.
2. Information about the weather is also known. Since this is the main deterrent factor of the BSS, and we can meet such information with some hours in advance. Therefore, we can have an idea about the immediate user's behavior.
3. A dynamic repositioning approach is recommended since a high rate use of the bicycles is expected (each bike used by several users a day).
4. There is a given fleet size of 350 bikes. The number of bicycles at stations was initially assigned by the operator following an empirical rule. Nevertheless, as a result of the repositioning process, such number is expected to change at the end of the day.
5. It is desired to meet a certain user service level represented as the availability of bikes or racks at the stations at the moment they arrive to check-in or check-out a bike.

a) Demand information

Data information provided by the Directorate of Environment and Public Services of Toluca City allow us to characterize it spatially and temporarily. In Figures 1 (a, b, c, d) and 2 there is shown some descriptive charts about the trips already happening at this system.

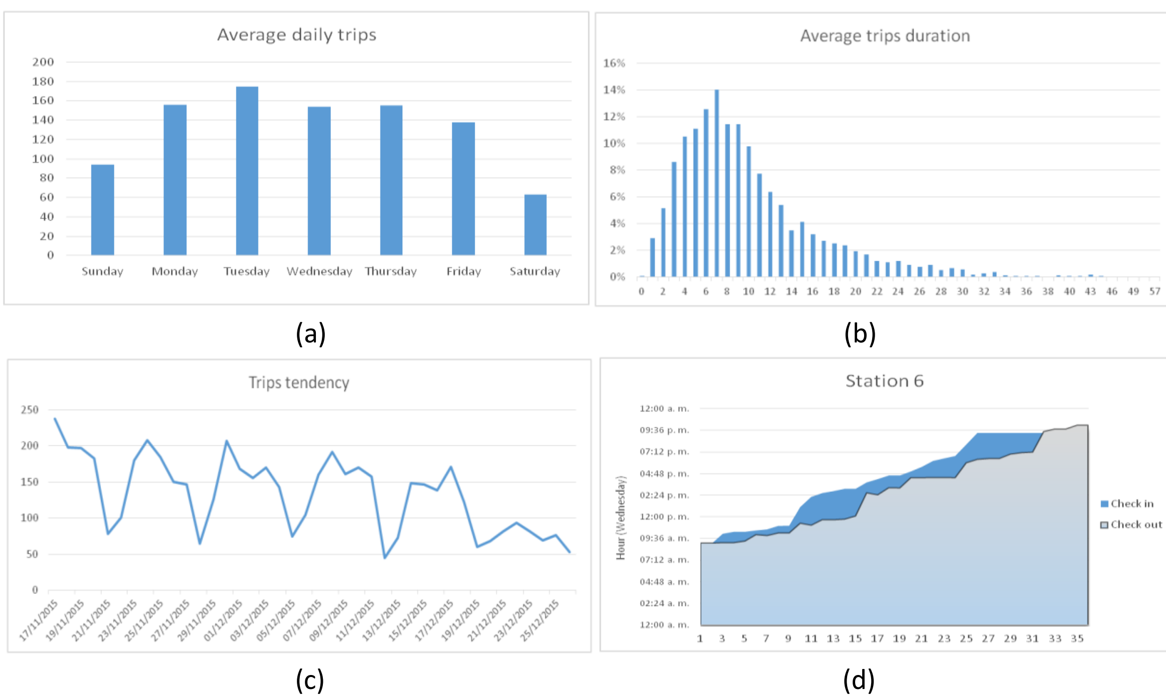

Figure. 1 – (a) Average daily trips, (b) trips duration at the Huizi system, (c) negative tendency in the last two months of the year, (d) check in/check out at Station 6.

Part of the bike repositioning is generated by the same BSS dynamics. Actually, the operator encourages people to turn the bike at the end of the day where it was originally borrowed. Nevertheless, the problem is not so simple. In order to have a good penetration in the society, several metrics or empirical rules have been developed by operators as indicators. One of them is related to the number of people that use one particular bicycle (daily uses per bicycle). The Institute for Transportation & Development Policy (ITDP, 2013) states that a successful BSS has rotation index in the range of 4 to 8, to avoid low cost benefit radio, and to assure bike availability.

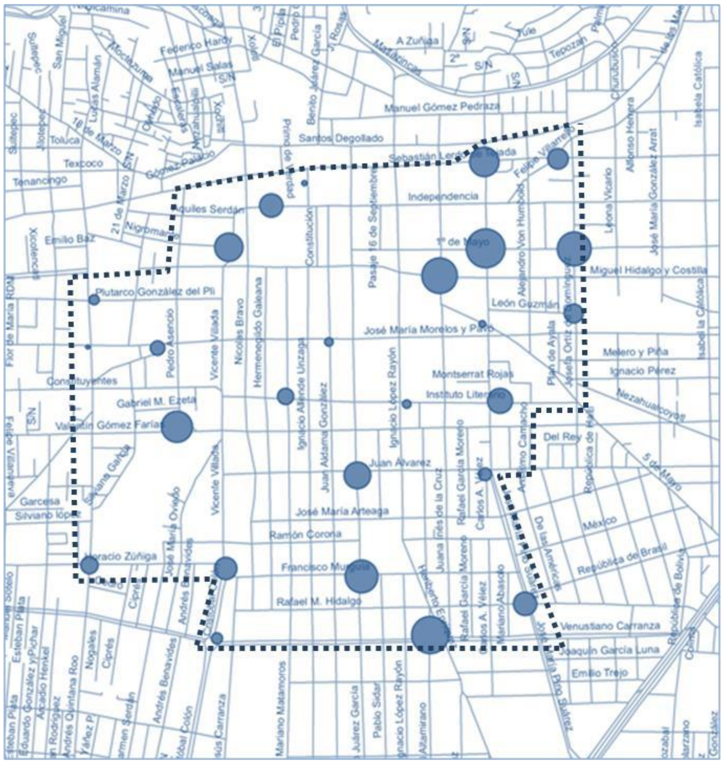

Figure. 2 – Activity at stations inside the Huizi Polygon

b) Weather information

The two main factors identified in the literature that reduce considerably the use of the bicycle as a usual transportation mode are those than restrain people to perform outdoor activities, such as heat, rain and snow. Unlike cities in the United States of America, Toluca city's weather allows the operation of the Huizi system in all stations of the year, since snowing is very unlikely to occur at any time of the year. On the other hand, heat in summer does not inhibit bike trips. The average daily temperature in Toluca city varies from 0°C to 24°C, and hardly ever is below -3° or above 27°C. The coldest month is January, in which the average low is 0°C, and high of 19°C. Historically, the hottest day of the year is April 30 with an average high of 24°C and low of 7°C.

Nevertheless, precipitation in this city occurs in most part of the year. Rain is likely to occur in at least five months of the year with more than 50% of probability. This typically happens in the months from May to September. The most common forms of precipitation, when occurs, are thunderstorms (52%), moderate rain (23%) and light rain (22%). Nevertheless, the intensity of the precipitation is typically to occur during afternoons. In Figure 3 it is shown the types of precipitation and occurrence probabilities. The order of severity is from the top down in this graph, with the most severe at the bottom. The data here presented is summarized from information about meteorological stations at Toluca city, which is available at the National Weather System (Sistema Meteorológico Nacional) in Mexico (SMN, 2015).

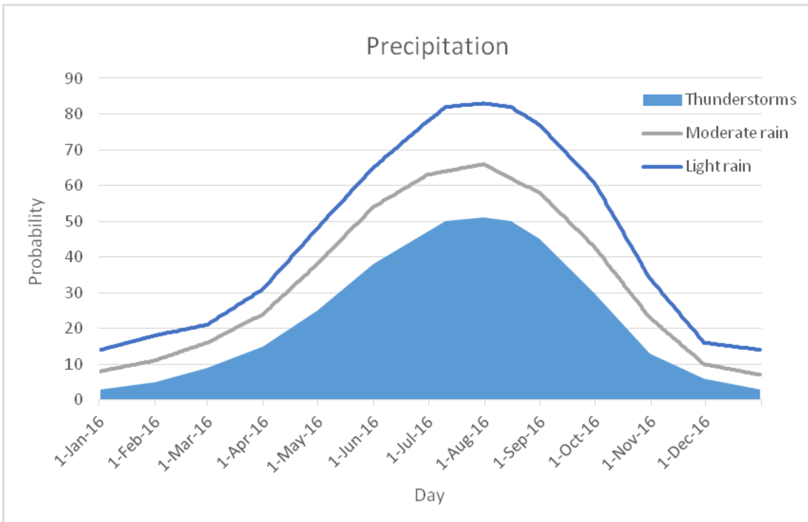

Figure. 3 – Chart of precipitation probability in Toluca city.

c) Methodology proposed

The methodology here presented relies in historical information from cyclist demand and weather. Moreover, there is one aspect, related to the time discretization, this is, the length of the periods of analysis. This number is not fixed for all the day, but is determined in terms of the need of repositioning. For instance, the time between two consecutives repositioning activities in a workday at noon is expected to be small, against repositioning activities in the afternoon on Sundays, which are expected to be large. In this work, we have not gone into deep in the experimentation on t, but this length has been explored in terms of the proximity of empirical repositioning activities.

The methodology follows the next steps:

1. Statistical analysis of the cyclist demand. We start from the historical data, in which daily, monthly and stations factors are computed to obtain an initial “required” number of bicycles to start a particular operations day for every station. This calculation is made in advance so that at the end of the previous day work is done so that the initial stage at the next one starts with this number at every station. In addition, this initial number is consistent with the number of bicycles available at the Huizi system. The time at this stage is set as t0.
2. Initial daily stage. Calculations of inventory level required at each station (expected need) are made in the following way. The number of bicycles in a given station is affected by the

expected number of receiving or taking away bicycles at the following period. This expected number is calculated by using the probability of having a specified number at the period t, and it is obtained by means of the historical dynamic behavior during the day at that particular station.

3. Weather information. Lately information about weather is real time data (RTD) since it is available online at several web pages. With this data, the forecasted demand at each station, at any given period, number, however, has to be affected by a weather factor, which is indeed a deterrent factor about the number of bikes that will be effectively used.

4. Inventory level determination at the bike stations under probabilistic approach. Given the amount of bikes needed at the station in a continuous scenario (all the operations hours), and the amount of trips generated among the different pairs of origin-destination stations, also as a probability that such trips could occur, it is generated an expected minimum amount of bikes.

5. Multiobjective Evolutionary Algorithm (MOEA) to solve the bi-objective BSS problem. A bi-objective routing problem is formulated where cost and users perceived service level, both are simultaneously optimized. The resolution of this problem leads to a set of Pareto solutions from which just one solution is systematically picked, which represent a compromise solution.

6. Rectification of data from the previous period. At this stage a comparison is made between the demand predicted and the actual demand experience in the previous period.

The methodology proposed for this problem is the following shown in Figure 4.

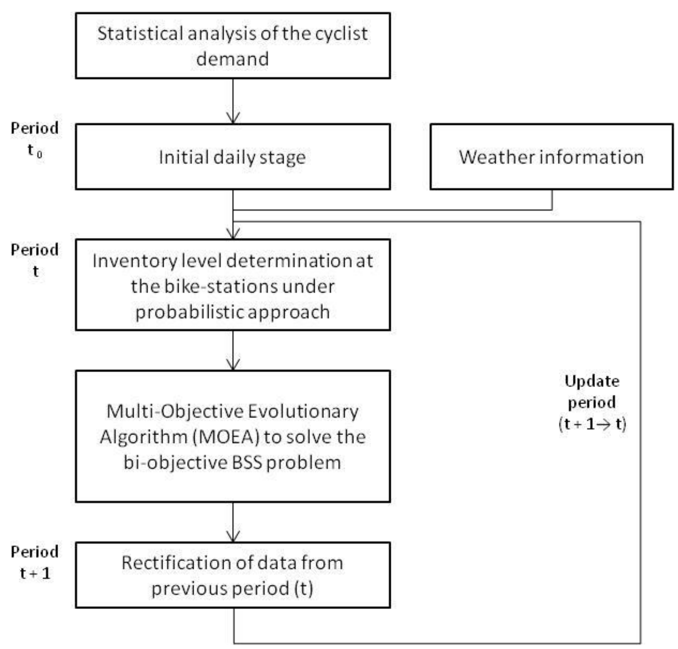

Fig. 4 – BSS repositioning methodology developed.

Bi-objective optimization model

Several researches have included service level as a measure of effectiveness in the system. For this case, users' service level is a determinant factor to assure the consolidation of the BSS, given that lack of bicycles as they are needed, highly inhibits the probability that the user at the next day could consider the use of public bicycle as a transportation mode.

Multi-Objective Evolutionary Algorithm (MOEA)

In multi-objective optimization is intended to find, for a multi-objective problem formulation either discrete or continuous, a number of representative Pareto solutions which is expected to resemble the true Pareto front. Multi-Objective Evolutionary Algorithms (MOEAs) have recently attracted scientific attention in the exploration of the Pareto fronts. Several reviews exist about different MOEA methodologies, search strategies, metrics of comparison, and real world problems such as Coello et al. (2007).

The multi-objective strategy presented in this work is based in the NSGA-II. This method (Non-dominated Sorting Genetic Algorithm II, NSGA-II) is a widely known algorithm that has been used for uncountable applications in the literature. It was developed by Deb et al. (2002), and it has been considered one of the most successful Multi-Objective Evolutionary Algorithms in the scientific literature. Several references exists in which NSGA-II logic is explain in detail.

For the resolution of routing problems NSGA-II has also been used with success. For instance, in Xu et al. (2008) an NSGA-II algorithm implementation combined with an Or-opt strategy was used for solving a multi-objective vehicle routing problem with time windows. Also, an implementation was developed for solving a green vehicle routing problem (Jemai et al., 2012) in the context of Green Logistics. Chand and Mohanty (2013) used a variation of the NSGA-II to solve routing problems and compared it with other multi-objective evolutionary algorithms. In another work, Beheshti et al. (2015) solve a vehicle routing problem with prioritized time windows with a co-evolutionary technique, and using NSGA-II as a benchmarking procedure. The NSGA-II follows the logic presented in Figure 5.

The goal of a Multi-Objective Evolutionary Algorithm is to obtain a set of solutions that resembles the true Pareto front. Nevertheless, the operational procedures at the BSS imply that repositioning processes are made systematically several times a day and apparently without a “decision maker” intervention. In multi-objective optimization, several approaches exist to end up with a single solution.

In this work the very next step is to systematically identify a solution with certain characteristics: computationally fast to identify and robust properties. In this sense, theory of knee solutions is taking into account at this step. Knees solutions are considered promising parts in the Pareto front in which optimal trade-off solutions might be identified. They were first studied and defined by Das (1999), and later, those ideas were extended to EMOAs by Branke et al. (2004). Moreover, decision maker preference has also been included in NSGA-II to overcome this issue, such the one presented by Chaudhuri and Deb (2010). A recent survey about incorporating preferences at is presented in Bechikh et al. (2015).

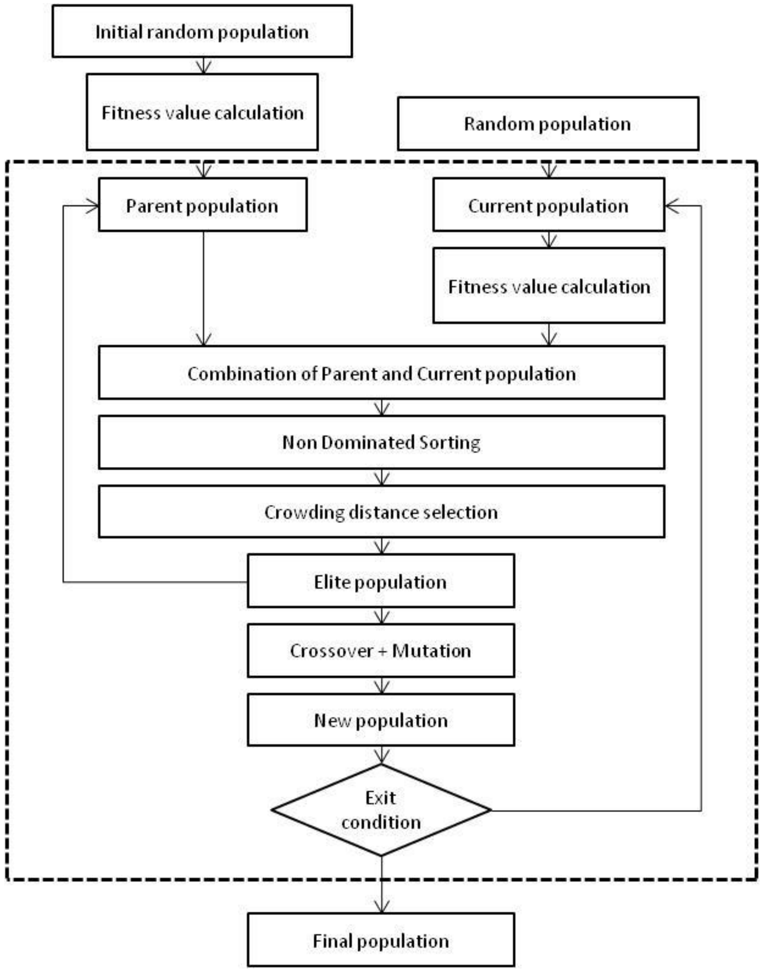

Figure. 5 – NSGA –II strategy for the BBS repositioning problem.

Recent studies support the use of knee points for solving bi-objective problems (Deb and Gupta, 2010). Given that this is a combinatorial problem where the Pareto front is finite, the individual minimal for the two objectives is know, this procedure consists in calculating such distance and identify the largest one. In Figure 6 it is represented the choice of the knee point in terms of the maximal distance from the Convex Hull of Individual Minima (CHIM) to the Pareto front.

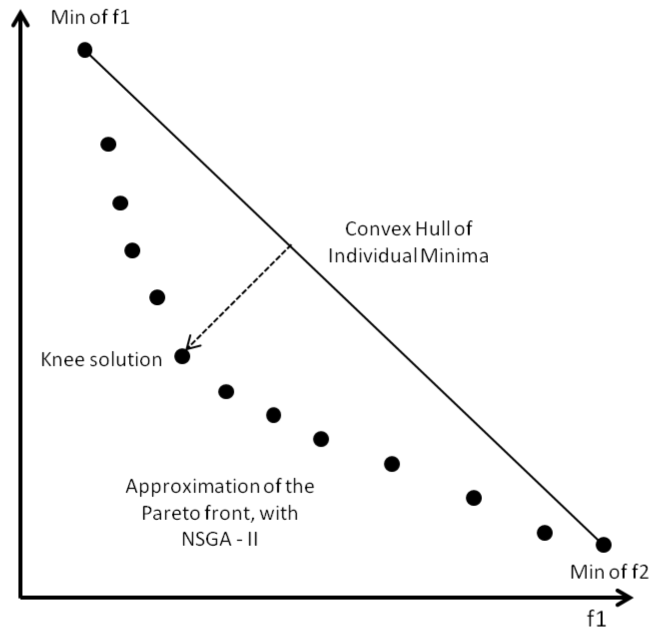

Figure. 6 – Knee point as the largest distance from the CHIM to the Pareto front.

Experimentation and results

The NSGA –II formulation for the BSS repositioning problem was coded in MATLAB. The inputs, as depicted in Figure 1 are the database of the Huizi system and the weather information generated continuously. The code is able to receive information for generating the next scenario. At this moment, the results obtained in computer are solved in negligible time, maybe due to the relatively small size of the routes generated compared when solving large distribution problems.

Conclusions and recommendations

In this work, we solved a problem that, due to the dynamic nature of the demand it has been difficult to model mathematically and to find an efficient way to provide the BSS operator a redistribution schedule that might be updated through the day based on the actual needs and capacities of the operator. First, we solved a dynamic redistribution problem having knowledge on demand behavior, using inventory strategies at stations, and finally constructing a sequence of routing solutions using two objectives, and solving them economically in terms of computational time by means of an evolutionary approach. Since exact algorithms to solve the stated combinatorial problem to optimality are highly expensive in terms of computational cost, it was justified the use of the meta-heuristic approach. Moreover, given the two objectives involved in the problem conception, the use of a Multi-objective Evolutionary Algorithm was a reasonable option since in recent years these techniques have been positioned themselves for their capabilities to quickly converge to good solutions. Also, we took advantages of "well behaved" Pareto solutions to systematically solve the sequence of problems without the inclusion of high level information from any decision maker or the BSS technical staff. We also developed a methodology to systematize the identification of such solutions. Regarding to the BSS network, the methodology here presented allowed identified deficiencies in the initial dimensioning mainly related to overestimation of the number of bikes on stations and underestimations of the number of racks actually needed.

On the other hand, the paradigm of facing the redistribution problem from a static approach is left aside. This idea would be unreal for many mid-size systems where the daily bike rotation is above from their recommendable use, at least, the operators of the BSS in Mexico clearly do not agree in adopting static redistribution strategies.

There are some recommendations addressed to the scientific community: even though there is a vast amount of multi-objective techniques, there is still a gap between the developed algorithms with are intended to provide a well-distributed set of Pareto solutions and the resolution of the problem itself. The development of algorithms that would include mechanisms to direct the search towards "well behaved" solutions without involving the generation of all the Pareto frontier would help in cases like the one here presented.

Due to the contributions derived from this research, and the acceptance level of the agency in charge of the Huizi system operation, we are currently working on an implementation that systematizes the resolution of the problem, and on the development of a Smartphone interface (Android) that might allow the operational staff to remotely receive information of the redistribution procedures in real time.

The problem related to the length of the parameter t is already being faced running several scenarios in order to characterize or at least, to find an empirical rule that allows us to run several daily scenarios with good performance.

References

Allouche, J. F., Benéjam, E., Massot, M. H., Parent, M. Praxitèle: Preliminary results from the Saint-Quentin experiment. In Proceedings of the 78th Annual Meeting of the Transportation Research Board, 1999.

Angeloudis, P., Hu, J., Bell, M.G.H. Strategic repositioning algorithm for bicycle-sharing schemes. In Proceedings of The 91th Meeting of the Transportation Research Board 2012, paper 12-3210. 2012.

Barth, M., Todd, M. User behavior evaluation of an intelligent shared electric vehicle system. Transportation Research Record: Journal of the Transportation Research Board 1760, 2001: 145-152.

Bechikh, S., Kessentini, M.; Said, L.B., Ghédira, K. Chapter Four - Preference incorporation in Evolutionary Multiobjective Optimization: A survey of the state-of-the-art, In: Ali R. Hurson, Editor(s), Advances in Computers 98, 2015: 141-207.

Beheshti, A.K., Hejazi, S.R., Alinaghian, M. The vehicle routing problem with multiple prioritized time windows: A case study. Computers & Industrial Engineering 90, 2015: 402-413

Benchimol, M., Benchimol, P., Chappert, B., de la Taille, A., Laroche, F., Meunier, F., Robinet, L. Balancing the stations of a self service “bike hire” system. RAIRO-Operations Research 45, 2011: 1-15.

Branke, J., Deb, K., Dierolf, H., Osswald, M. Finding knees in multi-objective optimization. In PARALLEL PROBLEM SOLVING FROM NATURE (PPSN-VIII) 2004, 2004: 722–731. Germany.

Büttner, J., Mlasowsky, H., Birkholz, T., Groper, D., Fernandez, A.C., Emberger, G., Banfi, M. Optimising bike sharing in European cities: A handbook, Intelligent Energy Europe program (IEE). Retrieved from http://obisproject.com. Accessed on October. 30, 2015.

Caggiani, L., Ottomanelli, M. A modular soft computing based method for vehicles repositioning in bike-sharing systems. Procedia Social and Behavioral Sciences 54, 2012: 675-684.

Caggiani, L., Ottomanelli, M. A dynamic simulation based model for optimal fleet repositioning in bike-sharing systems. Procedia Social and Behavioral Sciences 87, 2013: 203–210.

Chaudhuri, S., Deb, K. (2010). An interactive evolutionary multi-objective optimization and decision making procedure. Applied Soft Computing 10, 2010: 496-511.

Chemla, D., Meunier, F., Wolfler-Calvo, R. Balancing a bike-sharing system with multiple vehicles. In 12e congrès annuel de la ROADEF, Marzo 2011.

Coello, C., Lamont, G.B., van Veldhuizen, D.A. Evolutionary algorithms for solving multi-objective problems. Springer, 2007.

Contrado, C., Morenci, C., Rousseau, L. M. Balancing a dynamic public bike-sharing system. Retrieved from https://www.cirrelt.ca/DocumentsTravail/
CIRRELT-2012-09.pdf. 2012, Accessed on March 20, 2014.

Das, I. On characterizing the “knee” of the Pareto curve based on normal-boundary intersection. Structural Optimization 18, 1999: 107–115.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T. A fast elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation 6, 2002: 182-197.

Deb, K., Gupta, S. Understading knee points in bicriteria problems and their implications as preferred solutions principles. KanGAL Report Number 20100005. 2010.

Demaio, P. The bike-sharing phenomenon. The history of bike-sharing. In Carbusters Magazine 36. November, 2008.

Forma, I.A., Raviv, T., Tzur, M. The static repositioning problem in a bike-sharing system. In Proceedings of the 7th Triennial Symposium on Transportation Analysis (TRISTAN), 2010: 279-282.

Forma, I.A., Raviv, T., Tzur, M. A 3-step math heuristic for the static repositioning problem in bike-sharing systems. Transportation Research Part B 71, 2015: 230-247.

Fricker, C., Gast, N. Incentives and regulations in bike-sharing systems with stations of finite capacity. 2012, Retrieved from http://arxiv.org/pdf/1201.1178v1.pdf. Accessed on February 18, 2013.

Ho, S.C., Szeto, W.Y. Solving a static repositioning problem in bike-sharing systems using iterated tabu search. Transportation Research Part E 69, 2014: 180-198.

ITDP. The bike-share planning guide. Institute for Transportation & Development Policy (ITDP). 2013.

Jemai, J., Zekri, M., Mellouli K. An NSGA-II algorithm for the green vehicle routing problem. In Evolutionary Computation in Combinatorial Optimization, Lecture Notes in Computer Science 7245, Springer, 2012: 37-48.

Kek, A.G.H., Cheu, R.L., Chor M.L. Relocation simulation model for multiple-station shared-use vehicle systems. Transportation Research Record: Journal of the Transportation Research Board 1986, 2006: 81-88.

Metrobike LLC. The Bike-sharing World Map. 2016, Retrieved from http://www.metrobike.com. Accessed on January 10, 2016.

Nair, R., Miller-Hooks, E. Fleet management for vehicle sharing operations. Transportation Science 45, 2011: 524–540.

Rainer-Harbach, M., Papazek, P., Hu, B., Raidl, G.R. Balancing bicycle sharing systems: a variable neighborhood search approach. In Evolutionary Computation in Combinatorial Optimization, Lecture Notes in Computer Science. Springer, 2013: 121–132.

Raviv, T., Tzur, M., Forma, I.A. (2013). Static repositioning in a bike-sharing system: models and solution approaches. European Journal of Transportation Logistics 2, 2013: 187–229.

Regué, R. & Recker, W. Using gradient boosting machines to predict bikesharing station states. In the Transportation Research Board 93rd Annual Meeting 2014.

Sayarshad, H., Tavassoli, S., Zhao, F. A multi-periodic optimization formulation for bike planning and bike utilization. Applied Mathematical Modelling 36, 2012: 4944–4951.

Schuijbroek, J., Hampshire, R, Van Hoeve, W.-J. Inventory rebalancing and vehicle routing in bike sharing systems. Tepper School of Business. 2013.

Shaheen, S.A., Martin, E.W., Cohen, A.P., Finson, R.S. Public Bikesharing in North America: early operator and user understanding. Report 11-26. Mineta Transportation Institute. San José State University, 2012.

Shu, J., Chou, M., Liu, Q., Teo, C. P., Wang, IL. Bicycle-sharing system: deployment, utilization and the value of re-distribution, 2010, Retrieved from http://www.bschool.nus.edu.sg/Staff/bizteocp/BS2010.pdf. Accessed on May 15, 2014.

SMN. Data from the Mexican National Weather System (Sistema Meteorológico Nacional). Mexican National Water Commission, (Comisión Nacional del Agua, CONAGUA). Retrieved from http://smn.cna.gob.mx/. Accessed on October 25, 2015

Vogel, P., Greiser, T. & Mettfeld, D.C. Understanding bike-sharing systems using data mining: exploring activity patterns. Procedia Social and Behavioral Sciences 20, 2011: 514–523.

Vogel, P. & Mattfeld, D.C. Modeling of repositioning activities in bike-sharing systems. In Proceedings of 12th WCTR, July 11-15, 2010, Lisbon, Portugal.

Xu, H., Fan, W., Wei, T., Yu, L. An Or-opt NSGA-II algorithm for multi-objective Vehicle Routing Problem with Time Windows. In Automation Science and Engineering, 2008. CASE 2008. IEEE International Conference on, August 23-26, 2008, 2008: 309-314.

Zhao, J., Wang, J., Deng, W. Exploring bikesharing travel time and trip chain by gender and day of the week. Transportation Research Part C: Emerging Technologies 58(B), 2015: 251-264.

Javier Garcia-Gutierrez has a PhD in Industrial Engineering by the ITESM Toluca Campus. Professor at the Master in Supply Chain Engineering program at the Mexico State Autonomous University. Currently working on issues about supply chain, freight transportation and sustainable transportation.

Manuel González de la Rosa has a PhD in Industrial Engineering by the ITESM Toluca Campus. Professor of the Industrial Engineering Department at the Toluca Institute of Technology. Currently working on issues about discrete simulation and supply chain.

Javier Romero-Torres is PhD Candidate in Transportation Engineering by the Mexico State Autonomous University. Professor at the Transportation Engineering department at the Nezahualcóyotl Professional Academic Unit. Currently working on issues about public transportation, quality of service measuring, traffic engineering and discrete choice models applied to transportation engineering.