VARIABLE POPULATION MOPSO APPLIED TO MEDICAL VISITS

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Multi-objective optimization techniques are the ideal support tools for the decision-making process. They provide a set of optimal solutions for each of the significant aspects of the problem, thus summarizing the alternatives to be considered. Having a limited number of alternatives makes it easier for decision makers to perform their tasks, since they can focus their efforts towards the analysis of the available options.
In this paper, the main characteristics of multi-objective optimization are summarized, and a real experience is described regarding the optimization of mobile units assignment at a health care company in Argentina using a new method based on swarm intelligence called varMOPSO.

Keywords: *evolutionary computation, swarm intelligence, particle swarm optimization, multi-objective function optimization*

JEL Classification**:** *C61, C65*

1. INTRODUCTION

When facing an optimization problem, the criteria to optimize (fitness functions) must be defined. If there is only one criterion to optimize, the process is called mono-objective optimization. An example of mono-objective optimization would be buying a car based exclusively on its price. In this example, the optimal solution is the cheapest vehicle.

Mono-objective problems are widely studied in the literature, and most search- and optimization-related scientific research works are developed based on problems with a single fitness function.

In general, real-world problems require the simultaneous optimization of several criteria. Following the previous example, the buyer might want to minimize car price and maximize available equipment. It can be clearly seen that these two objectives are opposite – the lower the price, the less equipment and vice-

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versa. In this case, the challenge of the optimization problem is finding the set of solutions that optimize both criteria at once – those cars with the best levels of equipment given the various prices, or, in other words, those vehicles that, for each level of equipment, are the cheapest.

Optimization problems are present in every area. This is particularly so in economics, which is based on the optimal utilization of limited resources for multiple and unlimited uses; optimization is one of the central tools for this science, as well as one of the simplest tasks of nature. Finance does not stray from this concept, which is the most important one in this area – the optimization of money through the use of this resource in various investment instruments in order to maximize utilities.

Understanding the importance of optimization techniques, this article describes a new optimization method that has been applied to the optimization of a real-world problem. The purpose of this paper is showing the various aspects to be considered when implementing this type of techniques by using a specific case as an example.

2. PROBLEM TO SOLVE

The real-world case to solve is the automated assignment of mobile units to medical services in an emergency health care provider in Argentina.

The main purpose of this type of companies is to provide pre-hospital health care services of various complexity levels: medical emergencies, urgencies, home medical visits, and scheduled transfer of patients to health care centers.

These companies provide medical services for the timely and efficient health care of patients who are ill or have sustained some type of wound and/or injury. They are the second link in the emergency chain, the first one being the family or person accompanying the patient when the need for medical care arises, and the third one being the hospital or health care center and its facilities.

Each incident that is reported to this type of companies is classified based on its severity and some of the following categories:

- Red: Imminent risk of death.
- Yellow: Serious emergency, no risk of death
- Green: Home medical visit, low severity event.
- Blue: Scheduled transfer.

As it can be seen, this is a highly sensitive activity, since the time elapsed until the resolution of an urgent service can be the difference between life and death in the case of services categorized as red or yellow. For services classified within the green category, arrival time is important but in no case relevant for the long-term health of the patient. Therefore, it is important to differentiate the various types of events as a first step – red and yellow services, representing medical emergencies, and green services, related to home medical visits.

In the case of medical emergencies, the vehicle dispatching process can be summarized as follows: sending the suitable mobile that is available at the nearest location of the emergency. Thus, for this type of problems, the main challenge is achieving a suitable coverage level (simple or double) *prior* to the occurrence of the incident to ensure that any emergency within the service area is solved within the maximum times set. This type of problem is known as Ambulance Location Problem [1][2][3], and there is extensive literature dealing with the definition of the problem and its possible solutions [4][5][6].

In the case of non-urgent services (green), the problem is of a different nature – the previous location of the mobiles is not as relevant as the existence of an optimized dispatch process that is economically sustainable for the service provider and at the same time minimizes the time elapsed since receiving the request until medical care arrives. This problem can be considered as a variation of the classic Vehicle Routing Problem (VRP), and is one of the most significant combination optimization problems introduced by Dantzig and Ramser more than five decades ago [5]. This problem belongs to the set of NP-Hard problems [7][8].

In recent years, various metaheuristics have been used to tackle this type of problems [6][9][10][11], the results obtained being gradually improved, but focusing on mono-objective problems.

In this paper, the use of multi-objective metaheuristics to solve the problem of an optimum dispatch for non-urgent services, simultaneously minimizing arrival times and costs, is analyzed.

3. PROPOSED ALGORITHM (VARMOPSO)

This paper proposed optimizing the problem presented above by using a technique that is based on swarm intelligence.

Swarm intelligence is based on adapting a set of initially random solutions to the problem to be solved through operations that combine the ability that each of these solutions has to solve the problem on its own with the skills learnt by the set as a whole.

In particular, PSO (particle swarm optimization) has been used due to its good performance. This metaheuristics was originally proposed by Kennedy and Eberhart [12], and there are currently more than 30 variations that allow applying it to multi-objective problems. Among these MOPSO-like algorithm versions, SMPSO and OMOPSO are amongst the most remarkable, and are the ones with the best performance indicators [13].

In this paper, a MOPSO-type algorithm is used, called varMOPSO, that incorporates the concept of variable population. This algorithm was presented in [14], and it shows a very good performance when compared with other PSO-type proposals and state-of-the-art algorithms in multi-objective optimization.

The algorithm uses an external file to log all non-dominated solutions found. To calculate particle velocity, the velocity constriction equation proposed in [15], based on the constriction factor developed in [16], is used.

Population variation between generations is the result of adding the concept of age to the particles and using an insertion/removal procedure based on the ability of each individual to solve the problem posed. The algorithm uses the concept of elitism, and only dominated solutions are removed from the main population. These procedures are based on the mono-objective version of PSO presented in [17].

4. FUNCTIONS TO OPTIMIZE

The initial requirements of the company include the optimization of two opposing objectives – reducing arrival time and minimizing the use of third-party medical teams (costs).

Each of these objectives will have an associated mathematical equation, and the optimization algorithm will try to minimize both simultaneously.

Those individuals with lower values in each fitness function will be better than those with higher values.

Given the context for this project, multi-objective metaheuristics were defined that allowed simultaneously optimizing both aspects of the problem.

It is an important part of the solution that the decision maker can view, once the problem has been optimized, the set of optimal solutions obtained to decide which is the most appropriate solution. Similarly, the system should be able to propose one of the solutions from the Pareto front obtained, based on predefined settings.

Viewing the Pareto front allows the decision maker to better understand the problem, and the surface of the Pareto front reveals the interaction between opposing objectives [18].

It can be clearly seen that service quality improvement and the optimization of operational costs for the company are sought simultaneously (Figure 1).

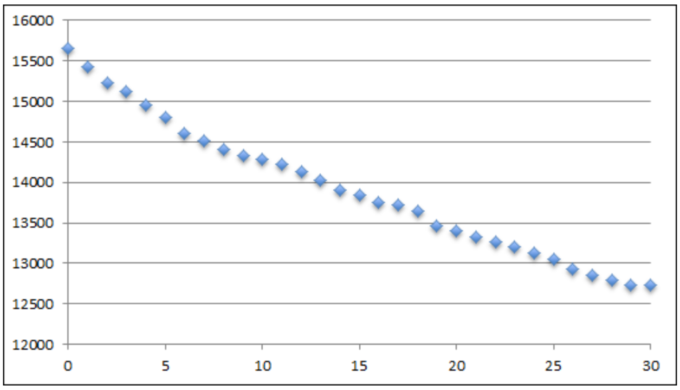

Figure 1. View of the Pareto front by the decision maker

5. MODELING THE PROBLEM

The optimization problem can be described by identifying its two main components – health care services (patients requiring health care) and medical mobile units (medical teams and vehicles).

In this section, the main attributes of both components are described in order to clarify the modeling of the problem.

The central attributes of a health care service are:

Code (P1)	**Service identification**
Call time (P2)	Time, in seconds, from the time the medical problem was reported to the call reception desk
Location (P3)	Coordinates (longitude and latitude) corresponding to the geographical location where the service is to be provided
Response time (P4)	Average response time estimated to reach the Location based on the category of the service

Medical mobile units are the currently high, medium, and low complexity units available to provide the required medical services. They are characterized by the following main attributes:

Code (M1)	**Mobile identification**
From Time (M2)	Time, in seconds, from which the mobile will be available to provide services. It corresponds to the on-call start time for that medical team.
To Time (M3)	Time, in seconds, from which the mobile will stop being available to provide services. It corresponds to the on-call end time for that medical team.
Location (M4)	Coordinates (longitude and latitude) indicating the location of the vehicle. This location can be calculated with various precision levels.
Average speed (M5)	Estimated average speed of the vehicle. It corresponds to the linear speed between locations with different coordinates.
Vehicle Owner (M6)	Attribute that indicates if the mobile unit belongs to the company or if it is a service provided by a vendor (third-party)

The problem to be solved in our case is deciding which medical mobile unit will be used to provide each of the services, taking into account the service time available for each medical team (mobile unit), minimizing response times, and reducing the use of third-party medical teams.

6. REPRESENTATION

Each problem has its mathematical representation. This representation can be a graphic of all function values (function to optimize) that are within the search domain. The "landscape" created by this graphic representation shows the degree of complexity of the function to optimize. The optima to be found correspond to the maximum or minimum points of the function (Figure 2)

The first question to solve is related to the representation to use for modeling the real-world problem. This representation should consider the characteristics of the problem that is being represented, and it directly affects the performance of the optimization algorithm. One problem can be easier or harder to solve depending on the representation chosen [7].

The algorithm proposed is conceived, in its original version, to work in continuous search spaces. Therefore, for this paper it was decided to use a continuous representation (search space) of the problem space. This decision allows, within the scope of this project, assessing a larger number of available metaheuristics and selecting those with better assessed performance.

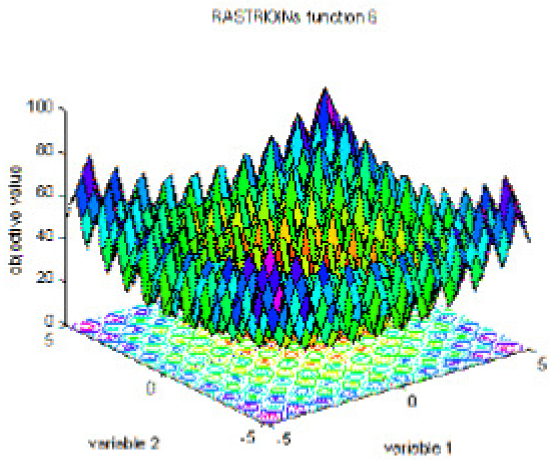

Figure 2. Example of function to optimize with two decision variables

The use of other representations, which usually involve the development of specific operators, would not have allowed developing the project within the specified scope, both regarding the variable of time as well as the variable of costs.

For this project, the following representation is proposed, which allows producing a mathematical representation of the problem at hand and defining the domain for the continuous, real-variable fitness functions.

Each individual is represented by a vector of real numbers. The dimension of the vector corresponds to the number of services to provide. Therefore, the size of the vector varies with the instance of the problem to solve.

The domain of the values for all dimensions is the same and is related to the number of available medical mobile units.

Formally, be m the number of services and n the number of medical mobile units, each individual I is equal to an m-dimensional vector of real numbers. The domain of the values for each dimension can vary from 0.5 to n+0.4999.
For instance, an individual might have the following values:

$$A = (2.3546, 0.6589, 1.2357, 1.7542)$$

The entire population is formes by P individuals with these characteristics, P being an initial parameter of the algorithm.

For instance, a population of three individuals could be as follows:

$$A = (2.3546, 0.6589, 1.2357, 1.7542)$$

$$B = (1.9536, 1.4500, 0.8229, 1.424)$$

$$C = (2.5546, 3.8956, 2.5700, 37556)$$

Note that the representation chosen meets the requirement of using a real representation of the search space.

7. DECODING THE INDIVIDUAL VECTOR

Each vector dimension represents a pending health care service. The real value of each dimension represents the vehicle (medical mobile unit) responsible for providing each service. It is defined by applying the rounding function to the real value of each dimension. This function returns an integer number that corresponds to the sub-index of the mobile unit that will provide the service in question. The restriction in the domain of the values for each dimension ensures that the function always returns a sub-index that matches an existing vehicle.

Each vehicle can provide more than one service. The order in which each mobile unit provides the various services is defined by the real value, without applying any type of functions, and is considered in an ascending manner.

For instance, if we have individual A from the table above, mobile medical unit number 1 will provide services 2 and 3, in that order, and medical team 2 will provide services 4 and 1, in that order. Similarly, for individual B, mobile unit 1 will provide services 3, 4 and 2, in that order, and mobile unit 2 will provide service 1. Note that there is always a mobile unit assigned to a service. The opposite cannot happen, meaning that it is possible to have mobile units with no services assigned to them.

This representation has the advantage of a simple and efficient implementation, since the required use of memory increases linearly with the number of services to provide, regardless of the number of available mobile units.

Given the hardware characteristics of current medium-range servers, and based on the size of the instances of real-world problems, the use of memory on the part of the algorithms to represent the population of solutions is negligible.

The same representation was used for all the algorithms analyzed.

It should also be noted that the relationship between problem space and search space is of the injective type, since each individual represents a single assignment, but each assignment is represented by many individuals.

8. FITNESS FUNCTIONS

The two fitness functions to minimize are defined as:

TE	Service average wait time
PT	Number of services that will be provided by third-party mobile units.

In the case of the first fitness function, its goal is to improve service quality, since the variable "arrival time" to provide the service is the main variable that defines quality of service, other than the physicians themselves, which is out of the scope of this paper.

In the case of the second fitness function, its goal is to increase business competitiveness by optimizing the use of third-party medical teams, since these pose a higher cost structure versus using company medical teams, and they also make it more difficult to ensure service quality on account of both medical and paramedical staff being external to the company.

To estimate the arrival time for each service, the vector representing each assignment is as a first instance organized by mobile units in ascending order, and it then indicates the order in which each service will be provided, following the guidelines described in the previous paragraph.

Waiting time is calculated as follows:

For the first service to be provided by the mobile unit

$$TL = M2 + TV1 \quad TE = TL + P2$$

TV1 being the travel time, in seconds, considering $M4, M5$ and $P3$.

For all services other than the first one to be provided by each vehicle, waiting time is calculated as follows:

$$TL = TEant + P4 + TV2 \quad TE = TL + P2$$

TEant being the TE of the previous service and TV2 the travel time from the location of the previous service to the location of the current service, considering P3, M5 and P3ant (P3 of the service provided before).

Then, all waiting times are added up and averaged by dividing them by the number of services to be provided by that particular mobile unit. This is done for all remaining mobile units until the entire vector is decoded.

To calculate fitness function 2, corresponding to the number of services provided by third-party mobile units, the number of services that will be provided by third-party mobile units (M6) are counted.

9. RESTRICTIONS

There are some restrictions that have to be considered in relation to the available time window (on-call times) of each medical team. Each mobile unit has a schedule during which it is not available, and no services can be assigned to it during that period of time.

To handle restrictions, a penalization function was created. This penalization is added to the calculated waiting time (TE). Thus, if a medical mobile unit is assigned to a service outside of its available schedule, the average waiting time (TE) will be significantly affected.

The penalization function is calculated as follows:

$$\text{Penalization} = \begin{cases} 0 & M2 \le TL \le M3 \\ (M2 - TL)^2 & TL < M2 \\ (M3 - TL)^2 & TL > M3 \end{cases}$$

Thus, if a mobile unit is assigned a service outside of its on-call times, the penalization is proportional to the square of the difference between the time assigned and the time the mobile unit becomes available.

Therefore, when a mobile unit receives an assignment outside of its available times, but close to its "from time"/"to time" ends, the penalization will be reduced. However, when a medical mobile unit is assigned a service outside of its available time period, and far from its "from time"/"to time" ends, the penalization will be greater, discouraging this scenario.

Unlike penalization functions, where the search space is divided into feasible and non-feasible solutions, this penalization function allows to get an approximation of the borderline solutions between these two spaces, with approaches both from the feasible and the non-feasible sides [19].

10. MUTATION OPERATOR

In order to improve the search ability of the metaheuristics used, a mutation operator was created to be used in all of the algorithms that were assessed.

This procedure is conceptually very simple and easy to implement. In 1% of the cases, changes are made to the individuals before assessing them. These changes consist in randomly selecting 5% of the individual dimensions of an individual and exchange the value of that dimension with that of another, randomly selected dimension.

Thus, the value of 10% of the dimensions is changed for 1% of the individuals.

The percentages mentioned above were determined empirically.

11. CONCLUSIONS

An application of evolutionary metaheuristics to a real-world case was presented. The problem to solve was the real-time automation and optimization of medical mobile unit assignment to provide services.

The varMOPSO algorithm [14] was used, in view of the good results reported elsewhere.

The multi-objective approach of the solution proposed is also to be noted, since it is an innovative approach for this type of problems. Offering a set of optimal solutions (Pareto front), the decision maker (DM) gains insight on the problem and can view the relationship between opposing objectives from a quantitative perspective.

The following major benefits can be highlighted:

- Optimized assignment of resources, reducing arrival times for the various services offered, increasing quality of service, and maximizing the performance of available resources.
- Maintenance of a general system status that summarizes updated situation statuses, allowing taking corrective and preventive measures based on Medical Management judgment.
- Information available regarding estimated arrival time for the various services to be provided, based on system status, service history information, and resource use simulation.
- Increased efficiency in resource utilization.
- Standardization of the dispatch process, taking into account the entire situation.

The use of technology from the research field for business applications is considered to be extremely important. In this case, there was a transfer of knowledge between the scientific world and the private sector.

The true value of investigation lies in the application of scientific knowledge to solve real-world problems.

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