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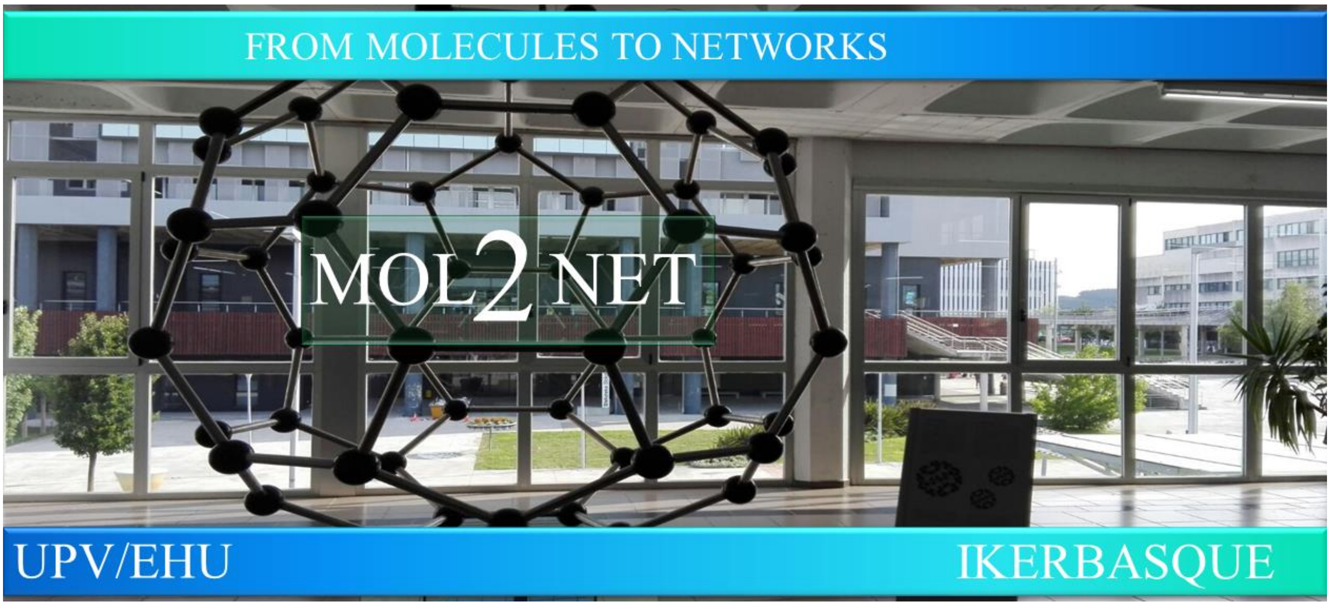

An Interactive framework under conditions of uncertainty for multi-objective optimization

Claudia Gómez-Santillán[a], Pablo Hernández[a], Eduardo Fernandez[b], Nelson Rangel-Valdez[a], Laura Cruz-Reyes[a], Gilberto Rivera-Zarate[c]

[a] *Tecnológico Nacional de México, Instituto Tecnológico de Ciudad Madero, División de Estudios de Posgrado e Investigación, Madero 89440, Tamaulipas, Mexico; claudia.gomez@itcm.edu.mx; g15071361@cdmadero.tecnm.mx; nelson.rangel@itcm.edu.mx; laura.cr@cdmadero.tecnm.mx*

[b] *Facultad de Contaduría y Administración, Universidad Autónoma de Coahuila, Torreón 27000, Coahuila, Mexico; eduardo.fernandez@uadec.edu.mx;*

[c] *División Multidisciplinaria de Ciudad Universitaria, Universidad Autónoma de Ciudad Juárez, Ciudad Juárez 32579, Chihuahua, Mexico; gilberto.rivera@uacj.mx.*

Abstract

To solve multiobjective problems, an evolutionary multi-objective algorithm is needed, which employs techniques to generate random solutions, uses selection processes to define the solutions that will be crossed, alters the new resulting solutions, and finally uses a process to choose the solutions that will pass to the next solution next generation. The last population generated by these algorithms contains the best solutions; however, this population may be too large, thus complicating the process of selecting the final solution that the decision-maker must perform. Therefore, a preference incorporation strategy must be integrated that approximates the interests of the decision maker to facilitate the solution's final choice. Different parameters are required to model the interests of the decision maker, such as the weights of the objectives to use the previously mentioned preference incorporation strategies. However, these values generally cannot be defined precisely by the decision maker, so ranges or intervals can be used to cover the uncertainty of these values. The decision maker's preferences can be considered before the execution of the evolutionary algorithm, at the end of the execution, or interactively during the algorithm's execution. This last method is the least studied because the process is more complex and slower than the a priori and a posteriori incorporation due to the intervention of the decision maker. Therefore, an interactive evolutionary framework has been proposed that uses preference disaggregation analysis and a chat-like interface. Then, through this proposal, the preferences of the decision maker can be efficiently incorporated, the number of tools that integrate this type of incorporation of preferences increases, and it demonstrates that the solutions converge before other types of articulation of preferences. Furthermore, with this proposal, the decision maker can see how the search moves in the solution space thanks to incorporating their preferences, thus facilitating the final choice of the solution.

Introduction

There are strategies to understand and solve real-life problems and thus achieve the best advantage; practically, the decision maker faces the uncertainty present in the problems since this can be found present in the information that comes from the uncertain future states of nature that cause variability; therefore, if the information is not processed or modeled appropriately, can lead to a poor decision (Bastiani S. et al., 2017). That is why it is necessary to make crucial decisions; for example, Ackoff, in his 1978 book The Art of Problem Solving (Ackoff R.L., 1978), describes that a problem is made up of five elements: the decision-makers facing the problem, the controllable variables of the problem that the decision-maker can control, the variables not controllable by the decision maker that will affect the outcome of the selection, the constraints of controllable and uncontrollable variables, and finally the possible outcomes of the choice made by the decision maker.

For Ackoff, a problem is best solved when the decision maker selects the values of the controllable variables that optimize the value of the result; In addition, you need to be very clear about the objective you want to achieve. However, real-world problems frequently include more than one objective, which has different degrees of importance or weight for the decision-makers. The selection process becomes somewhat complicated when you have a fairly large set of feasible solutions.

In this work, an interactive framework is proposed that allows a decision maker to analyze the solutions in stages and guide the search until the best solution that meets the objectives is found, that is, to find the compromise solution. To achieve this, a methodology was developed that integrates a set of software tools that will guide the search, and the methodology comprises various modules. First, the data entry (TELEGRAM API), some of the data includes uncertainty, that is, its value is a range of values and not a single value, for example, the costs and benefits of the projects; immediately the information is sent to the optimizer (MS-DOSS OPTIMIZATION FRAMEWORK) that looks for the best set of proposals for the decision maker, at this stage the uncertainty is included in the variables of the decision model in addition to those received from the input instances of the problem. It communicates with the module that orders the solutions based on the weights assigned by the decision maker (ITPOSIS), which also handles variables with uncertainty that come from the problem; from the ordered solutions, the best ones are taken. Finally, the module that is fed is fed. will recalculate the parameters of the decision model (PREFERENCE DISAGGREGATION ANALYSIS, PDA) in this module variable with uncertainty are also included since the parameters of the decision maker's preference model are handled, which will be included again in the MS-DOSS until the decision maker finds the best solution according to their objectives. The final results are presented by VisTHAA, which is a visual tool to analyze and graph the results obtained from the optimization algorithms.

Materials and Methods

This section will include the materials needed for the project development and thus meet the objectives of testing the proposed methodology.

Decision-making or selection of alternative problems is complex process involving multiple criteria, for which it is necessary to use tools that allow discerning between them to obtain a solution that best satisfies the combination of possible alternatives (Gómez O. and Cabrera O., 2008). Furthermore, the problems generally include multiple objectives, which conflict with each other, making this process more complex and thus generating the need for a tool or method that allows these multiple criteria to be compared against the range of possible alternatives (Balderas F. et al., 2022).

The alternatives to be evaluated can be included in tools that process a natural language input from a user and generate intelligent responses in context, which are sent back to the user; these tools are known as chatbots (Khan, R., and Das, A., 2018). The term chatterbot was first used in 1994 and was initially coined by Michael Mauldin, the creator of the verbal robot Julia.

Chatbots today are powered by rule-driven or artificial intelligence (AI) engines that interact with users, typically through text-based interfaces. They are independent computer programs that can be integrated into any platform messaging, allowing developers to use them through an API, such as Facebook Messenger, Slack, Skype, and Microsoft Teams, among others (Centribal, 2021).

The mobile application market, which is growing rapidly in information technology, uses APIs. These were developed primarily for exchanging information between two or more programs, enabling code reuse and improving software development productivity. Many tools are developed for mobile applications, but one of the most used is the Telegram API.

The Telegram Bot API is a set of procedures, protocols, and definitions used by third-party developers to integrate Telegram Bots with the central platform. In other words, it is possible to carry out the development of a Bot safely since many processes are used as black boxes without knowing all the processes they develop (Ofoeda J. et al., 2019).

Telegram bots are special accounts that do not require an additional phone number to create. Instead, these accounts serve as an interface to execute code on the developer's server. You do not need to know how the MTProto encryption protocol used by Telegram works, as your intermediary server will take care of all the encryption and communication with the Telegram API.

After receiving the data with Telegram, it will be sent to the Optimization Framework. A framework is a set of files and directories that facilitate the creation of applications since they incorporate functionalities already developed, tested, and implemented in a specific programming language. These are intended to make things easier when developing an application, allowing you to only focus on the real problem.

The optimization framework used is known as MS-DOSS (Ponce N., 2021), and its objective is to find the best solution from the set of options introduced through the telegram bot or some instance input file. MS-DOSS comprises various modules that interact to solve the problem at hand and deliver the best set of solutions for the decision-maker.

Among the modules necessary to find the best solution are: the instance module, which is designed to contain the instance of any problem in such a way that when generalizing its information, it can be addressed by the problem module, regardless of the format used by the authors of each instance. The problem module allows you to generalize different optimization problems, emphasizing their common characteristics and connecting with the preferences and algorithms modules.

Preference modeling plays a crucial role in decision-making, so interest in addressing multi-objective algorithms incorporating preference information has recently increased. The DM can provide preferential information in an a priori, a posteriori, and an interactive manner (Hwang & Masud, 1979).

Interactive approaches rely on the progressive definition of the DM's preferences and exploration of the target space. Preference articulation takes place during the optimization process so that progress towards a particular region of the Pareto optimal front is made. The DM must be willing to participate in the solution process and direct it according to his preferences. As the interactive process of identifying the best solutions progresses, the DM specifies his preferences, learns about the problem, and can adjust his aspiration levels.

The preferences module deals with a relational system of preferences composed of several binary relationships such as Indifference, Strict preference, Weak preference, Incomparability, K-preference, and No preference, and it works together with the algorithm module, which allows manipulating the information generated by the problem module, according to the behavior of each algorithm. This allows generalizing different algorithms, emphasizing their common characteristics, and facilitating the creation and extension of their classes. Finally, the solution module allows generalizing the solutions created by the algorithm module to be presented to the decision maker.

When MS-DOSS generates the best final solutions, these make up an extensive set of solutions, so to help make the best decision, MS-DOSS sends the results to the module where the found solutions will be ordered. It should be noted, as mentioned before, that the data includes uncertainty; Therefore, the TOPSIS algorithm (Balderas F., 2022) was modified to handle the uncertainty, generating the ITOPSIS algorithm.

ITOPSIS (Interval Technique of Order Preference Similarity to the Ideal Solution) is a method for multicriteria decision analysis developed by Yoon in 1981. The method is based on the idea that the desired solution should have the shortest geometric distance to the ideal solution and the longest to the anti-ideal solution. The ideal alternative is the one that has a geometric distance closest to the best solution. In contrast, the anti-ideal alternative has a distance that is very far from the best solution (Balderas F., 2017).

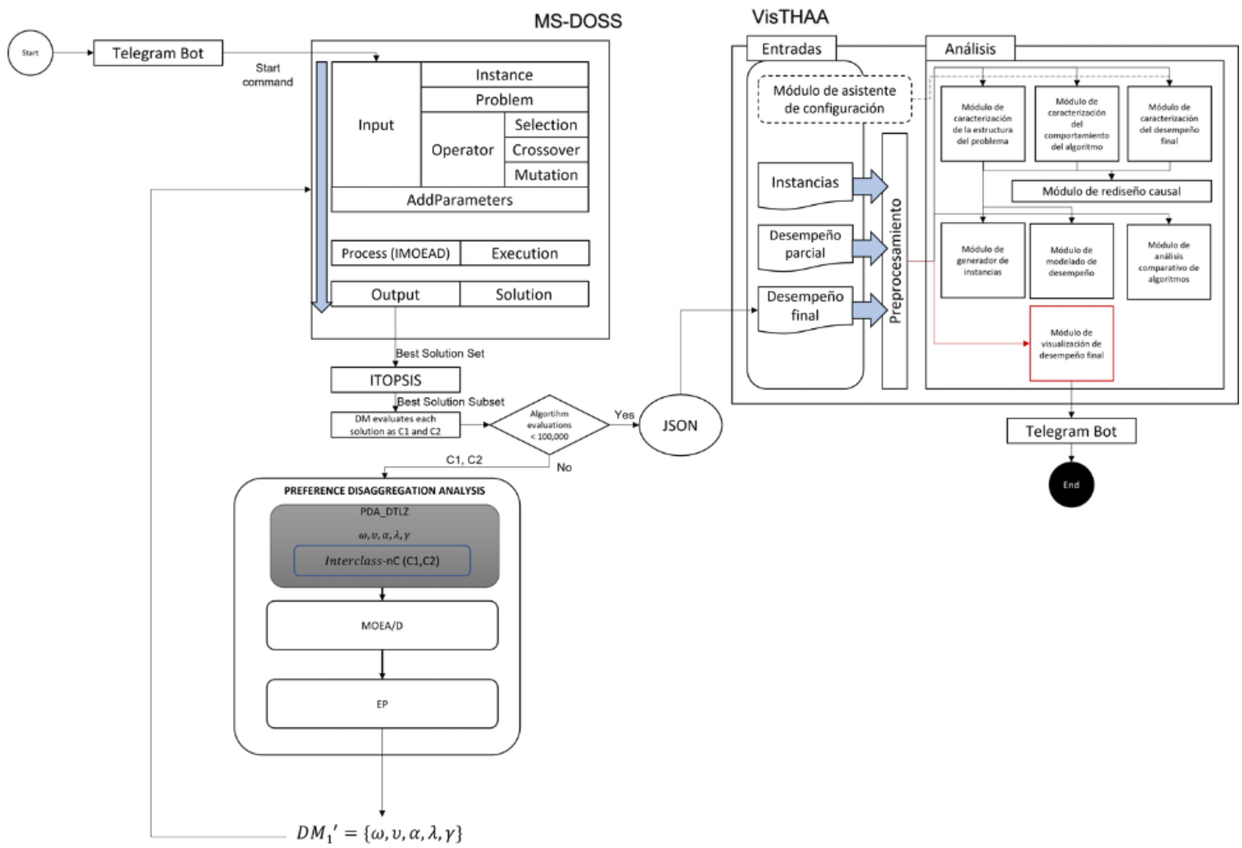

Figure 1. Diagram of the interactive framework under uncertainty conditions for multi-objective optimization.

After evaluating the set of solutions and being ordered by ITOPSIS, the best results will be taken and sent to the Preference Disaggregation Analysis (PDA) module, which consists of the analysis of the global preferences of the decision maker (DM) to deduce the relative importance of the evaluation criteria and thus develop the preference model corresponding to global preferences (Zopounidis & Doumpos, 1999). To solve the PDA you need a set of reference solutions (RS) previously evaluated by the DM as bad solutions (C1) or good solutions (C2). Subsequently, MOEA/D (Rosas-Solorzano L., 2020) must solve the PDA(RS) problem to estimate a new set of preferential parameters (weights, vetoes, credibility, majority, dominance) of the outranking model; said set of values will be loaded again in the MS-DOSS Optimization Framework module, until the decision maker considers having found the best compromise solution, that is, the one that meets his objectives.

The final results can be presented in text or graphic format. To help shape the results, the VisTHAA tool (Ponce J., 2020) is used as a visual tool to analyze and graph the results obtained. Optimization algorithms. Figure 1 shows the process followed by the interactive framework under uncertainty conditions for multi-objective optimization.

Results and Discussion

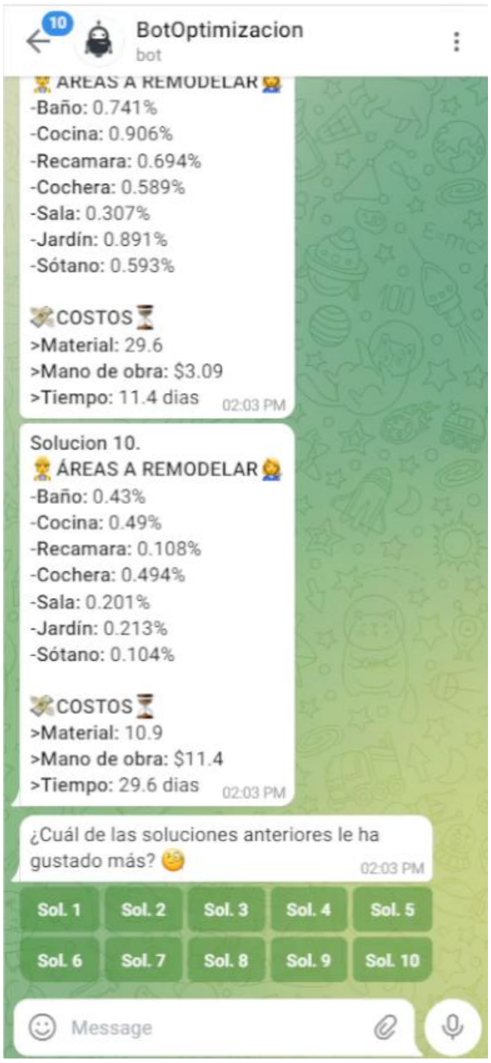

Figure 2. Telegram bot with data obtained by MS-DOSS.

Decision problems are periodically faced by all people or companies, in many moments of our lives, every day we make "good" or "bad" decisions that impact our well-being or that of our companies; that is to say: the good use of personal or organizational resources, as well as establishing a course of action in the short or long term.

As part of the interactive process, the first action of the bot is to provide the decision maker with ten random solutions from which the DM can only choose one, in order to obtain the compromise solution.

To verify that the random solutions obtained from the MS-DOSS framework correspond to those presented by the bot, a text file has been generated from the MS-DOSS framework, which contains each of the random solutions, to be able to compare them with the results. Telegram bot messages.

Figure 2 shows that the data obtained by the framework corresponds to the solutions shown to the decision-maker by the Telegram bot. Therefore, one of the tasks that the decision-maker must perform is to evaluate the solutions generated by the MOEA/D algorithm, which has been implemented in the MS-DOSS framework.

The DM evaluates solutions to say whether he likes the solution or not. To verify that the classification has been carried out correctly, it has been decided to display the DM's choices on the console to compare them with the reference sets R1 and R2 provided to the PDA.

Figure 3 shows the classification made by the DM through the bot; this corresponds to the reference sets provided to the PDA. Note that on the left side of figure 3, the zeros represent the solutions that the DM did not like, and the ones represent the solutions that he did like. In addition, the right part of figure 3 shows the reference set R1 corresponding to the "bad" solutions, so the ones represent the solutions that the DM did not like. In the reference set R2 the ones corresponding to the “good” solutions.

```
[
  0, 0, 1, 1, 0,
  1, 0, 0, 0, 1
]
resultados PDA obtenidos correctamente
```

```
#REFERENCE-SET-R1
1 1 0 0 1 0 1 1 1 0

#REFERENCE-SET-R2
0 0 1 1 0 1 0 0 0 1
```

Figure 3. Representation of the sets that feed the PDA.

Finally, the separation between the compromise solution and the last solution obtained in the interactive process has been calculated to validate the results obtained in the interactive process. The metric used in Figure 4 is the Euclidean distance (Fernandez E., 2022). As can be seen, there are differences between the obtained solutions and the compromise solution; this means that the DM has navigated in the space of solutions selecting those that he considers to be the best solutions, and this has helped the MS-DOSS optimization framework, which by being fed with new decision values has allowed him to find new solutions and reach the best compromise solution.

	3 Obj 7 Var					3 Obj 7 Var			
	MIN EUCLIDEAN					AVG EUCLIDEAN			
		VAR96	VAR97	VAR98		VAR96	VAR97	VAR98	
	1	203.550663	45.8777593	125.561901	1	273.868044	169.195676	249.698464	
	2	188.715928	40.623215	111.442111	2	259.8032	169.819105	242.675067	
	3	202.939087	35.2654519	117.780515	3	272.927794	163.185373	239.253531	
	4	197.118949	47.0603571	119.964055	4	261.478837	174.459651	249.876471	
	5	196.284303	38.0898162	106.018706	5	265.348386	167.454052	239.688257	
	6	195.758959	43.806429	127.473936	6	263.80469	173.941361	254.375027	
	7	200.248018	44.2348743	123.475991	7	266.005837	168.525971	243.937467	
	8	188.71088	27.7843309	126.216619	8	259.999907	166.154387	251.853754	
	9	196.226607	46.6384187	123.806421	9	265.726618	169.25213	248.708083	
	10	198.075036	49.0043711	123.02073	10	267.621626	170.214463	245.651257	
	11	187.366192	24.3183059	124.697474	11	254.049388	169.859952	247.853812	
	12	199.79218	33.5568175	124.126871	12	266.853328	171.47292	248.09881	
	13	204.869557	23.5102977	135.969129	13	271.216529	175.970017	250.807635	
	14	193.470397	41.0674031	120.389352	14	259.246939	177.478956	245.215906	
	15	189.063614	34.6734711	115.79367	15	258.527997	170.673169	244.096446	
	16	198.989047	50.2232608	116.949376	16	264.827233	170.05809	245.493972	
	17	203.083839	33.9748436	114.325413	17	266.686722	167.471558	238.659245	
	18	195.49427	40.7105195	114.907006	18	266.006034	172.28089	242.300179	
	19	196.653146	28.7546518	128.531825	19	261.966237	175.1905	246.99653	
	20	193.596003	36.7828982	129.292283	20	265.827245	171.69093	247.933502	
AVG		196.500334	38.2978746	121.487169	AVG	264.58963	170.717458	246.158671	
MIN		187.366192	23.5102977	106.018706	MIN	254.049388	163.185373	238.659245	

Figure 4. Euclidean distance of the best solutions.

Conclusions

In this research, an interactive framework has been designed and validated under uncertainty conditions for multi-objective optimization. To validate it, a software tool was built that is composed of a set of modules that communicate and interact with each other to solve the problem of finding the best solution that represents the objectives of a decision-maker.

Until now, we have experimented with instances of standard problems from the DTLZ (Fernandez E., 2022) library, and it has been proven that the interactive framework improves the quality of the solutions by exploring the search space, until finding the best compromise solution for the policyholder. of decisions. Future research work is to validate usability and check the contribution of interactivity.

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