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Author(s): B Cobacho, R Caballero, M González and J Molina

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Planning federal public investment in Mexico using multiobjective decision making

B Cobacho¹, R Caballero², M González² and J Molina^{2*}

¹Technical University of Cartagena, Cartagena (Spain); and ²University of Malaga, Malaga (Spain)

The scope of this article is showing how multicriteria decision making can be an efficient tool to manage public investment planning in complex situations. For this aim, we will analyse the problem in all its aspects: building the model from data using econometrical tools, solving the resulting highly complex model using modern efficient techniques (multiobjective meta-heuristics) and helping the decision maker to introduce his preferences in order to achieve the most preferred solution. This holistic approach let us provide an efficient solution to a complex public investment planning situation, improving the current state of the country relating not only economical aspects, but also social and human development aspects. The real situation studied is focused on Mexico, where, in recent decades, has undergone remarkable improvements in terms of economic growth, which has not been matched by significant improvements in several other basic aspects of human development, nor by reductions in regional inequalities. This suggests the need to establish policies aimed at improving these aspects and reducing inequalities. Federal public investment is an important tool in regional policy to promote and improve these aspects; so we introduce a multiobjective programming problem for planning federal public investment in Mexico. This model will focus on improving national levels in four main dimensions of human development (economic growth, education, health and housing), and on reducing regional inequalities for those dimensions.

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Introduction

Mexico is a Federal Republic made up of 32 states called *entidades federativas* (federative entities), between which there are massive contrasts regarding poverty levels and social differences. The differences and social deficiencies that exist in some of the federal states are at odds with the development level of Mexico. Several official agencies have reported on this issue (Ávila *et al.*, 2001; UNDP, various years; World Bank, 2004) and some research articles (Lustig, 1998; Lustig and Székely, 1998; Gamboa and Messmacher, 2003; García-Verdú, 2005) suggest the need to establish policies aimed at mitigating these deficiencies and inequalities.

For a long period, the route to development was studied only on the basis of economic growth. However, it has recently become obvious that there is a need to find routes to development that include other aspects, such as the capacity of some sectors of the population to have access to goods and basic resources, and to reduce inequalities. Recently, the United Nations Development Program (UNDP) published a series of human development reports, using the human development

index (HDI) as a measure of UNDP for several years. This index is a measure consisting of three basic dimensions of human development: access to resources (per capita GDP), long life (life expectancy at birth), and education (literacy rates and school enrolment). Although Mexico has developed strongly in recent decades, the reports show that serious between-regional inequalities still persist. The UNDP raises the need to eliminate these inequalities by promoting growth and improving public policies regarding education, health, and infrastructures, and suggests allocating public expenditure according to the federal state's HDI as a reference.

The report on marginalization in Mexico (Ávila *et al.*, 2001), published by the Mexican National Population Council (CONAPO), calculates a marginalization index (MI), which summarizes in a single measurement population deficiencies due to their lack of access to goods and essential services, such as primary education, suitable sanitation in housing, minimum monetary income, and deficiencies due to living in small, isolated and scattered villages, such as the lack of health services and suitable infrastructures. Ávila's report reveals that, in terms of marginalization, regional differences in Mexico increased in the 1990s because social development tended to concentrate on the more developed federal states, whereas those left behind advanced more slowly or even regressed regarding their levels of development. This study

*Correspondence: J Molina, Campus El Ejido s/n, University of Malaga (Spain).

E-mail: julian.molina@uma.es

also shows that the concentration of social development in the more developed federal states is a matter of concern that motivates the need to define strategies aimed at avoiding regional imbalances becoming worse.

The World Bank (2004) report on poverty in Mexico makes similar points: poverty has to be considered not only in terms of lack of income, but in its multiple dimensions, and highlights the severe inequalities between both social groups and Mexican regions, despite the remarkable progress the country has made in terms of income and human capacities. All these reports and other studies, whether focussing on human development, marginalization, or poverty, lead to the conclusion that a variety of criteria must be borne in mind when evaluating the development of a given country or region, as well as the need to set the reduction of inequalities as the goal.

Given this analysis of the situation in Mexico, the question is what can be done to improve it? Public investment plays an important role, due to its size, distribution, and productive effects on the economy. Thus, public expenditure aimed at economic development and social well-being is a key factor given the conditions of economic and social development in this country. Furthermore, public investment may act as a redistribution mechanism, especially given the federal structure of the country. However, studies, such as that of Rodríguez-Oreggia and Rodríguez-Pose (2004) show that policy making regarding the regional allocation of public investment in Mexico has been centralized for the last decades and lacks clear redistribution mechanisms. Following its first priority to achieve growth at the national level, it has favoured the most developed regions, and failed to promote regional economic and social growth and reduce interstate differences.

It can be argued that in practice it is really difficult to set just a single objective for policy making. Governments usually try to design policies to improve the economy of a country or region by using a single measure made of different economic indicators, in conflict generally, and this is when multicriteria decision techniques can be useful (André *et al.*, 2007). Something similar happens if a composite index is used to resume different (and normally in conflict) social and economic goals for public policy making. since poverty alleviation is an important sociopolitical concern, human development can therefore be viewed in a variety of ways, one of that is economic well-being, as measured by per capita gross domestic product. This measure alone, however, does not adequately account for sociopolitical policy considerations, such as health, education, environment, and political freedom; nor does it fully explain income distribution other social and economic benefits produced in society (McGillivray, 1991). The use of composite indexes as a reference for the distribution of resources has the disadvantage of overlooking situations that may need to be improved in relation to certain index measurements. This is the case for Baja California, which is the third best-placed state in the MI table for 2000, yet more than 20% of the population had not finished primary education.

The central idea of our research is set within this context; multicriteria decision making could become a new tool to guide decision making in the field of public policies aimed at different development goals. We introduce multicriteria techniques to complement the impact analysis of public expenditures in Mexico. Our approach includes three main aspects: (1) improving several development issues in Mexico as some of the objectives, not only at the economic level but also in the social context. Specifically we focus on the following: improving per capita GDP (economic issue), reducing infant mortality rates (health), improving the average number of schooling years (education), and improving sanitation in households (housing); (2) on the other hand, one of our aims is to reduce inequalities between Mexican states; and (3) we deal with the planning problem using a multiobjective approach, without combining all the indicators into a composite measurement. In this way, none of individual data provided by the different indicators are lost, and so the natural multicriteria character of the decision problem is maintained.

To achieve this, we introduce a multiobjective programming model based on the latest known data (in a period $t=0$), for planning the distribution of public investment between the investment sectors and Mexican states for the next period, $t=1$. We formulate the model based on the results obtained from the estimation of a previous econometric model. This model was constructed using panel data analysis techniques to study the means by which the different sectors of public investment may have contributed to improve living standards in Mexican states. This multiobjective problem has eight objectives: four aiming at improving development indicators at the national level (per capita GDP, infant mortality, years of schooling, and housing), and another four focussing on reducing between-state inequalities measured for those indicators. The nonlinear character of some of the problem's functions suggests the use of metaheuristic techniques for its resolution. The SSPMO (scatter search procedure for multiobjective optimization) method was used (developed by Molina *et al.*, 2007). This method is especially suitable for the resolution of nonlinear multiobjective problems with continuous variables, and has proven to provide better results than other methods designed for the same type of problem. Given that this method provides a large set of efficient solutions from which the decision maker (DM) should select the most suitable solution for his/her purpose, an interactive method was adapted to the specific characteristics of our problem. Thus, we have created an interactive frame that, on the one hand, assists the DM in the process of analysing solutions, and on the other, stores the decisions taken iteratively by the DM until he/she reaches the most suitable solution.

The rest of the article is structured as follows: A review on the literature on multicriteria decision making within the area of macroeconomic problems; the multiobjective problem for investment planning is formulated in one section, and next sections describe the metaheuristic method used to solve

the problem, the set of efficient solutions obtained, and the interactive process for selecting a final solution. Final section presents the conclusions.

Background to the problem

Some previous attempts to apply multicriteria techniques to macroeconomic problems can be mentioned. In André and Cardenete (2005), they use a multiobjective approach in a computable general equilibrium model to establish efficient macroeconomic policies and make an application to the Spanish economy. The objectives are based in two economic measures: economic growth and inflation. In André *et al* (2007), they use compromise programming as a way to reduce the set of rational macroeconomic policies. Kooros and McManis (1998) use a multiattribute optimization model for intertemporal investment distribution. By applying hierarchical goal programming, they maximize the overall investment decisions collected from a matrix designated by investment programmes and time. The model is applied to a capital investment program in New York. Lotov *et al* (1992) formulated a theoretical problem for maximizing a consumption indicator and minimizing pollution and unemployment indicators in the upgrading of production technologies. Kravtsov and Pashkevich (2004) proposed a three-objectives problem for Belarus: GDP, energy resources, and foreign-trade balance. Spivey and Tamura (1970) introduced goal programming to optimize a traditional econometric model. Grove (1986) studied a problem to maximize the utility function of some objectives related to decision-making variables using a linear system with estimated coefficients.

Peschel (1985) wrote an essay on the role multiobjective decision making in aggregated macro-models. A macroeconomic analysis of Finland based on an econometric approach is described by Wallenius *et al* (1978), who formulated a utility function of some endogenous variables (GDP, inflation rate, unemployment, and current account balance) as an objective, allowing variation intervals in some instrumental variables (indirect taxes, income transfers, public expenditure, and exchange rate). Multicriteria techniques have been applied to investment planning in works, such as that by Kartam *et al* (1993), that formulated a decision problem for investment planning in transportation with cost and benefit criteria; or such as the work of Shapiro (1976), that proposed a theoretical model of project selection by integer programming.

We introduce multicriteria techniques for planning public investment, taking into account not only economic but also social aspects, as well as the reduction of inequalities, and propose an application for planning public federal investment in Mexico. One of the main differences between our model and previous works is that we do not try to build a utility function with the objectives. Working with a utility function has the advantage of facilitating the resolution of the optimization problem, but on the other hand, it somewhat dilutes the

multiobjective nature of the original problem, being it much harder for the DM to establish suitable weights to construct such a function in practice.

A multiobjective programming model for investment planning

This model is designed to find an efficient distribution of Mexican federal public investment, based on improving several social and economic objectives, on the one hand, by encouraging per capita GDP growth and improving health indicators (infant mortality), education (average number of years at school), and housing (percentage of dwellings with access to basic sanitation), and on the other hand aims at reducing inequalities between the Mexican federal states. When formulating the multiobjective model, we used coefficients estimated on the effect that variations in investment categories may have on the federal states' indicators. To estimate such effects, a dynamic panel data model was used with $N = 32$ units (the number of Mexican federal states) in $t = 4$ time periods ranging over the years 1970–2000. The model was estimated using a simultaneous equations approach with techniques based on the work of Bhargava and Sargan (1983). The variables used in the estimations, as well as their source and the coefficients estimated are reported in the Appendix. The results show that investment in manufacturing activities (industry, mining, agriculture, and fishing) promote economic growth more than social investment. On the other hand, investment in education and health are the most effective investment components to improve social indicators in the education and health sectors: years of schooling and infant mortality, respectively. Investment in infrastructures and transport has a direct and indirect effects on economic growth, and household sanitation, but only a modest impact on educational and health measures. These results have to be taken into account when looking for efficient alternatives for investment planning, given that some types of investment improve specific objectives more than others. The DMs face a trade-off in the distribution of public investment; depending on the objectives they want to strengthen, investment will focus on certain federal states and investment categories. Thus, we propose a model which—based on an initial period ($t = 0$), corresponding to the years for which the most recent data are available (in this articles, average investments during 1996–2000, indicators for 2000)—will serve to plan average investment for the following period $t = 1$ (2001–2005). The distribution of investment will be done for the period $t = 1$ and each state i .

- Investment in the industrial and mining sector:
 $IndInv_{i1} = Inv_{i1}^1$.
- Investment in the agricultural and fishing sector:
 $AgrInv_{i1} = Inv_{i1}^2$.
- Investment in education: $EduInv_{i1} = Inv_{i1}^3$.
- Investment in health: $HlthInv_{i1} = Inv_{i1}^4$.

- Investment in the communications and transport infrastructures sector: $InfInv_{i1} = Inv_{i1}^5$.

Given that the distribution of investment by sectors and states during period $t = 0$ is known, we can use growth rates, $Inv_{i1}^k = (Inv_{i1}^k - Inv_{i0}^k)/Inv_{i0}^k$ as decision variables rather than investments in $t = 1$. The advantage is that by using smaller quantities (investment amounts are very large), the loss of precision in the calculations is much smaller. Therefore, the decision variables for our problem are finally variations on the five investment categories, Inv_{i1}^k , $k = 1, 2, \dots, 5$, and for each federal state $i = 1, 2, \dots, 32$. That is, a total of 160 decision variables.

The problem has two sets of objectives: the first includes national objectives aimed at improving four indicators: per capita GDP, schooling, infant mortality, and availability of sanitation in houses; the other has the objective of reducing inequalities in these four indicators, measured as standard deviations of the federal state levels from the national average. These two sets of objectives try to fulfil the criteria of efficiency and equity established by de la Fuente and Vives (1995), and which Rodríguez-Oreggia and Rodríguez-Pose (2004) show have not been followed by Mexican public investment policy in recent decades.

Therefore, the problem has eight objectives. The first attempts to maximize growth in the percentage of households with basic water facilities (piped water and sewage). Taking into account the effects estimated in the econometric model (Appendix, Table A.2), the investment categories affecting this indicator are health investment and investment in infrastructures, with coefficients β_{Hlth}^{Hou} and β_{Inf}^{Hou} respectively. These coefficients represent the estimated variation percentage on the housing indicator for percentual increases in investment categories. Thus, a $HlthInv_{it}$ variation in health investment in state i , from a period to the next, is expected to produce a growth of $\beta_{Hlth}^{Hou} \cdot HlthInv_{it}$ in the housing indicator and, similarly, a $InfInv_{it}$ variation would yield a growth equal to $\beta_{Inf}^{Hou} \cdot InfInv_{it}$ in the indicator. Thus, the growth of this indicator in state i based on the growth in those investment categories would be given by:

$$Hou_{it} = \beta_{Hlth}^{Hou} \cdot HlthInv_{it} + \beta_{Inf}^{Hou} \cdot InfInv_{it}$$

Taking this into account, and calculating the growth in the national housing indicator (Hou) as the mean of the state index's growth, weighted by the ratio of the population in each federal state, Pop_{i1}/Pop_1^N , the first objective is to maximize growth in this indicator:

$$\begin{aligned} \max Hou = & \frac{\beta_{Hlth}^{Hou}}{Pop_1^N} \sum_{i=1}^N Pop_{i1} \cdot HlthInv_{i1} \\ & + \frac{\beta_{Inf}^{Hou}}{Pop_1^N} \sum_{i=1}^N Pop_{i1} \cdot InfInv_{i1} \end{aligned} \quad (1)$$

The second objective is to maximize the growth rate in the average number of years of education in the population.

This is determined in a similar way to the housing indicator.

$$\begin{aligned} \max School = & \frac{\beta_{IEdu}^{Schl}}{Pop_1^N} \sum_{i=1}^N Pop_{i1} \cdot EduInv_{i1} \\ & + \frac{\beta_{Hlth}^{Schl}}{Pop_1^N} \sum_{i=1}^N Pop_{i1} \cdot HlthInv_{i1} \\ & + \frac{\beta_{Inf}^{Schl}}{Pop_1^N} \sum_{i=1}^N Pop_{i1} \cdot InfInv_{i1} \end{aligned} \quad (2)$$

The third objective is minimizing growth rate in the infant mortality rate:

$$\begin{aligned} \min InfMort = & \frac{\beta_{IEdu}^{InfM}}{Pop_1^N} \sum_{i=1}^N Pop_{i1} \cdot EduInv_{i1} \\ & + \frac{\beta_{Hlth}^{InfM}}{Pop_1^N} \sum_{i=1}^N Pop_{i1} \cdot HlthInv_{i1} \\ & + \frac{\beta_{Inf}^{InfM}}{Pop_1^N} \sum_{i=1}^N Pop_{i1} \cdot InfInv_{i1} \end{aligned} \quad (3)$$

And fourth maximizing growth rate in per capita GDP:

$$\begin{aligned} \max pcGDP = & \frac{\beta_{IInd}^{GDP}}{Pop_1^N} \sum_{i=1}^N Pop_{i1} \cdot IndInv_{i1} \\ & + \frac{\beta_{IAgr}^{GDP}}{Pop_1^N} \sum_{i=1}^N Pop_{i1} \cdot AgInv_{i1} \\ & + \frac{\beta_{IEdu}^{GDP}}{Pop_1^N} \sum_{i=1}^N Pop_{i1} \cdot EduInv_{i1} \\ & + \frac{\beta_{Isal}^{GDP}}{Pop_1^N} \sum_{i=1}^N Pop_{i1} \cdot HlthInv_{i1} \\ & + \frac{\beta_{Inf}^{GDP}}{Pop_1^N} \sum_{i=1}^N Pop_{i1} \cdot InfInv_{i1} \end{aligned} \quad (4)$$

The next four objectives attempt to minimize between-state inequalities for each indicator, measured by standard deviations of the indicators' values for each state compared to the national average.

$$\min STD_Hou = \left(\frac{1}{N} \sum_{i=1}^N (Hou_{i1} - Hou)^2 \right)^{1/2} \quad (5)$$

$$\min STD_Schl = \left(\frac{1}{N} \sum_{i=1}^N (School_{i1} - School)^2 \right)^{1/2} \quad (6)$$

$$\min STD_InfM = \left(\frac{1}{N} \sum_{i=1}^N (InfMort_{i1} - InfMort)^2 \right)^{1/2} \quad (7)$$

$$\min STD_GDP = \left(\frac{1}{N} \sum_{i=1}^N (pcGDP_{i1} - pcGDP)^2 \right)^{1/2} \quad (8)$$

The model's constraints are given by the budget limitations. Let $S_{it} = \sum_{k=1}^5 Inu_{it}^k$ the total investment for a given state i during period t , and $S_t^N = \sum_{i=1}^N S_{it}$ be the total national budget. The budget can be subject to constraints regarding potential variations at three different levels: national, federal state, and in investment or budget categories. The variation in the national budget is set at an amount $MaxN$:

$$\dot{S}_1^N = \frac{S_1^N - S_0^N}{S_0^N} = MaxN$$

The variation $MaxN$ sets up different possible scenarios. For this bound, we studied a continuous range of scenarios: from a restrictive policy of imposing reductions in the national budget for public investment of up to 5% ($MaxN = -0.05$), compared to the previous period, to carrying on with a similar policy at a fixed national budget ($MaxN = 0$), or developing a policy of expansion allowing an increase in public investment of up to 15% ($MaxN = 0.15$).

The constraints set at the federal level means that public investment growth in each state i is constrained by an amount $MaxS_i$.

$$|\dot{S}_{i1}| = \left| \frac{S_{i1} - S_{i0}}{S_{i0}} \right| \leq MaxS_i, \quad i = 1, 2, \dots, N$$

These constraints impose a limit on interstate transfers. In other words, if the total investment remains constant, an increase in the investment for a state would involve a decrease in the amount received by the remaining states; and these variations are bounded by $MaxS_i$. To set these bounds, we examined the investment transfers carried out in the 1990s. Most of the federal states experienced variations ranging from -15 to 15% , as variation bounds for all the states. Nevertheless, these parameters could be modified to use different bounds depending on the states. Finally, the constraints imposed on between-state investment transfers means that the expenditure growth for different categories is limited by some given bounds $MaxC_{ik}$.

$$|Inv_{i1}^k| = \left| \frac{Inv_{i1}^k - Inv_{i0}^k}{Inv_{i0}^k} \right| \leq MaxC_{ik},$$

$$i = 1, 2, \dots, N; \quad k = 1, 2, \dots, 5$$

This means that we can achieve our objectives by transferring resources from one category to another, but not all the resources from a given category can be transferred to another in a radical way. Analysis of the 1990s shows that the greatest variations are found in investment in the industrial sector, which declined 19%, or in health, which increased by around 18%. For the sake of simplicity, in our study, we considered that all the bounds involve $MaxC_{ik} = 0.20$.

In the following sections, we describe the methodology used for the resolution of our multiobjective problem and the efficient set obtained.

A metaheuristic for the resolution of the multiobjective problem

At present, a large number of techniques are available to solve complex multiobjective programming problems. We consider problems *complex* when they have features, such as nonlinearity in the objective function and/or in the constraints, uncertainty in the data or a large number of discrete variables, which is very frequent in real-life problems. Although some exact techniques have been developed to solve multiobjective problems, these have the drawback of working efficiently only with linear problems, and therefore, the special characteristics of complex problems seriously hinder their application, sometimes to the extent that they cannot be used. It is quite common to use metaheuristic methods to deal with these kinds of problems. These methods work quite well for calculating the efficient frontier in multiobjective programming problems in particular, and in optimization problems in general. A proof of this is the boom in the use of these types of methods in the last two decades, which has given rise to a great variety of methods and applications reported in various scientific journals and conferences (Gandibleaux *et al.*, 2000). Evolutionary algorithms are heuristic methods widely used to solve multiobjective problems. The work of Coello *et al.* (2002) is a landmark in the field of evolutionary multiobjective programming. Other algorithms, the so-called *hybrid* algorithms, combine different features from several methods in order to build a new and more efficient algorithm. Molina *et al.* (2007) have designed a method based on this type of hybrid metaheuristic, called SSPMO, which combines the flexibility of scatter search with the adaptive memory of tabu search, and is thus an excellent method which can be adapted to specific contexts. The method is especially applicable to nonlinear multiobjective problems with continuous variables. The results show that SSPMO is capable of finding efficient frontiers with a greater number and density of efficient solutions and a point distribution better than other methods designed for the same kinds of problems. The next section describes the results of applying the SSPMO method to our problem.

Results analysis

Applying SSPMO provides 32 550 efficient solutions. These solutions show how there is a tendency for the indicators to improve (the housing indicator index, years at school, and per capita GDP grow, whereas infant mortality decreases) as investment growth increases, although some other solutions tend to use this increase to reduce inequalities more than to improve the indicators.

Figure 1 shows the distribution of efficient solutions according to the number of objectives they improve. Around 34% of the solutions manage to improve six objectives, followed by 32% that improve five, 22% that improve seven, and 10% that improve all the objectives. Table 1 shows the descriptive data for the 3193 efficient solutions that improve

the eight objectives of the problem. The percentages of relative variations in the standard deviations of the indicators compared to their initial values are shown. Column *Mean (Norm.)* shows the mean value normalized to be between 0 and 1, in such a way that the best value for an objective reached in all the efficient solutions is 1, and the worst value is 0. The column *SD* shows the standard deviation between the solutions that improve the eight objectives. The remaining columns, *Mean*, *Min*, and *Max*, show the percentage of average variation, minimum variation, and maximum variation in these solutions, respectively. It should be pointed out that, contrary to what might be expected, the investment growth in these solutions is not high, barely reaching 2.4%

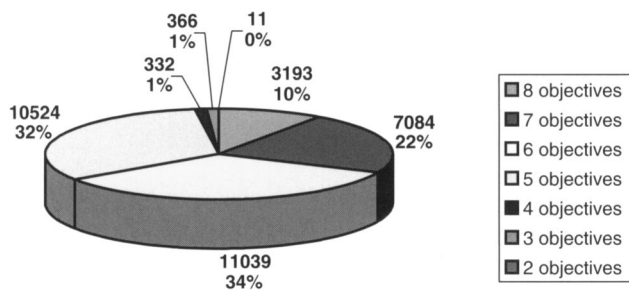


Figure 1 Solution distribution by number of objectives improved.

on average, ranging from -4.83 to 6.80% . None of these solutions reach maximum or minimum values in any of the objectives, and the values provided are intermediate on average: the mean lowest variation in the standard deviation is found in per capita GDP, (normalized value, 0.3787), and the highest in schooling years (normalized value, 0.6682). All the other normalized mean values range between 0.4 and 0.55 .

Table 2 shows the normalized objective values for several solutions selected from all the efficient solutions obtained, those presenting some extreme values in the objectives. The figures in bold indicate those values that improve the initial values. In addition to the eight objectives, row \hat{S}^N shows the growth in the national budget used by each solution, and row N shows the number of objectives improved.

We can highlight **sol1343**, which reaches the maximum in three of the eight indicators: housing, schooling, and infant mortality, and also yields very good results regarding growth in per capita GDP and the deviation in infant mortality. However, this solution is not good for the remaining deviations, given that it worsens their values compared to the initial period. On the other hand, this solution makes use of the maximum growth permitted by the national budget.

Selecting the final solution

Once an approximation to the efficient set is obtained, the next step is to select a final solution, a process that involves

Table 1 Descriptive data about the solutions that improve eight objectives

	<i>Mean</i>	<i>Mean (Norm.)</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>
Hou	0.4162	0.4070	1.7924	0.0007	1.0262
School	0.0162	0.4158	0.1167	0.0000	0.0482
InfMort	-0.1841	0.4068	0.7924	-0.4533	-0.0004
pcGDP	0.2989	0.3787	1.6453	0.0001	0.7286
STD_Hou ^(*)	-0.5087	0.5480	0.0004	-2.1086	-0.0007
STD_Schl ^(*)	-0.1658	0.6682	0.0008	-0.4112	-0.0002
STD_InfM ^(*)	-0.1516	0.5059	0.0049	-0.6765	-0.0001
STD_GDP ^(*)	-0.3391	0.5533	18.3451	-1.7241	0.0000
\hat{S}^N	2.39	0.3710	0.0192	-4.83	6.80

(*) Relative difference of deviation in $t = 1$ with respect $t = 0$.

Table 2 Some particular efficient solutions (normalized values)

	<i>Sol1343</i>	<i>Sol1335</i>	<i>Sol907</i>	<i>Sol28295</i>	<i>Sol1805</i>	<i>Sol28314</i>
Hou	1.0000	1.0000	0.1700	0.2425	0.3761	0.0993
School	1.0000	0.9621	0.3973	0.3570	0.3426	0.3748
InfMort	1.0000	0.9999	0.1702	0.2425	0.3758	0.0996
pcGDP	0.9714	1.0000	0.2631	0.2633	0.2699	0.1936
STD_Hou	0.1433	0.1433	1.0000	0.8240	0.1447	0.7633
STD_Schl	0.2337	0.2484	0.6365	1.0000	0.1963	0.3306
STD_InfM	0.9420	0.9420	0.0103	0.4140	1.0000	0.3143
STD_GDP	0.0334	0.0000	0.7778	0.4884	0.2186	1.0000
\hat{S}^N	14.90%	14.90%	1.94%	-2.48%	1.21%	-1.68%
N	5	5	5	6	5	3

taking into account the DM's preferences. Given the high number of efficient solutions obtained, the selection process is quite complex. We used an interactive method to include the DM's preferences. An interactive method involves scanning the feasible region to find the most satisfactory solution, and is characterized by shifting between decision-making and computation phases. At each iteration, several solutions are generated and examined by the DM; in this way, the information provided by the DM becomes part of the solution search process. The key factor in interactive methods is to bring human intervention (ie, the DM's preferences) closely into the solution search process.

Although the original interactive methods incorporate data during the resolution process (a review of these methods can be found in Miettinen (1999)), another way to increase DM interaction is to include their preferences on a given set of efficient solutions. The Tchebycheff method (Steuer and Choo, 1983) and the Z-W method (Zionts and Wallenius, 1976) are among the most cited in the literature, and have the advantage of making interaction with the DMs very simple. Taking this idea as a starting point, we developed an interactive method designed to include the DM's preferences in the process of selecting solutions once the efficient set has been obtained, and which preserves a user-friendly interaction with the DM. The method is based on a set of efficient solutions, whose values for each objective in the problem are known. We also evaluate their value in some other functions or aspects that might be relevant to the decision-making process, as for example the associated growth in total investment for each efficient solution.

Thus, we assume the following characteristics of problem:

- We have a set Ω_0 , with M efficient solutions $\{s_i : i=1, \dots, M\}$;
- Each s_i is evaluated according to p criteria;
- Each s_i is evaluated according to n relevant aspects.

That is, each solution s_i consists of a set of p objective function values, f_j , and a set of n relevant information values, ind_j :

$$s_i = (f_1, \dots, f_p, ind_1, \dots, ind_n)$$

As mentioned, the relevant aspects offer some kind of information that the DM considers useful to make a decision, but are not sufficiently important to be included as criteria.

Now, we want to design the interaction with the DM in order to reduce the size of the Pareto front and guide him/her to the most preferred solution in this set. Interactive methods are usually classified according to the type of information required from the DM at each iteration: local weights, local tradeoffs, reference points, and so on. The way interaction is performed, however, is not restricted to providing information; the DM can be asked to choose a solution from among a given set of solutions, to perform pairwise comparisons among a given set of solutions, to list the objectives to be improved

or sacrificed, and much more. That is, the interaction scheme can be designed in many different ways.

This is the case if we consider two of the most cited methods: the Z-W method (Zionts and Wallenius, 1976) and the Tchebychev method (Steuer and Choo, 1983). The key to success with these two methods is the same: interaction with the DM is very simple, as all he/she has to do is to choose a solution among a set. Thus, we want to design an interactive post-multiobjective metaheuristic (*i-PMOM*) method such that the interaction with the DM will be carried out by choosing a solution from among a given (suitable) set of solutions. The term *post-multiobjective metaheuristic* refers to the fact that this method is used once all the solutions are obtained using a multiobjective metaheuristic, but the method does not depend on the particular metaheuristic used; it just uses the solutions obtained regardless of how this is done. Once these solutions are obtained with this interactive method, we provide two tools to reduce the number of possible solutions to be chosen: a clustering tool and a filtering tool. Each of them plays a role in this method:

- The clustering tool lets the DM choose a solution from among a set in order to use this information to reduce the set of solutions, thereby removing some solutions far from the one chosen.
- The filtering tool lets the DM reduce the set of solutions using the objective function values or the relevant information.

The DM can use any of them in any iteration t , and will obtain a reduced set of solutions Ω_t . On the other hand, we also provide some graphics tools to help the DM to understand the characteristics of each solution, not only showing the objective function values of each of the displayed solutions but also the relevant information.

Reducing tools: filtering

This tool lets the DM delete a set of non-interesting solutions. That is, throughout the procedure, once the DM realizes that a given area of the Pareto front is of no interest, he/she can use a filter tool to eliminate these solutions from further consideration. This is done by simply providing some levels for criteria or relevant aspects. This simple tool proves very useful in the first steps of the procedure, where the DM simply realizes that some extreme solutions could not be implemented in the real situation or that at least certain criteria must achieve a given level of performance.

Thus, the filtering tool can be used at any iteration and follows the following scheme.

Iteration t : Filtering

- I. Provide upper or lower level to the desired criteria or relevant aspect
- II. Delete solutions violating any of the new levels
- III. Include the surviving solutions in the set Ω_{t+1}

Reducing tools: clustering

This is the core of the interactive method. What we try to do here is to show the DM a number ($Cl > p$) of reference solutions from which to choose the most preferred. These Cl reference solutions at iteration t will constitute the Reference Set, RS_t , and play the role of the representative item of a cluster. Given an iteration t and its corresponding set of solutions Ω_t , the following procedure is used to choose the reference solutions.

- I. For each $i = 1, \dots, p$ choose the best solution for criteria i and include them in RS_t
- II. While the number of solutions in RS_t is smaller than Cl , do:
 - Choose the solution in $\Omega_t \setminus RS_t$ maximizing the distance to RS_t
 - Include it in RS_t

Thus, this set contains a representative sample of Ω_t including its p extreme points and $Cl - p$ diverse compromise solutions. The remaining solutions in Ω_t are classified according to the Reference Set RS_t , that is, each solution will be assigned to the cluster whose representing item is closest to it. Now, the DM chooses a cluster and then we delete the cluster whose representing item is the furthest from the chosen cluster. Thus, we delete the solutions in the cluster that is furthest from the most preferred area according to the DM. The distance used is a weighted Euclidian where the weights used $A = \{\lambda_1, \dots, \lambda_p\}$ could be changed during the interaction as will be shown later. The remaining solutions are included in the set Ω_{t+1} for the next iteration. This clustering tool can be used at any iteration.

Iteration t : Clustering

- I. Build the Reference Set, RS_t :
 - \Rightarrow Choose the best solutions for the p criteria
 - \Rightarrow Include them in RS_t
 - \Rightarrow While the number of solutions in RS_t is smaller than Cl , do:
 - Choose the solution maximizing the distance to
 - Include it in RS_t
 - \Rightarrow End While
- II. Let the DM choose the most preferred solution in RS_t
- III. Delete the solutions in the farthest cluster
- IV. Include the rest of solutions in the set Ω_{t+1}

In this way, the DM will progressively reduce the size of the set of solutions with this tool by choosing the most preferred one in a reduced set of representative solutions. That is, we follow the scheme used in methods, such as the Z-W method or the Tchebychev method that have been proved very useful in real applications. This type of interaction seems very natural

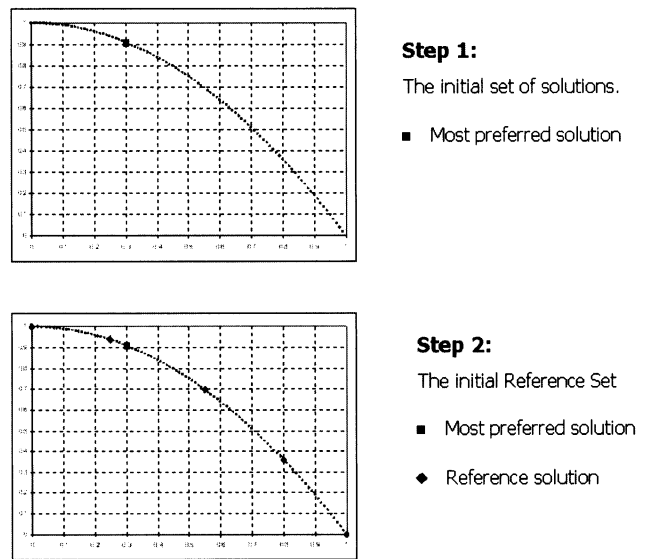


Figure 2 Initial set of solutions and the first Reference Set.

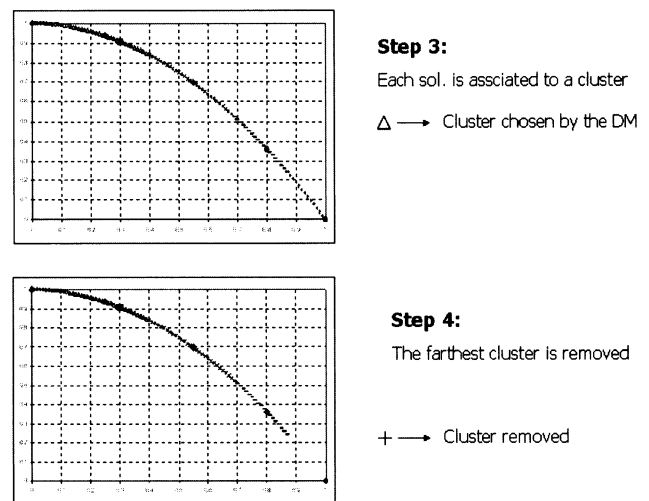


Figure 3 DM's choice and the first cluster elimination.

for the DM, and it does not require any information such as levels, reference points or trade-offs, which could be more difficult for the DM in some real cases. Figures 2, 3, and 4 show graphically how this method reduces the size of the set of solutions, in an example with two objectives. Figure 2 (Step 1) shows the initial set of solutions and the DM's most preferred solutions, that is, the solution to find. From this initial set, we select the optima of each criteria and three more solutions (we assume $Cl = 5$ for this example) as the first Reference Set (Figure 2, Step 2). In Figure 3 (Step 3), each solution is associated with a cluster, and the DM chooses the reference solutions closest to his/her preferred area. Then the farthest cluster is eliminated (Figure 3, Step 4).

This kind of interaction also offers the possibility of using a different type of information: the *less preferred* criteria. That

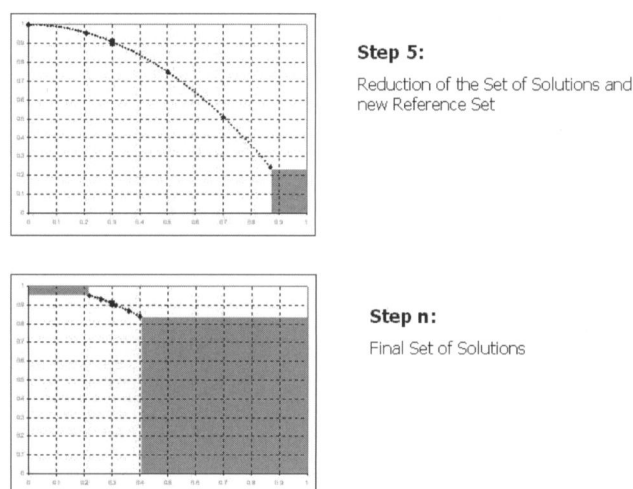


Figure 4 Space reduction and the final set of solutions.

is, once a cluster is chosen, the cluster eliminated (the farthest from the one chosen) is always extreme in the sense that it contains the optima of one of the objectives. This objective is what we call the *less preferred* objective in that iteration because it represents the one that is furthest away from the DM's preferences. Thus, we obtain a kind of *negative information*, because we can state what is not preferred at all. Therefore, instead of focusing on what is preferred, we simply remove what is not preferred at all, as shown in Figure 4 (Step 5). The process is more reliable under this strategy as it does not focus on a specific area too rapidly. Misunderstandings regarding the problem at the beginning is not critical, which is one of the weak points of many interactive methods. Although, the DM is learning throughout the process, at the beginning he/she probably does not have a clear idea of the problem being solved; however, as most interactive methods try to concentrate on an area from the very beginning, the DM sometimes focusses on the wrong area prematurely.

Thus, with this method, we try to reduce the size of the solution set at the beginning (instead of focussing on the chosen area) to avoid premature convergency and misunderstanding the problem. On the other hand, the process is slower and the DM can get tired. To speed up the process, once the DM feels his/her knowledge is reliable, we let him/her change the weights $A = \{\lambda_1, \dots, \lambda_p\}$ used in the clustering weighted distance. More specifically, we let the DM reduce the weights of the less preferred criteria, and once the weights are updated according to this procedure, the process is much faster.

Finally, the complete method is as follows:

- Step 1:* From the set, Ω_0 build the initial Reference Set, RS_0 , and show it to the DM.
- Step 2:* If the DM wants to do a clustering iteration, go to *Step 3*. If the DM wants to do a filtering iteration, go to *Step 4*. If the DM is satisfied with the current most preferred solution, go to *Step 5*.

Step 3: Do a clustering iteration, build the next Reference Set, RS_{t+1} , and go to *Step 2*.

Step 4: Do a filtering iteration. With the set of surviving solutions, Ω_{t+1} , build the next Reference Set: RS_{t+1} . Go to *Step 2*.

Step 5: Finish.

Thus, we provide DM with all the information needed in a well-organized and easy to understand manner, and a tool to reduce the number of possible solutions until they reach the most satisfactory one. To this end, we use a filtering and a clustering methods. Whenever the DM applies one of these methods to the efficient solution set, the set is reduced according to the filtering or clustering criteria.

Interaction with the DM

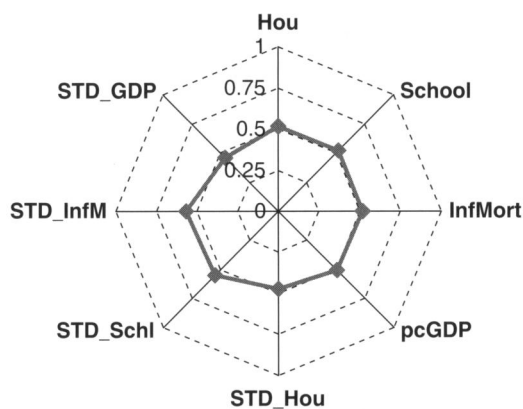
For the interaction with the DM, we implemented a software following the interactive method described. The interface's main screen presents, at each iteration, small blocks of representative efficient solutions (Reference Sets). To help the DM analyse the information during filtering and clustering, the software enables graphic comparisons between solutions, displays tables with indicators or investment by states, and compares the outcome for different states according to the solution selected. Once the DM finds a solution that interests him/her more than the rest, he/she can save it as a candidate final solution by simply selecting it on the main screen. Once the reference solutions have been explored, if he/she has not yet decided on a final solution, he/she can apply filtering and clustering iteratively to delimit the set of efficient solutions closer to his/her preferences. When the DM finds a suitable solution, selecting 'End' closes the programme and creates a text file with all the data corresponding to the final solution (ie, the values for the objectives and the decision variables).

To perform an hypothetical solution selection process, an external expert on the subject acted as DM. Some of the decisions taken during this process were as follows: those solutions in the efficient set that involved reducing investment were not considered, taking into account that in normal conditions public investment should never be reduced. This decision did not alter the optimal values of growth in the four indicators, but it did have an effect on the deviation values. The DM opted for an intermediate position, retaining only those solutions that improved both the four indicators and four deviations (by filtering solutions with value 0.000 as the lower bound regarding growth in housing, years of schooling, and per capita GDP, and as the higher bound in infant mortality and deviation variations). Once an improvement in the eight objectives was guaranteed, the DM tended to improve the indicators (especially household and per capita GDP) more than the deviations. When faced with solutions that provided similar values for the objectives—which tends to happen in the later stages of the process when few solutions remain—the DM selected the solutions by analysing the situation by state,

Table 3 Solution 17945 finally chosen. National data

	<i>Hou</i>	<i>School</i>	<i>InfMort</i>	<i>pcGDP</i>	$S^N(*)$
$t = 0$	0.7225	7.9687	14.2087	15127.96	33715.13
Growth (%)	0.7065	0.0338	-0.3126	0.6124	5.0463
$t = 1$	0.7276	7.9714	14.1642	15220.61	35416.51
$t = 1$ (Norm.)	0.5184	0.5238	0.5182	0.5077	0.5048
	<i>STD_Hou</i>	<i>STD_Schl</i>	<i>STD_InfM</i>	<i>STD_GDP</i>	
$t = 0$	0.13473	0.8735	4.6731	6994.9324	
Growth (%)	-0.0475	-0.0767	-0.2526	-0.0099	
$t = 1$	0.13467	0.8729	4.6613	6994.2400	
$t = 1$ (Norm.)	0.4727	0.5492	0.5676	0.4600	

(*) Millions of Mexican Pesos in 1993.

**Figure 5** Solution 17945 (normalized values).

and paying special attention to those with lower development levels, such as Chiapas, Oaxaca, or Guerrero.

Table 3 shows the data for the national objectives and other additional data regarding the scenario proposed by solution **sol17945** finally chosen by the DM in this simulation.

This solution requires a modest growth in national investment, 5.04%, and yields an improvement for the four national indicators and their deviations. The percentage of houses with access to sewage disposal and running water would increase by 0.7065% (from 72.25% at the initial period to 72.76% in $t = 1$). The growth of the national per capita GDP would be 0.612% (from 15127.96 to 15220.61 pesos). Infant mortality, with a reduction of 0.31%, would decrease from 14.21–14.16 per thousand. Finally, years of schooling involves the lowest percentage (0.034%), growing from 7.9687–7.9714 years (barely 1 day).

Compared to the total of the efficient solutions obtained for our multiobjective problem, the solution chosen holds an intermediate position for all the objectives, as shown in Figure 5, where the normalized values of the eight objectives are all around 0.5.

Under this proposal, investment would increase in all the states except for Aguascalientes, Sonora, and Tlaxcala,

whose total investment would be reduced by 0.15, 0.83, and 1.52% respectively. Other federal states, despite experiencing increases in total investment, would undergo reductions in some of their indicators due to redistribution (ie, Coahuila, Nuevo León, Querétaro, and Quintana Roo). Apart from these cases, the rest of the federal states would improve their four indicators. Out of the 32 states, 29 would experience improvements in housing, 25 in years of schooling, 29 in infant mortality, and 28 in per capita GDP. The states with the lowest per capita GDP at the initial period would undergo the greatest improvement in this indicator. The state Oaxaca, for example, would show good improvements not only for per capita GDP (1.29%), but also for the other three indicators: 1.48% in housing, 0.1% in years of schooling, and -0.65% in infant mortality. In general, those states with lower development levels at the initial period would grow at a higher rate than developed states, so regional inequalities would be slightly reduced.

Conclusions

This article proposes a method to guide decision making when planning public investment with a multiobjective approach, and simulate an application with real data in Mexico. We show in this article the complete process in order to make a decision in this field: from input data to final decision, how to build a multiobjective model including all the relevant aspects, how to solve it, and how to help the DM to choose the most suitable solution among the multiplicity of them obtained.

The model proposed has the objectives of improving some country's economic and social indicators (per capita GDP, average number of years at school, infant mortality rate, and percentage of households with access to basic sanitation), while reducing regional differences in such indicators. Using estimations about the effects of public investment on those indicators, we set a problem that tries to find alternative distributions of total investment in the country between different categories, and between different regions, taking into account eight objectives: four regarding improvements in socioeconomic indicators at the national level, and four

to reduce between-state inequalities in the same indicators, under certain budget constraints regarding growth of the total budget, variations in investment between regions, and variations between expenditure categories. This kind of approach has the advantage of preserving the multicriteria character underlying a decision-making problem in this field, without the loss of information implicit in a compound index.

Given that some functions in the multiobjective problem were nonlinear, we used a meta-heuristic method to solve the problem: the SSPMO method, a hybrid of tabu and scatter search algorithms, that has shown good results in multiobjective continuous and nonlinear problems. For our case study, SSPMO method provided 32 550 efficient solutions, within a variation in the total national budget ranging from -5 to 15%, set up by the constraints in the problem. Given this high number of solutions in the efficient set, together with the fact that dealing with eight objectives when evaluating the solutions involves working with a great deal of data, selecting a final solution from the efficient set is not a simple task. To aid the DM in the final solution selection process, we developed an interactive user-friendly method to our problem. This interactive method is applied through software that iteratively shows the DM all relevant data on the efficient solution set in small blocks (Reference Sets) to facilitate the analysis, while it manages the decision-maker's preferences, until he/she finds some satisfactory solution. This interactive process was tested by a DM expert in the current problem. The distribution finally proposed from among all the available possibilities would require a moderate increase in total investment (around 5%), while the levels of improvement for the four indicators and their deviations for the final solution proposed were in the middle range within the set of efficient solutions. It was a balanced solution improving the indicators at the national level as well as their deviations.

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Appendix

See Table A.1 and Table A.2.

Table A.1 Variables in the model. Definition and sources

- **pcGDP** – *Per capita* GDP. Data from *Instituto Nacional de Estadística, Geografía e Informática (INEGI)*.
- **School** – Years of schooling of the population older than 15 years. Data from the *Integrated Public Use Microdata Series – International (IPUMS-International)*.
- **InfMort** – Infant mortality (number of newborns dying under a year of age per a thousand of live births during the year). Data from *INEGI*.
- **Hou** – Average percentage of households with basic water facilities (piped water and sewage). Data from *IPUMS-International*.
- Investment in manufacturing activities: **IndInv** – investment in the industrial, energetic and mining sector, and **AgrInv** – investment in the agricultural and fishing sector.
- Social investment: **EduInv** – investment in education and **HlthInv** – investment in health.
- **InfrInv** – Investment in the communications and transport infrastructures sector. All the data about public investment come from the statistical appendixes in the *Presidencia del Gobierno de México* reports (Rodríguez-Oreggia and Rodríguez-Pose, 2004).

Table A.2 Estimated effects of the investment variables on the indicators

<i>D.V. I.V.</i>	<i>Hou</i>	<i>School</i>	<i>InfMort</i>	<i>pcGDP</i>
IndInv				$\beta_{Ind}^{GDP} = 0.0242$
AgrInv				$\beta_{Agr}^{GDP} = 0.0255$
EduInv		$\beta_{IEdu}^{Schl} = 0.0057$	$\beta_{IEdu}^{InfM} = -0.0001$	$\beta_{IEdu}^{GDP} = 0.0041$
HlthInv	$\beta_{IHlth}^{Hou} = 0.0524$	$\beta_{IHlth}^{Schl} = 0.00091$	$\beta_{IHlth}^{InfM} = -0.0231$	$\beta_{IHlth}^{GDP} = 0.0153$
InfrInv	$\beta_{Infr}^{Hou} = 0.0512$	$\beta_{Infr}^{Schl} = 0.00089$	$\beta_{Infr}^{InfM} = -0.0226$	$\beta_{Infr}^{GDP} = 0.0579$

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