Integrating System Dynamics with exploratory MCDA for robust decision-making

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Abstract. The aim of this paper is to propose a process to support decision making, in which System Dynamics is combined with Multi Criteria Decision Aid methods to mitigate the limitations of the two methodologies when used alone and find robust policies. The proposed process is based on Exploratory Modeling and Analysis, a framework that allows the use of multiple methods – under different perceptions, detail, and levels of abstraction – in order to address issues of uncertainty and robustness. A case study is used to illustrate how the process can offer deeper insights and act as a valuable decision support system. Finally, it also demonstrates the potential of Exploratory Modeling and Analysis to deal with uncertainties and identify robust policies.

Keywords: Exploratory Modeling and Analysis, System Dynamics, Multi Criteria Decision Aid, decision support system

1 Introduction

To support decision-makers cope with the complex nature of decisions, a set of quantitative methods has been used in the literature. These methods provide a formal structuring of the reasons for which a policy is considered a solution to a problem [1]. Two such methods that make use of computational models are System Dynamics (SD) and Multi-Criteria Decision Aid (MCDA).

SD is a methodology that helps to understand the behavior of complex systems over time [2] [3]. Its main elements are feedback loops and time delays that give rise to dynamic complexity [4]. The main goal of SD is to understand how a system's behavior emerges over time and use this understanding to design and test policies in a consequence-free environment [5]. However, SD models do not concern themselves with an explicit evaluation of the policy's performance [5] and whether a policy is preferred over another is often based on the modeler's intuition [6]. Consequently, MCDA can be used to facilitate decision makers to organize the information obtained by the SD models and identify a preferred course of action [5].

MCDA is a branch of Operational Research that aids decision makers to structure a problem, assess alternatives/policies and reach an informed decision [7]. There are many MCDA methods and the choice of one over another depends on the familiarity

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with the method, the number of criteria, the number of stakeholders involved, the degree of compensation [8], the expected outcome [9] and the level of uncertainty of the problem in hand [10].

However, MCDA suffers from several limitations. First, the incorporation of the points of view of diverse stakeholders (supporting different preferences, different criteria etc.) creates substantial problems to an analyst. Second, the large number of MCDA methods makes it difficult to identify and use the most appropriate one. Finally, an MCDA methodology can be considered static, since the evaluation of the policies occurs at specific points in time [11].

In addition, uncertainty is inherent to both decision making and the methods used to facilitate it. Several sources of uncertainty can be identified:

- The difference between the real system "as is" and "as it is perceived to be"
- Sources of uncertainty in the measurement of data
- Uncertainties associated with every method
- The interactions with the decision-makers may cause distortion/ additional sources of uncertainty [12] [13]

As a result, the presence of uncertainty on many levels cannot be avoided. Nevertheless, the deployment of these methods is supposed to help decision makers despite uncertainty. Thus, the chosen policy must withstand uncertainty or be robust. In the international literature, several definitions of uncertainty exist, however, in the context of the present paper, the notion of robust conclusion is adopted; where robust means valid in all or most of the versions of the computations (combination of parameters, choices etc.) [14].

One approach to mitigate several of the disadvantages of SD and MCDA when used alone and direct the analysis to a more robust conclusion, is to integrate/combine the two methods [15]. This combination occurs with proposed policies being simulated with the SD model, the identification of criteria and their values from the variables of the SD model and the use of MCDA to provide a structured way of policy assessment [16]. Several attempts focused in the past on the combination of the two methods. In [5], SD and MCDA were combined to create a framework for more efficient performance measurement in organizations. In [6], the authors combined the two methodologies to study the impacts of a construction boom on an urban environment. In [16], the aim was to improve intermodal transportation sustainability. In [17] the purpose is to define appropriate strategies in hypercomplex socio-economic structures, while in [18] the methodologies were used to provide recommendations during a malpractice crisis.

However, there are several limitations in the aforementioned works. First, little effort has been devoted into incorporating different points of view of the system under study. Moreover, the uncertainties associated with each method, how to mitigate their effects and the static nature of MCDA are still a work in progress. Finally, the nature of robustness and its uses in the literature, makes it difficult to identify policies that are valid in almost all versions of the computations. Hence, several sources of uncertainty that could still be mitigated are still present.

The objective of this paper is to combine System Dynamics and MCDA with the purpose of simulating and identifying robust policies, while reducing the effects of several sources of uncertainty. The achievement of the objective will be accomplished by the development of a process, through a computer algorithm.

The rest of the paper is structured as follows: Section 2 provides the framework and details of the proposed process. To illustrate the process and assess its potential, a case study is reported in section 3. In Section 4 a discussion on the process and future directions of research are presented.

2 Methodology

This section provides an overview of the general framework of the proposed process and its specific details.

2.1 Exploratory Modeling and Analysis

As already mentioned, the large number of MCDA methods and the difficulties associated with the choice of one, led the research towards the notion of "satisfaction of the decision maker" [8]. This approach led to the use of more than one MCDA methods for validation purposes [19].

However, the use (or the integration) of more than one modeling methods, falls into the category of Exploratory Modeling and Analysis (EMA). EMA is a framework and a methodology that relies on computational power to analyze deep uncertainties [20]. In contrast to conventional predictive modeling, where a single model is used to predict a system's behavior, EMA acknowledges that building such a model is impossible in the context of long term policy analysis. Thus, under the EMA framework, different models of the same system can be built under different levels of detail, abstraction and points of perception. These models can then be explored under computational experiments in an effort to reveal insights of the uncertainties [21]. In the context of SD modeling, the EMA framework has been used in many works e.g. [15]; [21]. In the MCDA field a first effort to use EMA was performed in [19].
In the rest of this section, an overview of the proposed process is described.

2.2 Exploratory MCDA

The first step in the process is the development and simulation of an SD model that describes the system under study. Next, the policies are designed and simulated in the model and the generated results will provide the data for the next steps. These policies will be the same for all decision makers and known at the beginning of the analysis.

To take into account different perceptions of a system means to incorporate different points of view of the system "as is perceived to be". Hence, any number of decision makers can be identified, with a different set of criteria and preferences and the common policies will be evaluated separately for each one. That way it is secured that the system and the proposed policies will be examined under different perspectives and approaches on what consists a satisfactory solution.

Regarding the criteria, each one can be an element of the SD model (stock, flow or auxiliary) and its values will be generated by the simulations. Each decision maker can identify different sets of criteria and choose whether they need maximization or minimization.

In addition, more than one MCDA methods will be used for the evaluation of the simulated policies. These methods are: performance targets, SMART and PROMETHEE II. The choice of the particular methods covers the criteria of the classification proposed by [22] and their popularity [23].

For the performance targets, a policy is required to meet a minimum threshold on every criterion. Thus, each decision maker will provide a range of targets/thresholds for each of their respective criteria. Consequently, the policies will be tested for all possible combinations of these thresholds for all the criteria. When all the policies have been tested against all combinations of the thresholds, the process will calculate the number of times each policy failed i.e., at least one of the criteria failed to meet the threshold in each of the different combinations. The policy that failed the largest number of times along with the policies that have a number of failures that falls within a range of a certain percentage of the policy with the largest number of failures, will be excluded from the following steps of the analysis. The testing against the thresholds will be performed for every time step of the SD model; thus, the decision-maker could investigate which policies perform satisfactory on which points in (the simulation) time.

The limit can be chosen arbitrarily by each decision maker and by choosing such a limit, it is ensured that different number of policies might succeed the performance targets. For illustrative purposes in the context of this paper this limit is set to 75% of the policy with the largest number of failures. Furthermore, the limit could be changed to meet the needs of a particular analysis. For example, instead of two groups of policies, there could be three that are separated by the limits of 10%, 25% and the rest. In conclusion, the performance targets offer an opportunity of an initial screening of the simulated policies. Only those that appear robust against the combination of thresholds that each decision maker provides, will continue to the next steps of the analysis.

In SMART, a set of utility functions that are sufficient for most of the cases [24] are:

$$U(x) = a-b*\exp(-c*x) \tag{1}$$

$$U(x) = a+ b*(c*x) \tag{2}$$

$$U(x) = a +b*\exp(c*x) \tag{3}$$

The shape of the equations (1), (2) and (3) is concave, linear and convex respectively, indicating the attitude of the decision maker towards risk (risk averse, neutral and seeking, respectively). In the context of the proposed process, the decision-maker can provide the utility function for each criterion in the form of equations (1), (2) and (3), by providing a range of values for the parameters a, b and c-assuming that the shape of the equations does not change during the various time steps of the simulation. Moreover, a wide range of parameters can be provided and the process will calculate all possible combinations for every utility function for all criteria.

PROMETHEE II has been used despite the lack of the incomparability notion of PROMETHEE I, because the complete ranking facilitates the aggregation of the results with those obtained with the SMART method. In the context of the proposed process, the decision maker can provide the preference function for each criterion, assuming that it does not change for the analysis. However, the parameters of each preference function can change each time step. The decision maker can provide a range of values for each parameter (per time step) and the process will calculate all possible combinations and will produce all possible rankings.

Finally, regarding the weights, each decision-maker can provide a range of weights (values) for each criterion. The process will calculate all the possible combinations and will take into account only those combinations that lead to $\sum_i^n w_i = 1$, where n is the number of criteria. The notion of weight has different meanings for SMART (level of compensation among the criteria) and PROMETHEE (values of importance). Despite the different meaning, the same weights are used for both the methods in the process. The notion however, is not distorted; the large set of values that is swept during the calculations and the numerous combinations ensure that the preferences of the decision maker are met.

The exploratory MCDA process was developed with the Python programming language. The process is interactive and each time point, the decision maker provides the values that are asked by the program. Figure 1 illustrates an example of the questions asked by the program (ending at the question mark) and the various values that are required by the decision maker during the execution of the process.

```
Weight linspace for Crit4 (start, end, number)=? 0.15,0.75, 3
Give marginal utility function for Crit4=? Risk_neutral(a,b,c)
Factor a linspace values for Crit4 (start, end,number)=? (1, 2, 2)
Factor b linspace values for Crit4 (start, end,number)=? (0.5, 0.7, 3)
Factor c linspace values for Crit4 (start, end,number)=? (-0.01, 0.1, 5)
Give preference function for Crit4=? U_form_min(q)
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Fig.1 Example of the values that are required by the decision-maker during the execution of the process. For example, for criterion 4, the decision maker has decided to give a minimum weight of 0.15, a maximum of 0.75 and 3 values in between. The process will keep only those values that in addition to the other criteria, satisfy $\sum_i^n w_i = 1$, where n is the number of criteria

Finally, in accordance with the definition provided in the introductory section, the robustness of the simulated policies is studied under the notions of “similarity” or “closeness”. Since many rankings will be created (each one for a different combination of the input parameters), two sets of policies will be defined: the first one containing those that have a score higher or equal to the 75% of the policy with the highest score in the specific ranking and the second set will contain the rest of the policies. The limit is chosen arbitrarily for illustration purposes, but it could be modified to address the needs of a specific analysis.

Subsequently, it will be calculated how many times each policy appeared in each set and the policies with the highest number of appearances in the first set will be considered the most robust. Hence, the decision maker could have an overview not only of the consistently "good" or "bad" policies, but also of those that appear to be sensitive under the different combinations of parameters.

To conclude this section, it should be stated that the choices made for the development of the process might not be ideal. However, it is a pilot methodology that could be incorporated and transformed into a Decision Support System that could be adapted to the needs of the decision-maker and increase the confidence in the decision-making process. Figure 2 illustrates the flow of the proposed process.

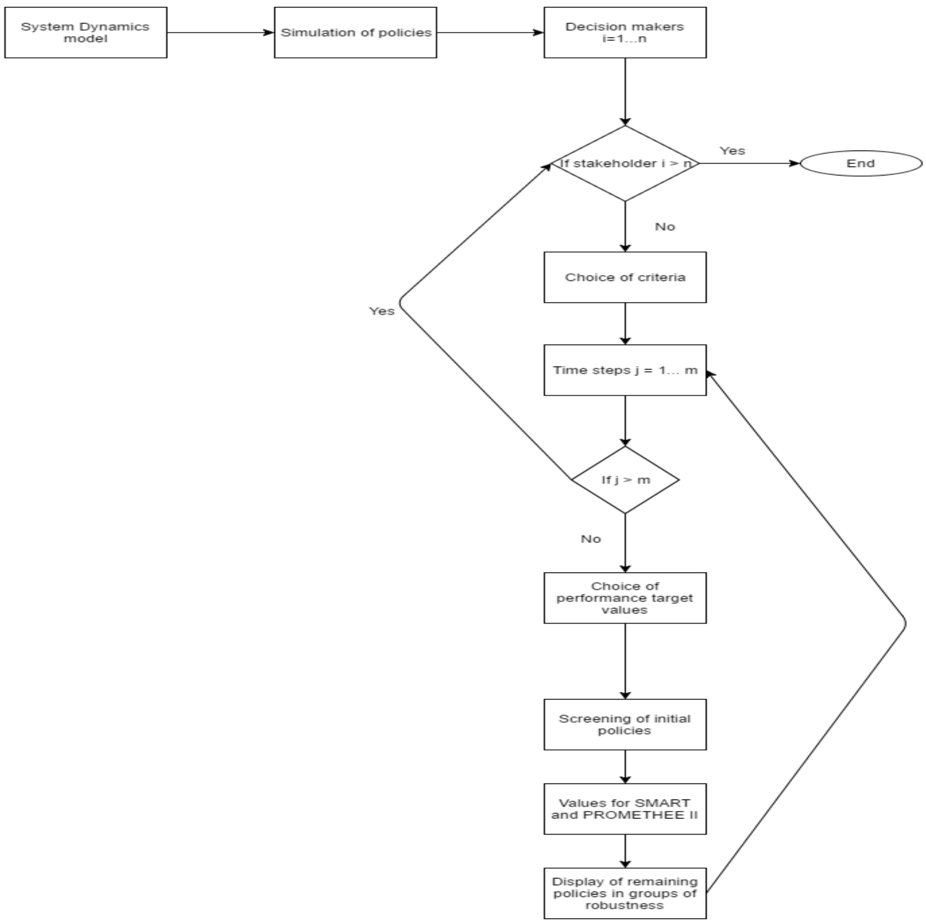

Fig. 2 Flowchart of the proposed process

3 Case Study

To illustrate the process, a model by Tsaples et al. [25] is used. The model is concerned with urban development and especially the stagnation that is caused by the depletion of the available land and the aging process. The model and the data are generic and experimental. Similar for the exploratory MCDA part of the analysis, which only illustrates the potential of the proposed process.

Many SD works regarding urban development exist and the developed model is based on the work by [26]. The simulated urban environment is divided into four zones (zone 1 to zone 4). Each zone has a housing sector, a business sector, a population of workers and unemployed and finally, a simplified economic system that is applied to the entire urban region, whose main elements are the three taxes (tax on income, tax on business and land value tax). The population of each zone (workers and unemployed) can move among the zones based on how attractive the destination zone is compared to the origin. Similarly, the population can move in and out of the entire urban environment based on the notion of relative attractiveness. Figure 3 illustrates the main elements of the model and the relationships among them. For example, the population of each zone affects and is affected by the housing availability in the zone; the larger the population in the zone the smaller the housing availability (a relation where an increase/decrease in one variable causes a decrease/increase in another is denoted by the - in the causal arrow), but as the housing availability falls, the zone becomes unattractive for the population, thus the population falls (that type of relation where an increase/decrease in one variable causes an increase/decrease in another is denoted with the + sign)

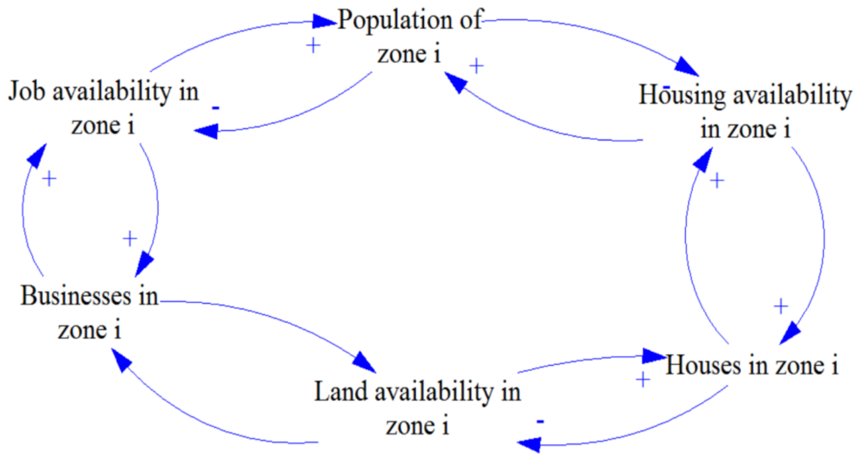

Fig. 3 Causal Loop Diagram of the main elements of the SD model

The policies that are simulated in the model are different combination of taxes in different points in the simulation time. They are summarized in the table below.

Table 1 Summary of the simulated policies tested in the SD model

	Land Value tax	**Property tax**	**Business tax**
alt1	0.1	0.1	0.1
alt2	0.2	0	0
alt3	0.1 + step(0.2,50)	0.1 – step(0.1,50)	0.1 – step(0.1,50)
alt4	0.1 + step(0.2, 25)	0.1 – step(0.1, 25)	0.1 – step(0.1, 25)
alt5	0.1 + step(0.2, 25)	0.1	0.1
alt6	0.1 + step(0.4, 25)	0.1 + step(0.2, 25)	0.1 + step(0.2, 25)
alt7	0.1 + step(0.4, 25)	0.1 – step(0.1, 25)	0.1 – step(0.1, 25)
alt8	0.1 + step(0.2, 10)	0.1 – step(0.1,10)	0.1 – step(0.1,10)
alt9	0.1 + step(0.4 10)	0.1 – step(0.1, 10)	0.1 – step(0.1, 10)
alt10	0.1 + step(0.2,10) +step(0.2, 50)	0.1 + step(0.2, 10) – step(0.3, 50)	0.1 + step(0.2, 10) – step(0.3, 50)

The names of the policies are identified in the first column and the rest of the columns show how the values for the three taxes can change during the simulation time. The numbers represent the tax as a percentage on the value of the entity (business, building etc.) on which they are applied. For example, *alt3* is a policy where the land value tax is increased from 0.1 to o.3 in simulation time of 50 (years), while the other two taxes are nullified at the same time.
Some indicative results are shown in the figure below.

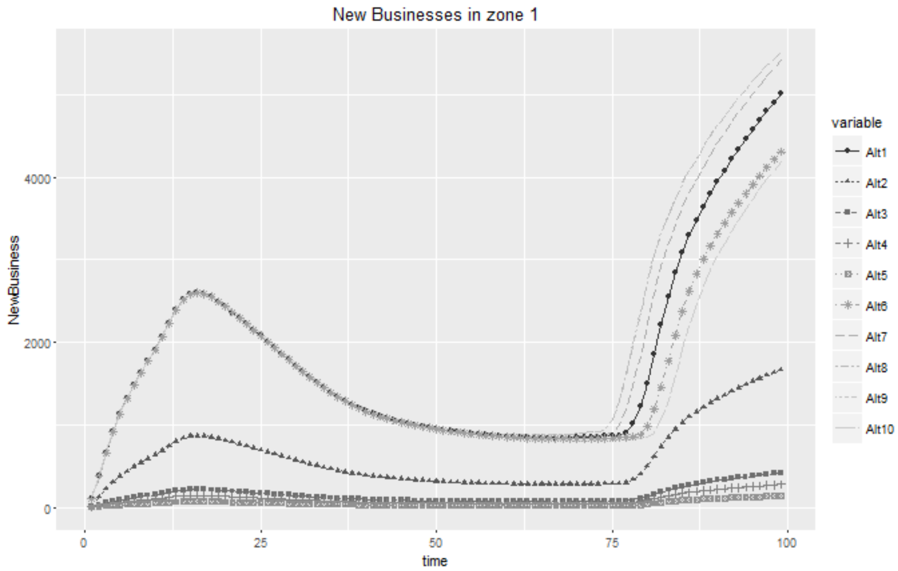

Fig. 4 New business under the different policies for zone 1

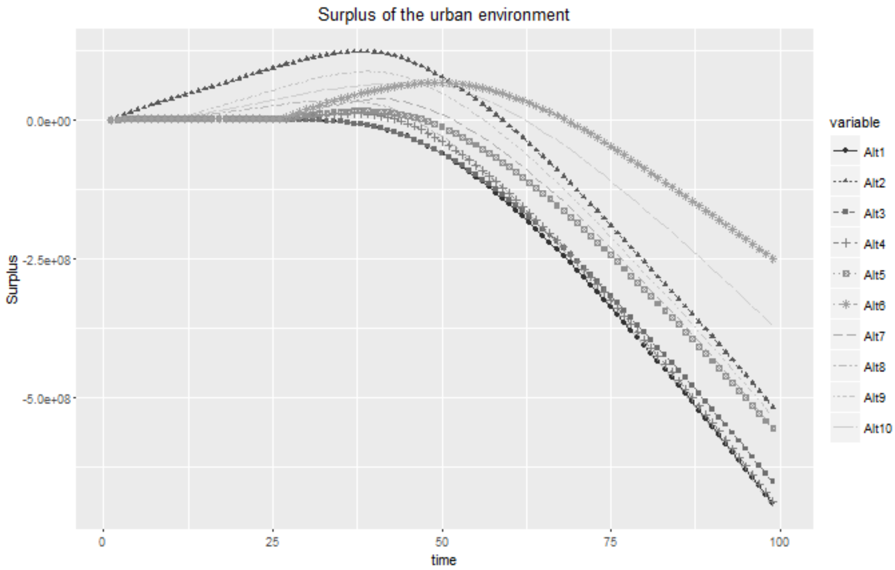

Fig. 5 Surplus of the urban environment for the different policies

The upper graph illustrates the number of new businesses that are created in a period of 100 years for zone 1 of the simulated urban environment. The different lines in the graph show how the number changes with the different simulated policies. Similarly, the graph on the bottom illustrates the behavior of the city's surplus for the same period under the different policies. Hence, it can be observed that deciding which policy is the most beneficial is not easy based solely on the results of the simulation; a situation which becomes more complex if more than one decision-makers, with different objectives, are considered.

The next part of the analysis is the evaluation of the policies with exploratory MCDA. The first part is the identification of the decision-makers and for the particular example, two are chosen: *CityHall* which represents the authorities of the simulated urban environment and *Business,* which represents the business community-assumed to directly influence the decision-making process and act as a whole.

For the two decision-makers different sets of criteria, whether they need maximization or not and the various values for the input parameters are identified. Table 2 summarizes the criteria for the two decision-makers.

Table 2 Summary of the criteria for the two decision-makers

	Criterion name	**Max or Min**
CityHall	Revenues	Max
	Jobs in the city	Max
	Unemployed immigration in zone 1	Min

	Unemployed population in zone 1	Min
	Slum houses in zone 1	Min
Business	New Business value in zone 1	Max
	Unemployed immigration in zone 1	Max
	Jobs in the city	Min
	Business tax multiplier	Min

The two decision-makers have different objectives, which are operationalized by different sets of (conflicting) criteria. Similarly, the input parameters cover a wide range of values for all methods used in the exploratory part of the analysis. Moreover, the times for which the evaluation of the policies is performed is at year 50 and 100 of the simulation time. Finally, the whole process was programmed in python.
The results for the decision-maker *CityHall* are depicted in figure 6.

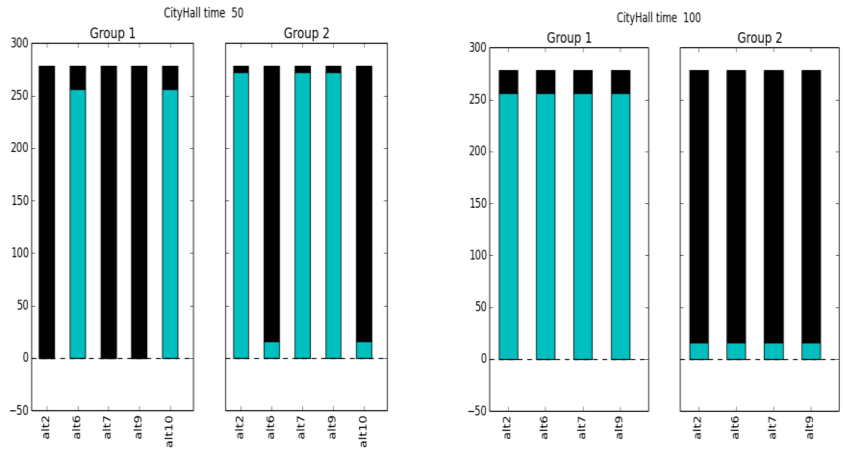

Fig. 6 Results for CityHall for time 50 (left) and 100 (right)

The graph on the left shows the two sets of policies for time 50 of the simulation. Firstly, it can be observed that from the 10 original simulated policies only 5 have passed the first stage of the performance targets. Second, the policies that passed are further divided on Group 1 (large number of high ranking) and Group 2. The color in the columns of each policy, shows the total number the policy appeared in Group 1. Thus, for *CityHall* on time 50 only *alt6* and *alt10* are preferred. However, *alt10* did not pass the performance targets for time 100. Hence, for *CityHall* the policy named *alt6* seems to appear robust under all combinations of parameters.

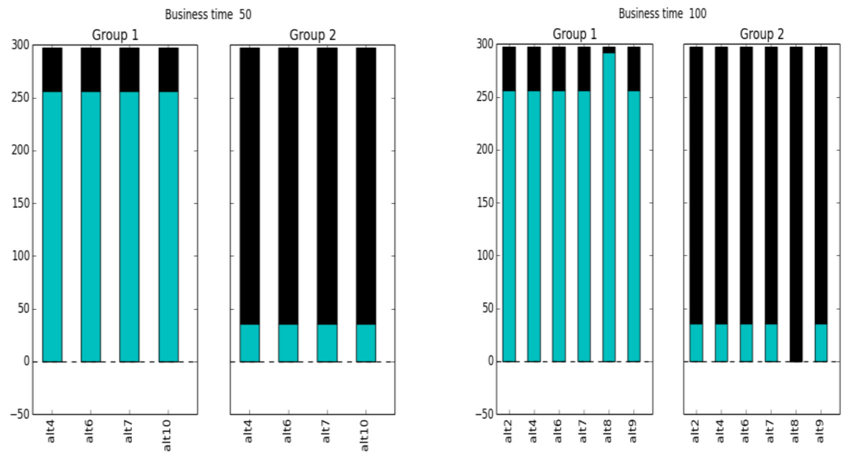

Fig. 7 Results for *Business* for time 50 (left) and 100 (right)

For *Business* on the other hand, only 4 simulated policies passed the performance targets at time 50 and all show similar robustness. For time 100 though, *alt10* once again does not pass the performance targets and two new policies are added. From those, the most robust is *alt8,* which did not pass the initial screening at time 50. The results for the two decision-makers are summarized in the table below.

Table 3 Summary of the results for the two decision-makers

	Time =50 years		Time = 100 years	
`	**Passed Performance targets**	**More robust**	**Passed Performance targets**	**More robust**
CItyHall	alt2, alt6, alt7, alt9, alt10	alt6	alt2, alt6, alt7, alt9	alt2, alt6, alt7, alt9
Business	alt4, alt6, alt7, alt10	alt4, alt6, alt7, alt10	alt2, alt4 alt6, alt7, alt8, alt9	alt8

It appears that the two decision-makers can find common ground if the process involves some negotiation. Otherwise, it can be observed that even for the same stakeholder across different points in time, there is no policy that is consistently the most robust.

For the proposed process, one of the limitations is on the very large number of combinations that could be generated if different stakeholders, with different objectives and at different times are inserted in the process. That overflow of information could lead to performance downgrade. However, a careful structuring of the decision problem could help decision-makers identify robust policies and investigate what are the common interests and points of friction with other parties that do not share their perception of the system.

The values and preference of each decision-maker had to inserted manually; this act of collaboration could help to keep preferences and objectives structured and well-organized. Thus, a decision-maker is not only presented with the results, but is forced to logically structure priorities, objectives and preferences [27].
Finally, the process that was presented can serve as the backbone of a Decision Support System that could be adapted to the needs of decision-makers or situations and be used to explore robust policies in hypercomplex situations.

4 Conclusions

The purpose of this paper was to investigate the integration of System Dynamics with MCDA under the framework of Exploratory Modeling and Analysis and to develop a process to address the disadvantages that exist when these methods are used individually and identify robust policies. A case study showed that the process could offer insights into the identification of robust policies and policies that could be points of friction among different parties in the decision-making process.
The choices that were not made during the development of the process show that there are different approaches to a structured decision-making process, while the choices that were made demonstrate potential avenues of future research and improvement.

Finally, the rise of computational power makes Exploratory Modeling and Analysis more feasible to use; although not without its limitations, it could offer great insights into the decision-making process and the paper is a demonstration of its potential.

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