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Configurable DSS for uncertainty management by fuzzy sets

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Abstract

In this paper, we propose a Configurable Model Based DSS capable of dealing with generic problems being modeled by Linear Programming (LP) and by Fuzzy Sets (FS) in a deterministic and uncertain context, respectively. The DSS assumes the transformation of the original model with fuzzy coefficients into an equivalent crisp model where the fuzzy coefficients are represented as alpha-parametric values, which can vary in a predefined interval based on the alpha parameter. Through the DSS, solutions obtained by solving the deterministic model and the equivalent crisp model for different alpha-values are compared based on the objectives and performance parameters defined by the Decision Maker (DM). Due to the uncertainty in data, expected performance of solutions can change under real situations. The DSS allows simulating future real situations by generating different projections of uncertain parameters. New performance of previously generated solutions can be tested under these hypothetical real situations by means a third model (Model for the Real Performance Assessment). Finally, the DM can choose the solution to be implemented taking into account the performance of solutions under planned and real uncertainty.

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1. Introduction

In today's dynamic and complex environment, it is necessary to provide Decision Makers (DMs) with powerful tools easily adaptable to changing problems in the presence of uncertainties. Most of these problems are unstructured in nature and require the use of reasoning and human judgment, representing the DSSs a solution. Though DMs

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should face with different and dynamic problem situations, Model-Driven DSSs are usually *ad-hoc* developed for specific situations making its reusability very limited. Each problem requires its own model that can require model changes along its use, making the original DSS unusable. Therefore, practitioners and researchers need more versatile DSSs capable to be adapted to changing problem situations in a dynamic and uncertain environment.

Indeed, the DSS proposed in this paper, emerges as a necessity of a national research project for which a variety of mathematical programming models for supporting the decision-making in different processes and scenarios were developed[1,2]. The Configurable Model Based DSS, dubbed as CFS-DSS, developed is capable of dealing with problems that can be modeled by linear programming (LP) and by fuzzy sets (FS) in a deterministic and uncertain context, respectively. Since these two optimization tools have been used to solve many real problems, the wide DSS applicability is ensured and reinforced by some novel characteristics adopted by the CFS-DSS such as:

- High DSS reusability by:
  - Solving different problems. The CFS-DSS separates the LP models from the own DSS. As a consequence, adaptation to new problems is made changing the input model file and their Data Base (DB), not being necessary any change in the DSS components.
  - Adapting existing models to the dynamic environment. Through the manipulation of the LP model files, the DM can add/delete new objectives, constraints and/or performance measures. Changes in the problem data are collected in the input DB associated with the LP models.
- Effective DSS capability for uncertainty management through:
  - Generating solutions in a deterministic and uncertain environment in any input data modeled by FS.
  - Assessing the quality of these solutions under planned and real situations. Due to uncertainty there is no guarantee that the result of the action (real performance) will be the one intended (planned performance), therefore it is necessary to assess the quality of the above solutions not only in planned situations but also in real ones where the uncertainty in the different parameters has been realized. This is achieved by projecting values of the uncertain parameters under different probability distributions simulating a real occurrence. This feature allows simulating the realization of different degrees and forms of uncertainty.
  - Comparing quality and robustness of different solutions based on customizable performance indicators defined by the DM.
- DSS capability of exporting all or selected outputs to .xls format extending the possibilities of analysis that could have not been contemplated in the initial DSS design.

The rest of the paper is organized as follows. Section 2, briefly describes the underlying mathematical principles on which the LP models used by the DSS are based on. Section 3 and 4 describes the DSS architecture and its functionalities, respectively. Finally, some conclusions are provided in Section 5.

2. Modeling uncertainty by fuzzy sets theory

Linear programming (LP) is one of the most frequently optimization technique applied in real-world problems[3]. However, any real-world situation involves a lot of uncertain parameters originated by different sources. The Fuzzy Set (FS) Theory provides a means for representing uncertainties[4] and is a marvellous tool for modeling uncertainty associated with vagueness, imprecision and/or lack of information on a particular element of the problem at hand, whenever statistical data are unreliable, or are not even available. Examples of FS applications can be found in[1,2]. Some Fuzzy DSS developed for specific situations can be consulted in[5,6] .

The proposed GFS-DSS deals with uncertainty in LP models with parameters assumed to be fuzzy numbers but whose decision variables are crisp. The solution methodology proposed by Jimenez et al.[3] is adopted as the basis of uncertainty management in the proposed DSS. These authors define an approach to convert the original model (1-3) with fuzzy coefficients on constraints into an equivalent crisp model by transforming constraints with fuzzy numbers (2) into equivalent crisp constraints (4-5).

Maximize

$$z = \sum_{j=1}^{n} c_j \, x_j \tag{1}$$

Subject to

$$\sum_{j=1}^{n} \tilde{a}_{ij} \, x_j = \tilde{b}_i \qquad i = 1,2, \ldots., m \tag{2}$$

$$x_j \geq 0 \qquad j = 1, \ldots, n \tag{3}$$

Can be expressed as follows:

$$\left[\left(1-\frac{\alpha}{2}\right)\left(\frac{a_{1i}+a_{2i}}{2}\right)+\left(\frac{\alpha}{2}\right)\left(\frac{a_{3i}+a_{4i}}{2}\right)\right]x \leq \frac{\alpha}{2}\left(\frac{b_{1i}+b_{2i}}{2}\right)+\left(1-\frac{\alpha}{2}\right)\left(\frac{b_{3i}+b_{4i}}{2}\right)$$
$$i = 1,2.., m, \mathrm{x} >= 0, \alpha \in [0,1] \tag{4}$$

$$\left[\left(1-\frac{\alpha}{2}\right)\left(\frac{a_{1i}+a_{2i}}{2}\right)+\left(\frac{\alpha}{2}\right)\left(\frac{a_{3i}+a_{4i}}{2}\right)\right]x \geq \frac{\alpha}{2}\left(\frac{b_{1i}+b_{2i}}{2}\right)+\left(1-\frac{\alpha}{2}\right)\left(\frac{b_{3i}+b_{4i}}{2}\right)$$
$$i = 1,2.., m, \mathrm{x} >= 0, \alpha \in [0,1] \tag{5}$$

This approach represents the fuzzy coefficients $\tilde{a}_{ij}$ and $\tilde{b_i}$ through a trapezoidal membership function. For instance if b= [b_1, b_2, b_3, b_4] where b_1 and b_4, represent the lower and upper limits of the interval, respectively, and b_2 and b_3 represent its intermediate numbers, its expected interval can be calculated as [(b_1+b_2)/2, (b_3+b_4)/2]. The fuzzy coefficients of the equivalent crisp model are represented as alpha-parametric values (α), which can vary in a predefined interval based on the alpha parameter. The value of the α parameter belongs to the interval [0, 1]. The parameter α represents the uncertain or the risk level of the fuzzy number in its respective variation range through its membership function. A high value of alpha represents a behavior closer to the deterministic one assuming a lower risk when modeling the uncertainty in the fuzzy number. A lower value of alpha considers more uncertainty and can achieve better results but risking more in the real execution of the final solution of the model. So, the DM desires to find a balanced solution between two objectives in conflict: to improve the objective function value and to improve the degree of satisfaction of constraints. The CFS-DSS will assist the DM in choosing the most suitable solution under uncertainty by allowing him/her to obtain the projected and real value of the objective function and other specified performance indicators under different values of alpha parameter. Next section describes in more detail the DSS architecture and functionalities to perform this analysis.

3. CFS-DSS Architecture

The CFS-DSS architecture follows the generic dialog-data-modeling architecture proposed by Sprage [7]. This architecture continues to evolve with new proposals for its components(e.g. [8]).Our proposal includes the following components (Fig. 1):

- Dialog components:
  - The user interface designed for providing a friendly interaction of the user with the DSS.
  - The user functionalities to provide the necessary interaction with the DB and the models.
- Modeling components:
  - The Model-base management system (MBMS) provides independence between specific models that are used in a DSS from the applications that use them.
  - The Solver management system allows solver selection as well as its setting parameters in order to improve solution performance.
- Data components:

- The Data Base Management System (DBMS) is in charge of the creation, access and update of data.
- Data is the collection of interrelated data organized to be use in the decision process. It includes Analytical Data as data required in the decision process, and Decision Data as information obtained in the decision process through the models' resolution.

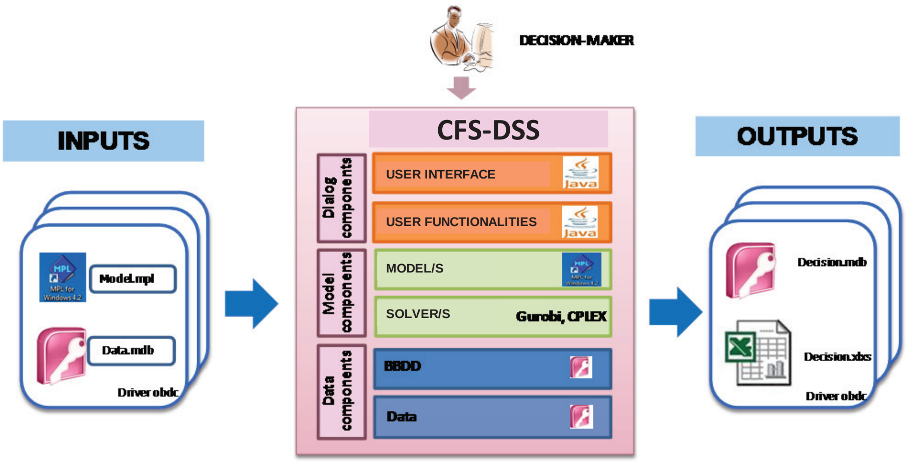

Fig.1. CFS-DS Architecture

Java v7 and the ECLIPSE platform have been used for developing the dialog components. MPL v4.2 has been selected to translate the LP models to a readable-machine format. The DSS allows choosing different solvers (CPLEX, Gurobi, etc.). DB in Access has been used to store the corresponding data.

4. CFS-DSS Functionalities

The CFS-DSS functionalities intend to provide the DM with support in understanding the system behavior and in choosing the most appropriate solution to be implemented taking into account the environmental uncertainty. In order to better understand the applicability of the CFS-DSS, sometimes we take as an example the master production planning problem described in [2].

4.1. Selection of Deterministic and Fuzzy Models

As it has been exposed before, one of the most interesting characteristics of the proposed DSS is its independency from the problem to be modeled. In these sense, the DSS can be used to solve different models in MPL format developed for supporting different processes. The DSS assumes that MPL files for the deterministic and the fuzzy models as well as their associate DB have been previously created. Therefore, this functionality allows performing the following actions:

- **Selection** of the **models** to be solved and its associate DB: two types of models are distinguished:
  - Deterministic Model: it is the model that assumes that all parameters are known with certainty
  - Fuzzy Model: it is the model dealing with uncertainty by means FS and transformed to an equivalent crisp model (as explained in section 2)
- **Modification** of the selected **models**: since many problems may be unstructured, this functionality assists the user in modifying preselected models. For this reason, this first DSS functionality allows for both, deterministic and fuzzy models, to edit, save them and save as new models after modifying them in an easily manner. For instance, in the deterministic model of [2] a new constraint limiting the maximum quantity to be backlogged (BLK_{ikt}) as a percentage of a demand at each period can be introduced by the managers. This change requires only the modification of the deterministic and uncertain mpl file without any change in the DSS itself.

- **Definition of** the **alpha parameter (**α) values for solving the Fuzzy Model: to do this, the user should specify the minimum and maximum value of alpha and the step of increments. The fuzzy model will be solved as many times as alpha values obtained from the minimum to the maximum value of alpha with increments equal to the defined step. For instance, in [2] the minimum, maximum and the step of alpha was set to 0, 1 and 0.1, respectively. As a consequence, the Fuzzy Model will be solved eleven times: for alpha equal to 0, 0. 1, 0. 2, 0.3,0.4, 0.5, 0.6, 0.7, 0.8 , 0.9 and 1.

4.2. Generate and Compare Solutions

Once the models and their DB have been loaded, it is time to solve them. Through this functionality, the DSS provide the DM with different solutions to the problem under consideration through:

- **Setting solver parameters**: Previously to solve the models, the DSS allows the DM to **choose the solver** and **adapt its parameters** (gap, maximum solution time, etc.) by means of the "Solver Parameters" option.
- **Solve models**: this option solves the **deterministic and the fuzzy model** for the different alpha values providing multiple solutions to be tested. The DM can also choose other solutions to be tested from the Solution Saved Option.
- **Compare solutions** in terms of their objective values, other performance indicators defined as MACROS in the MPL file and the value of decision variables
- **Export Solutions**: It is possible to export solutions to excel in order to perform more customizable analysis.
- **Save solutions**: at this point the DM can select one solution to be implemented finishing the process or can follow to the next DSS functionality in order to assess the real behavior of the solutions generated. For this last case, the DM can select all or only certain solutions.

4.3. Robustness Assessment

Until now, the DM is provided with several solutions and its performance in case the input data behavior remains as expected. But due to uncertainty, the real values of the uncertain parameters will not be known until the future periods become the actual ones. Furthermore, these real values can be close to those estimated by the deterministic or the fuzzy model or on the contrary, due to unexpected events, it may significantly differ from the original estimated values.

Therefore, the DM should be interested in quantifying the performance of a solution under simulated real situations obtained through projections of the uncertain parameters based on different probability distribution representing different levels of uncertainty. This analysis is made possible by means the Model for the Real Performance Assessment (see pp. 11 to 16 of [2].). This model is usually very similar to the deterministic one: the main difference stems from this last model considers the value of some decision variables of the deterministic and the fuzzy model as input data instead of decision variables. Once the deterministic and the fuzzy model have been solved, the values of the decision variables are known (e.g. quantity to be produced of each product). The purpose of the Model for the Real Performance Assessment is to compute the performance of each solution (e.g. profits as the difference among incomes from sales and backlog and inventory costs) under different projections of uncertainty parameters (e.g. real projected demand versus forecast demand). The differences between the mean real performance of a solution and the planned one should provide the DM with a measure of the robustness of each solution. Following with the example, once fixed the quantity to be produced, the sales, backlogs and inventory levels depend on the value of the demand at each time period that is considered to be uncertain. Different projections of customer demand will provide different values of the sales, inventory and backlog and, therefore, of the objective function. Finally, the DM should choose the solution to be implemented taking into account not only its planned performance but also its mean real performance and robustness. To implement this functionality several steps should be carried out by the DM:

- **Real Assessment Model definition:** it consists of selecting the .mpl file of this model and loading its associate DB. Furthermore, it is necessary to specify which values of the decision variables of the deterministic and fuzzy model, once they were solved, will be passed to the Real Assessment Model in order to evaluate their performance. It is worth noting that transferred decision variables of the deterministic and fuzzy models become input data for this third model. For instance, in the case of [2], the Auxiliary Model considers the sizing of lots not as decision variables but as an input parameter provided by the solution of the deterministic and fuzzy model

- **Real Scenarios Definition**: with the aim of testing the behavior of the selected solutions (values of the transferred decision variables) it is necessary to project real situations. Therefore the DM should:
  - Select which parameters of the Real Assessment Model will be modified. It is possible to choose any parameters except the decision variables values transferred to the Auxiliary Model. For the problem of [2] to simulate these real situations, projections of beta parameters ($B\beta_{ilt}$) for each MP lot and for each customer order size ($ordq_{ik}$) inside their membership functions were produced.
  - For each parameter selected, it is necessary to specify its distribution function and the number of the real projections to be made (n). Because multiple parameters can be chosen with different number of real projections, the DSS will assess each solution as a combination of all them. For instance, if uncertainty in beta parameters and customer order size is considered and, 8 and 5 real projections are made respectively, then 8x5=40 real simulated scenarios were projected.
- **Result Analysis**: This functionality provide additional information to the DM about quality and robustness of the selected solutions to make a final decision about the solution to be implemented.
  - **Real Performance Assessment**: The best, the worst and the mean value for the objective function as well as each performance parameter for selected solutions under all real scenarios is obtained.
  - **Robustness Assessment**: Finally, to assess the robustness of each solution a percentage of the difference between the planned objective value and the representative real one obtained as the mean of all real projection realized is obtained.

5. Conclusions

The proposed CFS-DSS allows DMs to deal with uncertainty for a broad range of real problems modelled by LP translated to the MPL format. Because of these models can be adapted during the decision process, two types of users exist: advanced and normal users. Advanced users need some mathematical modelling knowledge but not programming one, because the DSS itself does not change when dealing with different models. Normal users accept the models as they are and use the DSS to find satisfactory solutions to their problems under uncertainty. Therefore, CFS-DSS provides practitioners and researchers with a powerful tool for making right decisions and experiments.

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References

1. M.M.E. Alemany, Hanzel Grillo, A. Ortiz, Vicente S. Fuertes-Miquel, A fuzzy model for shortage planning under uncertainty due to lack of homogeneity in planned production lots, *Applied Mathematical Modelling* 2015; **39**: 4463-4481
2. M.I. Mundi, M.M.E. Alemany, R. Poler, V.S.Fuertes-Miquel, Fuzzy sets to model master production effectively in Make to Stock companies with Lack of Homogeneity in the Product, *Fuzzy Sets Syst.* 2015, doi:10.1016/j.fss.2015.06.009 in press.
3. M. Jiménez, M. Arenas, A. Bilbao, Linear programming with fuzzy parameters: an interactive method resolution, *Eur. J. Oper. Res.* 2007; **177** (3): 1599–1609.
4. M. Inuiguchi, J. Ramik, Possibilistic linear programming: a brief review of fuzzy mathematical programming and a comparison with stochastic programming in portfolio selection problem, *Fuzzy Sets Syst.* 2000; **111** (1): 3–28.
5. V Bugarski, T Bačkalić, U Kuzmanov, Fuzzy decision support system for ship lock control, *Expert Systems with Applications* 2013,**40**: 3953 – 3960
6. A Ustundag, A Budak, A web-based DSS for fuzzy distribution network optimization, *Journal of Enterprise Information Management* 2015; **28** (2): 260 – 274.
7. R.H. Sprague, A Framework for the Development of Decision Support Systems, *MIS Quarterly* 1980; **4** (4): 1-26
8. D. J. Power, R. Sharda, Model-driven decision support systems: Concepts and research directions. Decision Support Systems (2007), **43**(3), 1044-1061.