

# Including Multi-Objective Abilities in the Hybrid Intelligent Suite for Decision Support

Diogo F. Pacheco, Flávio R. S. Oliveira and Fernando B. Lima Neto

**Abstract**— Hybrid intelligent systems (HIS) are very successful in tackling problems comprising of more than one distinct computational subtask. For instance, decision-making problems are good candidates for HIS because of their frequent dual nature. This is because supporting decision-making most often involves two phases: (i) forecasting decision scenarios and (ii) searching in those scenarios. In addition to reducing the inherent uncertainty and effort in decision making, previous works in the area of decision support have shown that some of the inconveniences of the ‘Inverse Problem’ can be overcome by the use of *Hybrid Intelligent Decision Suites* (HIDS). This paper extends HIDS by including a third module that deals with multi-objective (MO) tasks through Evolutionary Multi-Objective Optimization (EMOO). This EMOO module helps by creating the Pareto front for each forecast scenario produced by Artificial Neural Networks (ANN), acting here as the predictive engine of the decision support system. In order to interface better with decision makers, we use a fuzzy-heuristic module of the original HIDS. To test this concept we have applied our new approach to two distinct problems: (1) diagnosis of heart diseases (of the *proben-1* data-set) and (2) automobile feature selection (of *UCI* data-set). Results have indicated that this new ensemble of intelligent techniques enhances the quality of decision making.

## I. INTRODUCTION

The frenetic dynamic of current business-to-market relations makes further decision-making even more difficult [1]. Regarding evaluation, as with any other activity in the business environment, decisions have a quality aspect associated with them. In addition to producing a favorable impact on companies, good decisions are (i) made speedily, (ii) consider all objectives parsimoniously and (iii) do not demand too many resources (*e.g.* reasoning time) of the decision makers [2]. And this is precisely the problem concerning current managerial decisions; as they become more complex they tend to involve many objectives, require extra time, are often biased towards a subset of objectives and are cumbersome for decision makers [3].

As computers get faster and cheaper, and the availability of efficient intelligent techniques grows steadily, the existing difficulties in decision-making – commented on above –

may be dramatically reduced [4]. That is, users want to be helped to solve their real-world problems, with accuracy, expediency and without great effort on the man-machine interface [5]. This great challenge translates into complex multi-dimensional combinatorial search problems in large search spaces; the inverse problem is an extra complication to deal with as well.

If one assumes that the inverse problem could be abstracted, decision-making may be reframed as a heuristic search where decision factors have to be acted upon for the materialization of the desired results. The *Hybrid Intelligent Decision Suite* (HIDS) proposed by Lima Neto *et al.* [6] and earlier work by Oliveira *et al.* [33] were shown to be effective in fulfilling this role for decision makers. From this perspective, the decision maker would only need to provide the goals to be achieved and specify his/her feeling about the relative importance of the objectives.

One last key aspect to be commented upon is the abovementioned input provided by the decision makers. They can focus either on variables or objectives [3]. This slight change of perspective is very important for modelers and must be handled with care within decision support system. Examples of this are:

- I. Focusing on variables: doctors may want to improve patient prognosis by prescribing medicines based on patients’ previously known clinical indicators. Notice that there is no change of importance among the indicators in this case;
- II. Focusing on objectives: car designers may aim at increasing the appeal of their products by concentrating on engine power rather than fuel consumption. Notice that here one of the objectives receives increasingly more attention than the other.

These kinds of challenge pose interesting research problems for several areas of knowledge, particularly to computational intelligence, where researchers are working on new models, frameworks and techniques to improve: (i) acquisition of features of the problem being modeled, (ii) mimicking of the dynamics of the system and (iii) adaptation to environmental changes. Some examples of Intelligent Computation techniques used in decision making are: artificial neural networks [7], evolutionary computation (EC) [3] and fuzzy logic (FL) [8].

In decision situations, it is often difficult to one find readily available information for decisions to be taken; hence the use of computational tools is frequently mandatory. For this purpose, ANNs have been successfully applied in data correlation, classification, prediction and

Diogo F. Pacheco, author, is with the Department of Computing and Systems, Polytechnic School of Engineering, University of Pernambuco, Brazil, (e-mail: dfp@dsc.upe.br).

Flávio S. R. Oliveira, author, is with the Department of Computing and Systems, Polytechnic School of Engineering, University of Pernambuco, Brazil, (e-mail: frso@dsc.upe.br).

Fernando Buarque de Lima Neto (SM’07), the corresponding author, is with the Department of Computing and Systems, Polytechnic School of Engineering, University of Pernambuco, Brazil, (e-mail: fbln@dsc.upe.br).

information extraction [7].

Additionally, real problems commonly: (i) aim at conflicting objectives, (ii) impose a number of constraints and (iii) by definition, have several optimal solutions. In line with this, traditional computing applications are used to simplify or make different interpretations of a given problem, but they can only cope with single solutions. Alternatively, EC is able to deal with these problems in a much fairer fashion, where all the objectives are prudently contemplated [3]. As a result, one may obtain a set of optimal solutions (from a Pareto front) to the problem.

With all these techniques at hand, it would be highly desirable to build a decision tool that could (computationally) suitably handle features of real problems such as their continuity and imprecision. The use of linguistic variables as proposed by FL can significantly simplify the man-machine interaction [8].

The *Hybrid Intelligent Suite for Decision Support* aids decision making by integrating predictive techniques with search and optimization techniques. However, users have to parameterize (*i.e.* guide) the search by transforming complex problems into single objective optimizations. If the initial hypothesis used to guide the search is wrong, or if it is necessary to evaluate different decision scenarios, a whole new computation has to be carried out. This approach is rather expensive for multidimensional decisions.

In this paper two major improvements were made to HIDS. The first improvement was to incorporate real multi-objective optimization capability into HIDS. As a result, the decision and the objective spaces can now be explored and exploited impartially, in an  $n$ -dimensional way (*i.e.* considering all objectives involved in the problem formulation). The second improvement to HIDS was the addition of a heuristic module that interfaces manager preferences and system suggestions on the best option among the optimal set found by the Multi-Objective (MO) module.

The *Hybrid Intelligent Suite Decision Support with Multi-Objective Abilities* (MO-HIDS) was tested on the same problems used to validate the previous version of HIDS. The results indicate that MO-HIDS outperforms the vanilla HIDS. MO-HIDS was also effective in dealing with more complex problems (*i.e.* it can cope with more decision variables).

The remaining part of this paper is organized as follows: in section 2 there is a brief review of intelligent techniques applied to decision making. In section 3, MO-HIDS is detailed and compared with its previous version – HIDS. Experimental results are then presented in section 4. Section 5 contains the conclusions of this paper and a list of future work.

## II. BACKGROUND

Decision Support Systems (DSS) have been evolving for more than forty years [10]. The trajectory of research performed in this area since the 1960s has been described in

several early works [10], [11], [12]. However, this section aims to show how intelligent techniques have been contributing to decision-making problems.

### A. Artificial Neural Networks

Artificial Neural Networks (ANN) as universal function approximators can help decision makers in future scenario formulation and in information generation [7]. Examples of recent successful applications are management of urological cancer [13], prediction of vesicoureteral reflux in children [14], business failure prediction [15], pharmacokinetic data mining and regimen adequacy prediction [16] and classifying ecological status [17].

### B. Evolutionary Computation

The ability to extinguish unfit individuals present in Evolutionary Algorithms is responsible for successful applications of multi-objective optimization (EMOO). It can aid managers by providing sets of solutions representing optimal trade-offs between all evaluated objectives. Hence the decision maker can take an informed decision [3]. Recent successful applications are optimization of predictive ecosystem models [18], airline schedule recovery [19], optimization of solid waste flows [20], scheduling electric energy [21] and supporting a sugarcane harvest [22].

### C. Fuzzy Logic

The concept of fuzzy membership functions enables the construction of computer applications that deal well with the uncertainty present in most real-world problems [8]. Therefore, by using FL, one avoids linguistic mistakes of man-machine interfaces. Good examples of recent applications of FL in decisions are: astronomical pipeline processing [23], brain tumor characterization [24], logistics outsourcing [25], safety management systems for airlines [26] and wildlife translocations [27].

### D. Hybrid Intelligent Suite for Decision Support

HIDS [6] combined two intelligent techniques to help in minimizing the effects of the “inverse problem” during decision making. As a result HIDS reduced uncertainty and improved the quality of decisions.

Fig. 1 shows how a decision can be decomposed. Notice that  $\mathbf{D}_p$  represents the set of possible solutions for a specific problem. Each individual decision  $\mathbf{d}_i$  is composed of components  $\mathbf{c}_j$  made up of attributes  $\mathbf{a}_i$ .

Each  $\mathbf{d}_i$  could be assessed by the summation of relevance of each of its components, given by Eq.1. The overall assessment of a decision is given by Eq. 2. Notice that each  $\mathbf{f}_i$  represents one objective function of the problem (predicted by the ANN). The relevance of components is directly influenced by  $\mathbf{w}_i$ , the decision maker preferences.

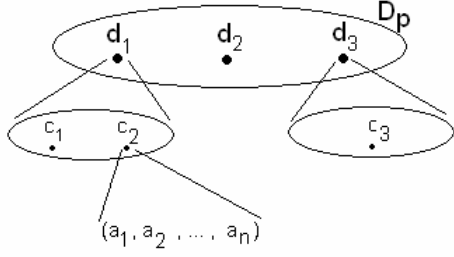


Fig. 1 Decision ontology as proposed by Oliveira *et al.*[33] Each decision can be decomposed as components and their attributes (*i.e.* variables).

$$R(c_j) = \frac{\sum_{i=0}^n w_i * f_i(a_i)}{\sum_{i=0}^n w_i} \quad (1)$$

$$F(d_k) = \sum_{j=0}^n R(c_j) \quad (2)$$

In HIDS the distinction between *factors* and *indicators* of a decision allows the suite to generate future scenarios and to perform a search for an optimum decision within them. The criterion used was sorting all decisions according to their strength (*i.e.* quality). The modules of HIDS are presented in Fig. 2. Because of its organization in modules, different intelligent techniques can be applied without major impacts on the system. However, vanilla HIDS uses weights ( $w_i$ ) to guide the search, that is, it is only able to perform single objective optimizations.

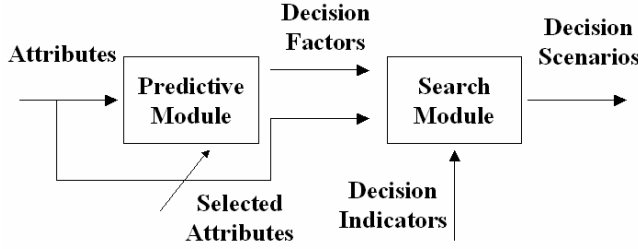


Fig. 2 Overview of vanilla HIDS, extracted from [6].

### E. The Inverse Problem

In decision making the inverse computation of a given effect as function of decision factors would be greatly beneficial. However, this backward computation is sometimes hard to carry out. Fig. 3 presents two examples in which domain sets are mapped into image sets. Using this analogy, a decision (image set) can be reached based on a number of factors (domain set). The problem arises when the same decision is reached from different factors (*i.e.* causes); decisions not reached are normal in real situations.

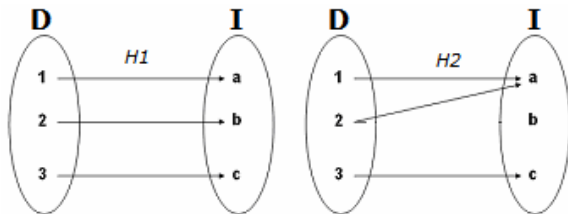


Fig. 3 Schematic view of two functions mapping sets **D** (Domain) into sets **I** (Image). *H2* leads to the inverse problem. Adapted from [6].

## III. CONTRIBUTION

Evolutionary Multi-Objective Optimization (EMOO) presents many advantages for modeling real problems when compared to systems based on preferences [3]. Accordingly, this paper proposes some modifications in HIDS enabling it to perform multi-objective searches.

### A. Abstract Model for Multi-Objective Decision Making

We assume that decision set **D** is composed of feasible ( $D_f$ ) and unfeasible decisions ( $D_u$ ). Focusing on objectives instead of variables, each decision  $d_i$  encompasses a set of objective functions  $o_i$  that are dependent of one or more decision variables; as seen in Fig. 4, the new abstract decision model extends the idea presented in Fig. 1.

Conceptually there are two possible search spaces when dealing with MO: (i) the decision (variables) space and (ii) the objective space [3]. In the decision space there are boundaries for each variable as opposed to constraints for the objective space. For instance, constraints may rule out decisions (*i.e.* make them unfeasible). This is represented as the  $D_u$  regions in Fig. 4.

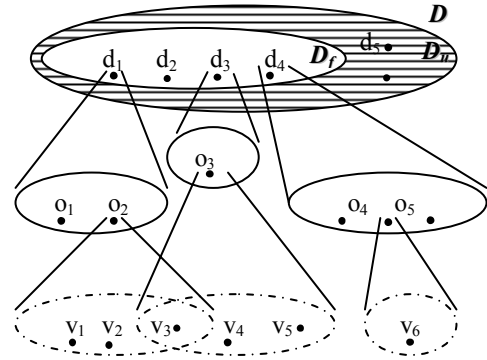


Fig. 4 New decision ontology that focuses on objectives rather than variables. Each feasible decision can be decomposed as objective functions and their decision variables.

The implications of these two approaches to decision spaces are huge, especially when components and objectives are compared. In HIDS, components were calculated by a single equation that aggregates weighted-functions, while in the new approach, objectives remain as functions. Thus, any component of HIDS could be directly compared, while objectives of MO-HIDS are not meant to be compared.

As decision evaluation is the sum of the values of its components, in vanilla HIDS, they could be ordered and subsequently selected. In the current approach, since objectives cannot be compared individually, the comparison must be at the decision level, using the dominance concept [3]. Therefore, a set of optimal solutions (decisions) can be achieved, representing trade-offs between functions. That is, all objectives are considered parsimoniously.

### B. Including Multi-Objective Abilities in HIDS

The direct impact of our new approach is the elimination of Equations 1 and 2, in other words, the elimination of  $w_i$ . Notice that, in doing that, the decision maker has to select a

single solution within a set of optimal ones. This might be seen as a setback. However, Deb has proved that the use of high level preference information after optimization (*a posteriori* decision) is better than the opposite (*a priori* decision) [3]. The explanation is simple, the latter makes it possible to measure and compare the best solutions without outside interference. As a bonus, different decision scenarios can be provided easily, without the additional cost of re-running the application.

Another difficulty discussed in this paper is the fact that selecting the best solution can be difficult or time consuming, depending on the size of the optimal set and the complexity of the problem (*i.e.* number of variables). To aid decision makers with this last step in the decision process, a third module – the heuristic module – was added to the suite. This module was conceived with the aim of helping in the selection of one decision from the Pareto front produced by the MO search module.

To this end, the weights discarded in the former search module (of vanilla HIDS) are now put back to work in this *a posteriori* search. To make it more real, nominal preferences were considered instead of only crisp ones, *i.e.* fuzzy logic was included in this last module.

The heuristic module incorporates the expertise of decision makers and uses problem-dependent metrics to choose the best decision. Fig. 5 presents the hybrid structure of MO-HIDS.

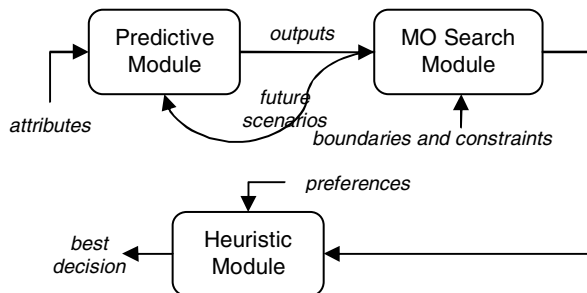


Fig. 5 Overview of the new HIDS with multi-objective decision support abilities.

#### IV. EXPERIMENTS

This section details the implementation, validation and evaluation of two custom applications of MO-HIDS. Both applications are used as proofs of concept for the proposed framework. As this paper proposes modifications in HIDS the same benchmark problems used earlier are simulated here to confront the benefits of the new approach. For this evaluation, a number of metrics were defined considering the inverse problem and the need for minimal changes in variables; these metrics are detailed in subsequent subsections. The predictive module was calibrated with a Multilayer Perceptron trained and tested in the same manner (*i.e.* architecture, parameters, patterns, etc) as in Lima Neto *et al.* [6] and Oliveira *et al.* [33].

All modules were supported by the jMetal framework [9]. jMetal versions of two state-of-the-art algorithms were used in the problems tested: NSGA-II [28] and SPEA2 [29].

These were configured using the same parameters, as shown in Table I, where  $n$  represents the number of decision variables. The operator for crossover was SBX and for mutation, polynomial [30]. The stop criterion was the number of function evaluations. The attribute archive size is only applicable to SPEA2.

TABLE I  
PARAMETER SETUP FOR NSGA-II AND SPEA2 IN TESTED PROBLEMS

Parameter	Value
Crossover probability ( $p_c$ )	0.9
Mutation probability ( $p_m$ )	$1/n$
Crossover distribution index ( $n_c$ )	20
Mutation distribution index ( $n_m$ )	20
Population size	100
Archive size	100
Function evaluations	25000

The heuristic module aims at choosing the best decision according to the preferences of decision makers. To achieve this, a membership degree selection process was employed, inspired in Fuzzy Logic concepts. Each variable considered in the problem can be subject to the following degrees of change: (i) very low, (ii) low, (iii) moderate and (iv) high. The main advantage of using linguistic variables is to approximate how well a decision maker thinks (and speaks) to the way its system operates.

This classification is carried out according to the percentile value of variation for each variable, which is translated into membership degrees. The highest membership degree indicates the classification of each variable. Ranges for each variable are calculated differently, affording an additional level of adaptability to the heuristic module.

For example, a physician may say that it is possible to achieve a moderate degree of change in the clinical indicator of patients. This means (for the heuristic module) that decisions classified as having moderate, low or very low degrees of change in that indicator will all be considered and those classified above, *i.e.* having a high degree of change, will be discarded.

After the initial classification, all remaining decisions, which are in agreement with the preferences of the decision maker, will be ordered according to the existing objectives. This gives the decision maker the decision best deemed to tackle the problem.

##### A. Test Problem Definition

Two classes of benchmark problems were selected with two decision tasks each, as proof of concept to validate the proposed suite. Two of them are exactly the same as those used to validate HIDS and allows us to make a valid comparison between vanilla HIDS and MO-HIDS. The other two are advanced versions of the previous problems and allow us to evaluate issues concerning robustness and scalability. The problems selected are:

1) *Cardiologic Diagnosis*: this problem was defined from the public benchmark database *Heart* of Proben1 [31]. This database is composed of collection of medical data such as: age, sex, chest pain type, fasting blood sugar, at-rest electrocardiography results, and death risk level.

The problem can be briefly explained as possible outcomes of cardiac patients when they visit their physicians for an assessment. From clinical exams the medic has to provide a prognosis about the patient's death risk level. This prognosis is frequently based on his experience and can be affected by his current perception of patient status. According to his beliefs, the physician must try to reduce the cardiac risk by prescribing the right treatments for each patient.

For an effective treatment it would be desirable for the medic to know how each attribute influences the level of death risk and how much he should manipulate them. For example, considering two patients with similar clinical indicators but one with diabetes, despite knowing that reducing blood sugar would be very helpful, other actions would probably be advisable to achieve success in the treatment of the diabetic patient.

As mentioned above, there were two versions for this problem. The (variable) reduced version aims at reducing the death risk with minimal changes in only three variables: serum cholesterol (*sc*); maximum heart rate (*mhr*); and chest pain type (*cpt*). This approach was simulated when HIDS was introduced [6], but its formulation only allowed independent manipulations on each of the problem variables.

The (variable) expanded version, simulated here, aims at reducing death risk with minimal simultaneous changes in the previous five clinical data: at-rest blood pressure (*rbp*); serum cholesterol (*sc*); maximum heart rate (*mhr*); ST depression induced by exercise relative to rest (*oldpeak*); and the number of major vessels colored by fluoroscopy (*mvc*). Chest pain type management was removed to make the problem handling more realistic, since this change could be achieved as a result of the manipulation of other variables.

2) *Automobile Market Evaluation*: this second problem was devised using data from another public benchmark, the UCI repository - *Automobile Database* [32]. It is composed of various car characteristics (*i.e.* specifications), such as insurance risk rating and normalized losses in use as compared to other cars. Other characteristics are brand, fuel-type, number of doors, bore, horse power, among others.

The decision problem is as follows: periodically, automobile factories create new car models and these models are the result of complex studies that try to satisfy consumers' needs, especially matching car price to the purchasing power of target users. Supported by these studies, car designers create conceptual cars. For these prototypes to enter regular production their prices have to attain the expected target price, profit margins and low risk levels on release. To achieve this, car designers greatly need simulation tools able to make reliable final price estimates. One advantage of such tools is the presence of analytical capabilities to estimate how slight changes in the car specification would affect the final product price.

This problem also has two versions. The (variable) reduced version proposed in HIDS [6], which can only perform independent manipulations, and the (variable) expanded version which handles the problem more realistically. The first of these attempts to reduce the difference between the final price – predicted by the ANN module – and the desired

price through manipulations on three model specifications: city fuel consumption (*mpg*); horse power (*hp*); and peak RPM (*pr*). The second formulation of the problem considers ten more specifications. The thirteen simultaneously considered specifications are: wheel base; car length, width and height; weight; engine size; bore; stroke; compression ratio; horse power; peak RPM; and city and highway fuel consumptions.

### B. Applying MO-HIDS to Test Problems

Both test problems have similar goals. Their objective functions measure attribute variations as in Eq. 3 and can be described as the mean magnitude of relative change. Where  $a_{i-1}$  represents the original value for attribute and  $a_i$  represents the new value;  $abs(.)$  is the absolute number of the operation.

$$f_i(a_i) = \frac{abs(a_{i-1} - a_i)}{a_{i-1}} \quad (3)$$

1) *Cardiologic Diagnosis*: in both versions the same two different patients were used as in the vanilla HIDS evaluation. They have different clinical data and death risk levels. Table II presents clinical details of Patients A and B.

TABLE II  
CLINICAL DATA OF PATIENTS UNDERGOING TO CARDIOLOGIC DIAGNOSIS

Clinical data	Patient	
	A	B
Resting blood pressure ( <i>rbp</i> )	0.4167	0.2917
Serum cholesterol ( <i>sc</i> )	0.3327	0.0000
Maximum heart rate ( <i>mhr</i> )	0.4667	0.1467
ST depression induced ( <i>oldpeak</i> )	0.2955	0.1818
Number of major vessels colored ( <i>mvc</i> )	0.0000	0.0000
Chest pain type ( <i>cpt</i> )	asymptomatic	
Death risk level	0.6371	0.7123

2) *Automobile Evaluation*: as before, we chose the same two prototypes used to validate vanilla HIDS, the car specifications are listed in Table III.

TABLE III  
SPECIFICATION OF PROTOTYPES IN AUTOMOBILE MARKET EVALUATION

Specifications	Prototype	
	A	B
Wheel base	90.00	90.00
Car length	190.00	190.00
Car width	65.00	70.00
Car height	50.00	59.00
Curb weight	2000.00	3000.00
Engine size	250.00	90.00
Bore	3.10	2.90
Stroke	3.00	3.00
Compression ratio ( <i>cr</i> )	13.00	13.00
Horse power ( <i>hp</i> )	140.00	180.00
Peak RPM	5000.00	4500.00
City consumption ( <i>c-mpg</i> )	20.00	15.00
Highway consumption ( <i>h-mpg</i> )	30.00	26.00
Estimated price ( <i>ep</i> )	13545.32	19225.41
Desired price ( <i>dp</i> )	12500.00	18000.00

An example of constraint considered is shown in Eq. 4, where  $fp$  is the final price,  $dp$  is the desired price and  $ep$  is the estimated price.

$$fp = dp \pm [0.3 * (ep - dp)] \quad (4)$$

Decision variables limits for both problems are presented in Table IV. In the *Cardiologic Diagnosis* the (variable) reduced version handles four minimizations while the

(variable) expanded version deals with six objective minimizations. In the *Automobile Market Evaluation* the (variable) reduced version handles four minimizations while the (variable) expanded version deals with fourteen objective minimizations. The additional objective minimization is risk level associated with each decision.

TABLE IV  
DECISION VARIABLES BOUNDARIES

Lower limit	Attribute	Upper limit	Problem
0.20	<i>Sc</i>	1.00	<i>Cardiologic</i>
0.00	<i>Mhr</i>	0.80	<i>Diagnosis</i>
86.60	<i>wheel base</i>	120.90	
141.10	<i>Length</i>	208.10	
60.30	<i>Width</i>	72.30	
47.80	<i>Height</i>	59.80	
1488.00	<i>curb weight</i>	4066.00	
61.00	<i>engine size</i>	326.00	
2.54	<i>Bore</i>	3.94	<i>Automobile</i>
2.07	<i>Stroke</i>	4.17	<i>Market</i>
7.00	<i>Cr</i>	23.00	<i>Evaluation</i>
48.00	<i>Hp</i>	288.00	
4150.00	<i>RPM</i>	6600.00	
13.00	<i>c-mpg</i>	49.00	
16.00	<i>h-mpg</i>	54.00	
12186.40	<i>final price A</i>	12813.60	
17632.38	<i>final price B</i>	18367.62	

### C. Performance Metrics

As MO-HIDS proposes to aid in the whole decision-making process, only the final decision chosen by the Fuzzy heuristic module is to be evaluated. In this way and according to each problem tested, performance metrics considered are reduction of main objectives (*i.e.* *problem-1*: death risk and *problem-2*: price difference) combined with minimal changes in the other variables.

### D. Experimental Results

For each problem, 100 independent simulations were carried out. The new results include mean value and standard deviation in percentile.

1) *Cardiologic Diagnosis*: Table VI shows compatibility values according to the original results presented in Table V.

TABLE V  
HIDS ORIGINAL RESULTS FOR THE *CARDIOLOGIC DIAGNOSIS*

Pat.	<i>cpt</i>	<i>sc</i>	<i>mhr</i>	<i>Risk Level</i>
	0.00	0.00	<b>66.10</b>	0,5535
A	0.00	<b>51.27</b>	0.00	0,5983
	<b>100.00</b>	0.00	0.00	0,2567
	0.00	0.00	<b>427.97</b>	0,5267
B	0.00	<b>28.33</b>	0.00	0,7049
	<b>100.00</b>	0.00	0.00	0,4600

TABLE VI  
COMPATIBILITY TEST FOR THE *CARDIOLOGIC DIAGNOSIS*

Pat.	<i>cpt</i>		<i>sc</i>		<i>mhr</i>		<i>Risk Level</i>	
	mean	$\pm \sigma$	mean	$\pm \sigma$	mean	$\pm \sigma$	mean	$\pm \sigma$
	0.00	0.00	2.08	1.61	<b>45.82</b>	<b>18.53</b>	0.5801	2.36
A	0.00	0.00	<b>15.68</b>	<b>13.34</b>	2.72	2.23	0.6238	1.04
	<b>151.00</b>	<b>87.03</b>	0.70	1.15	1.47	2.14	0.2509	1.19
	0.00	0.00	1.37	1.12	<b>350.56</b>	<b>92.31</b>	0.5647	4.30
B	0.00	0.00	<b>3.63</b>	<b>7.34</b>	3.51	6.64	0.711	0.32
	<b>135.00</b>	<b>67.23</b>	0.76	1.34	10.08	13.75	0.4572	5.02

Since HIDS performed only one-dimensional searches, values highlighted from Table V to Table VIII indicate the explored dimension for each experiment. This exploration simulates the evaluation performed by doctors when trying to find the best line of treatment for a given patient.

For these compatibility tests, the heuristic module of MO-HIDS was parameterized, allowing a high degree of change for the highlighted values and a very low degree for the others. The results are comparable, but MO-HIDS was able to achieve similar final values of Risk Level, using smaller changes in control variables, except for the *cpt* value. This could be explained by the fact that decisions selected as best by the heuristic module contain low degrees of change in other variables, which contributed to the achievement of better results, with less impact on the medical treatment.

The other experiment carried out was a multidimensional search using a very low degree of change for *cpt*, a moderate degree for *sc* and a high degree for *mhr*. Results are shown in Table VII for both patients. The Risk Levels obtained are presented in Table VII and were lower than those found in the one-dimensional optimizations (presented in Table VI), with no change in the *cpt* value.

TABLE VII  
MO-HIDS RESULTS FOR THE *CARDIOLOGIC DIAGNOSIS*

Pat.	<i>Cpt</i>		<i>sc</i>		<i>mhr</i>		<i>Risk Level</i>	
	mean	$\pm \sigma$	Mean	$\pm \sigma$	mean	$\pm \sigma$	mean	$\pm \sigma$
A	0.00	0.00	26.37	8.94	60.73	6.34	0.5391	0.71
B	0.00	0.00	11.93	7.21	410.21	15.30	0.5311	0.80

3) *Automobile Market Evaluation*: Table VIII presents the original values for the Automobile test case, obtained with HIDS. The Price Reduction values are inversely proportional to how good each decision is, since it is a percentile measure of how far the calculated price was from the desired price. For example, a Price Reduction of 0.20% indicates that the resulting price could not match the desired price by as much as 0.20%. Each highlighted value simulates the evaluation of a different aspect of a car setup, performed by a car designer.

TABLE VIII  
HIDS ORIGINAL RESULTS FOR THE *AUTOMOBILE MARKET EVALUATION*

	<i>mpg</i>	<i>hp</i>	<i>pr</i>	<i>Price Reduct.</i>
	0.00	0.00	<b>12.52</b>	80.52
A	0.00	<b>4.29</b>	0.00	86.46
	<b>38.05</b>	0.00	0.00	0.20
	0.00	0.00	<b>7.71</b>	99.07
B	0.00	<b>50.00</b>	0.00	34.24
	<b>74.00</b>	0.00	0.00	0.06

Table IX presents compatible values obtained with MO-HIDS for the Automobile test case, using a similar test setup used for the Heart test case. The heuristic module was parameterized allowing a high degree of change for the highlighted variable and a very low degree for the others.

The results are also comparable, but MO-HIDS again achieved better final Price Reductions. With the exception of the search prioritizing *pr* in prototype B, all reductions were lower than 5% while in HIDS those values were higher then 34% and in most cases over 80%.

TABLE IX  
COMPATIBILITY TESTS FOR THE *AUTOMOBILE MARKET EVALUATION*

Prot.	<i>mpg</i>		<i>Hp</i>		<i>pr</i>		<i>Price reduct.</i>	
	mean	$\pm \sigma$	Mean	$\pm \sigma$	mean	$\pm \sigma$	mean	$\pm \sigma$
A	14.34	3.42	12.57	2.94	<b>14.05</b>	<b>14.05</b>	4.99	5.28
	6.64	5.71	<b>32.45</b>	<b>7.97</b>	0.91	0.91	0.32	0.58
	<b>35.99</b>	<b>8.72</b>	6.37	4.62	0.94	0.94	0.36	0.59
B	4.64	3.17	2.30	2.29	<b>10.57</b>	<b>10.57</b>	93.38	5.86
	1.37	2.39	<b>70.70</b>	<b>4.79</b>	0.71	0.71	2.87	6.43
	<b>74.92</b>	<b>5.94</b>	1.48	1.85	0.76	0.76	4.68	5.65

Next, a multidimensional search was also carried out to evaluate how well MO-HIDS would perform in this test case. The parametric values for the heuristic module allowed a very low degree of change for *mpg*, a moderate degree for *hp* and a high degree for *pr*. Table X shows the results for this multidimensional evaluation. Regarding Prototype A, MO-HIDS achieved a better Price Reduction in to the one-dimensional equivalent experiments. As for Prototype B, it achieved a final Price Reduction of only 29.30%. However, it seems that the most significant variable was *mpg*, which was allowed only a low degree of change. Thus, the result of 29% was a substantial improvement when compared to the 93.38% obtained in the one-dimensional prioritization of *pr*.

TABLE X  
MO-HIDS RESULTS FOR THE *AUTOMOBILE MARKET EVALUATION*

Prot.	<i>mpg</i>		<i>hp</i>		<i>pr</i>		<i>Price reduct.</i>	
	mean	$\pm \sigma$	mean	$\pm \sigma$	Mean	$\pm \sigma$	mean	$\pm \sigma$
A	9.55	5.63	21.81	7.24	9.82	9.82	0.15	0.18
B	4.34	3.34	50.88	2.99	11.70	11.70	29.30	5.75

In the (variable) expanded version, experiments were carried out so that all preferences were manipulated simultaneously with the same values. Initially all preferences were set to a low degree of change, then to a moderate degree and finally to a high degree. This sequence was employed to verify whether the MO-HIDS would escalate well. In addition, we wanted to observe whether the consideration of extra variables would be beneficial to the improvement of decision quality. Notice that the objective was not to make an extensive exploration for optimal parameter setup.

In the Heart test case, after performing the selection, the only decisions allowed were ones with a high degree of change. Nevertheless, for both patients it was possible for the decision maker to achieve an extremely low final Risk Level (values around 0.07).

In the Automobile test case, in all three experiment setups, a greater variability was found for achieving valid decisions. Since 16 variables were used, the sum of variations was high. However, the final Price Reduction was also extremely low, reaching values close to 0.5%.

The computational time to perform the (variable) expanded version was almost equal to the (variable) reduced version in all experiments, *i.e.* less than one minute using regular personal desktop computers. This gave us the impression that the system escalates well.

The fact that not all setups achieved valid decisions can be explained by the nature of the heuristic used. Since it

discards all decisions which fail in at least one preference, the more preferences (equal to variables in the problem), the harder it is to be in agreement with all of them. To overcome this setback, an even more flexible heuristic could be employed, allowing the decision maker to inform a tolerance level of the failed preferences.

## V. CONCLUSION AND FUTURE WORKS

We have proposed the inclusion of multi-objective abilities in HIDS. This new approach modifies the search module of vanilla HIDS and adds a heuristic module (HM) to help the decision maker to choose from optimal solutions.

The predictive module performs mappings between domains (causes) to images (effects). The MO search module generates future scenarios (*i.e.* Pareto fronts) using forecast outputs in fitness function evaluations.

Since the HM uses a Fuzzy Logic-based model to handle linguistic variables as the nominal managerial preferences, it can discard the numerical weights mandatory in HIDS. This use of nominal preferences incorporated extra flexibility for decisions to be taken (in the foreseen scenarios) as it becomes easier for a operator to inform preferences using high communication level, rather than using crisp numbers.

The results of experiments carried out here have shown that MO-HIDS usually outperforms HIDS. Moreover, it was also capable of performing multidimensional optimizations. Even in situations in which results were no better than those obtained by HIDS, the ability to optimize in many dimensions at the same time is a desirable capability. The reason for this is the potential for saving reasonable amounts of time during the decision-making process.

Another time saving feature is related to the use of preferences only after (rather than before) the MO optimization is concluded. This approach allows for the evaluation of decision scenarios comprising different preferences expeditiously and with low computational costs.

In all the experiments, some standard deviation values were comparable to the mean value. This can be explained by of the high variability of possible decision obtained in the Pareto front constructed by the MO module. In a decision support system, this is a desirable feature, since it indicates that the search was broad enough to give insightful information to the decision makers.

The approach here proposed was robust enough to handle different problems with similar setup values and a small number of parameters. Also, it was able to optimize more complex versions of both problems without a significant increase in processing time. This indicates that this approach presents good scalability properties, derived specifically from its MO module which constructs the Pareto front only once, and *posteriori* preference handling. It is worth mentioning that none of these good results obtained by MO-HIDS would be possible if there were no forecast of decision indicators provided by ANN (of predictive module).

Future works could improve the heuristic module by adding new functions to its Fuzzy-based selection capabilities and also introducing a greater level of user interactivity. These improvements and other computation

intelligent techniques are highly necessary in decision dialogues of real problems, which is the next target of our research efforts. Sensitivity and specificity, that are of great importance in medicine could be easily included as objectives in the optimization, if they were available in the database benchmark of [31].

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