Hybrid Intelligent Suite for Decision Support

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Abstract— **Decision making is sometimes a hard task mainly due to data and environment complexities associated with the decision process. Without using a suitable supportive tool, this process can be slow, ineffective and error-prone. Decision support systems and techniques of artificial intelligence (AI) can be quite helpful on reducing the inherent uncertainty and effort of decision making. This work presents a suite of hybrid intelligent techniques helpful in decision making, the *Hybrid Intelligent Decision Suite* (HIDS). The system is composed of two complementary modules, one for forecasting new decision variables and the other, for searching among generated results of future scenarios (*i.e.* candidate decisions). HIDS is also suitable to obtain conditioning factors leading to desired decision, thus, overcoming some of the challenges posed by the 'Inverse Problem'. To test this concept we have applied our approach on two distinct problems: (1) diagnosis of cardiologic diseases (of the *proben-1* data-set) and (2) automobile feature selection (of *UCI* data-set). In the simulations carried out here, the HIDS suite of Artificial Neural Networks (ANNs) and Fuzzy Logic Controllers (FLCs) were coupled to produce acceptable decision scenarios in both examples. Results proved that the ideas presented here can be effective to assemble useful tools for decision makers.**

I. Introduction

Decision making in dynamic environments is usually a difficult task. Most of the difficulty arises from: (i) time variability or (ii) non-availability of all necessary data for the decision to be made. Moreover, the inadequate number of variables and the lack of structure of the decision environment may contribute to the decision process effort. It is not uncommon that some decisions may also have to deal with conflicting interests, namely economical vs. technical.

In light of all that, a decision can be understood as a selection process, taken by the decision maker, which maximizes an objective function over time. Consequently, a Decision Support System (DSS) is a tool to help increasing confidence in tackling such a search problem. Besides, it would be a bonus if a given DSS could provide the decision maker with some additional inputs such as risk assessment and future impacts associated with the decision. Hence, a good DSS has to care, not only, with quantifiable objectives to be achieved but also with intangibles ones, such as effectiveness, precision and reliability.

In this work we present a new type of DSS that profit heavily on the abilities of AI techniques such as forecasting and searching in complex domains. Actually, we offer a hybrid suite for decision support – Hybrid Intelligent Decision Suite (HIDS) – that: (a) forecast new decision variables, (b) search for acceptable results (i.e. decisions) in future scenarios and is capable of (c) finding conditioning factors. The latter, when the decision maker knows beforehand desirable outcome for a given problem.

The Hybrid Intelligent Decision Suite is composed of two main modules: the predictive and the search modules. Together they help on reducing uncertainty (i.e. the non-availability and time variability of data – referred before) and informing the decision maker of possible outcomes. We think that by using HIDS decisions in some complex domains will be very much simplified.

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II. Background

A. Decision Support Systems (DSS)

DSS is a particular type of information system, generally computer aided, mainly utilized in mid-managerial levels of organizations. They aim at helping on semi-structured decision processes and most of their applications are in control and in management [1]. By semi-structured decision we mean that decisions may change in some form or shape thru time. Thus, a DSS can be very useful on helping decision makers to analyze possible scenarios and effects of decisions upon those scenarios. In all, DSS are important allies of decision makers for them to emit informed decisions.

As non-functional requirements, DSSs should be fast enough to produce various scenarios analyses within small amounts of time as well as to be flexible for interacting with the decision maker in a non-monotonic manner. Moreover, a 'good' DSS has to have the flexibility to incorporate some context information of the businesses such as: changes in priorities and consideration of novelties. Hence, DSSs have to combine information extracted from existing databases as well as to profit from the expertise of experienced decision makers.

DSSs are classified based on their objectives. The most important ones are used for: *simulations* – they respond "what – if" questions, in order to determine the impact of changes or output of given variables; *reach goals* – they start from pre-set goals to whose the system recommends main and alternative routes. They also may include effort assessing functionalities; and, optimizations – they aim at specific targets by adjusting variables values of an analytical model of the problem [1][2].

B. Artificial intelligence techniques

Artificial intelligence is a prolific area of computing that deals with understanding and construction of intelligent systems [3]. The idea of intelligence here is highly correlated with learning. This means that intelligent applications draw their own "conclusions" from past experience or can also profit from external set of rules before starting their own reasoning process. Thus, the generalization component of every intelligent processing here will help on new decision instances.

1) Artificial Neural Networks: Artificial neural networks (ANNs) – a.k.a. connectionist models, comprise a prominent sub-field of Artificial Intelligence (AI) due to their parallelism, generalization ability and capability to adapt themselves learning by their own mistakes. ANNs can be used with great efficiency in classification, function approximation and prediction problems [4]. As it will be shown the predictive ability of ANNs is highly desirable for producing output (future values) for the decision process.

2) Fuzzy Logic: In real world problems, there are always some degree of uncertainty attached to variables, so that they are likely to never be well expressed by using crisp numbers. In order to achieve more realistic description of data, it is desirable a linguistic metaphor that better bridges computers and humans [8]. For instance, the Aristotelian membership function (*i.e.* 'yes' or 'no') could be replaced by a more flexile one (*e.g.* 'almost').

Figure 1 shows how a crisp input is classified using fuzzy input membership functions. The inputs are evaluated in accordance to linguistic rules describing the controller behavior ('fuzzification'), given in "If – then" format. Each rule has its firing strength computed and finally using an output membership function, it is possible to calculate the crisp output value.

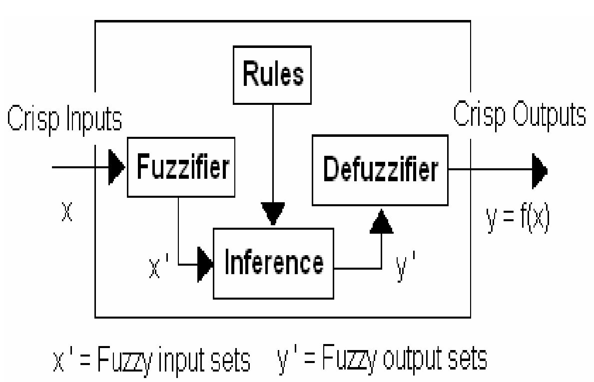

Fig. 1. Schematic view of a Fuzzy Logic Classifier

In the decision domain a fuzzy membership function would very much accommodate the necessary flexibility to the gradual assessment of elements in relation to a given set (i.e. decision instance of a given scenario).

III. Hybrid Intelligent Decision Suite (HIDS)

A. Abstract Model for Decision Making

The abstract model for decision put forward here has three axioms:

(i) *Problem-Decision maker* relation: given a decision problem $\mathbf{p_k}$ from a class of problems **P** and a decision maker $\mathbf{m_k}$ from a class of decision makers **M**, the latter is necessarily able and empowered to solve problems of class **P**.

(ii) *Problem-Decision components* relation: assuming the existence of a decision space $\mathbf{D_P}$, so that $\mathbf{D_P} = \{d_1,d_2,...,d_n\}$, where every $\mathbf{d_k}$ is a decision potentially fully capable of attending all requirements of problems of class **P**, to solve a problem $\mathbf{p_k}$ each decision $\mathbf{d_k}$ encompasses a subset of decision components **C**, upon which **M** should reason separately.

(iii) *Decision components-Attributes of components* relation: given $\mathbf{d_k} = \{c_1,c_2,...,c_n\}$, where every $\mathbf{c_j}$ belongs to **C**. Each decision component $\mathbf{c_i}$ is composed by a set of tangible attributes which characterize it, so that $\mathbf{c_j} = (a_1,a_2,..., a_n)$.

In such formalism (refer to Figure 2) we suggest:

(1) the range of values for all $\mathbf{a_i}$ are to be drawn from the **M-P** interaction and can assume either qualitative or quantitative values;

(2) the $\mathbf{c_j}$ components associated with their $\mathbf{a_i}$ validity criteria are to be drawn from the **M**-**P** interaction;

(3) the priorities among candidate decisions $\mathbf{d_k}$ of $\mathbf{D_P}$, as well as assessing their suitability regarding the posed problem, are also to be drawn from the **M**-**P** interaction;

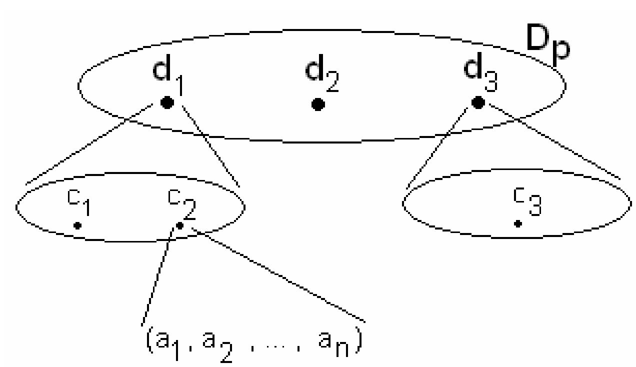

Fig. 2. Decision space over Problem class P encompassing decisions, components and their attributes, extracted from [5]

Values for some attributes $\mathbf{a_i}$ can be drawn from a especial function **Φ** used as a predictive element**.** This function maps a vector of external inputs $\mathbf{I} = \{i_1,i_2,...,i_m\}$ and a vector of attributes $\mathbf{A_j} = \{a_1, a_2, ..., a_m\}$ into a tuple of other attributes $\mathbf{A'} = (a'_1, a'_2, ..., a'_r)$ belonging to component $\mathbf{c_j}$. According to the processing model used by **Φ**, it is possible to use external factors to make a behavior forecasting of one or several attributes of $\mathbf{c_j}$. Equation (1) shows the mapping of **I** and **A** into **A'**.

$$\Phi(I, A) = (a'_1, a'_2, ..., a'_n) \quad (1)$$

The above suggested interventions of decision makers are only parametrical information that will guide the hybrid intelligent decision system described next. These parameters are the coefficients of the evaluation functions of attributes. In other words, $\mathbf{f_i}$ $(\mathbf{a_i})$ are *ad hoc* metrics for evaluating the attributes of components of a decision. Andover, $\mathbf{m_k}$ must provide a weight vector $W = \{w_1, w_2, ..., w_n\}$; $\mathbf{w_i}$ is individually ascribed to each attribute of decision's components. Vector $V = \{v_1, v_2, ..., v_n\}$ is the validity criterion concerning every attribute.

Output values of $\mathbf{f_i}$ are normalized within the interval [0,1] to avoid distortions during decisions evaluation. For example, scale differences of attributes could bias some decisions towards one particular aspect of it.

Based on vector W, it is possible to evaluate the relevance of each component $\mathbf{c_j}$ of the decision d_k, which is given by Equation (2):

$$R(C_j) = \frac{\sum_{i=0}^{n} w_i * f_i(a_i)}{\sum_{i=0}^{n} w_i} \quad (2)$$

The overall evaluation of each decision is given by function $\mathbf{F(d_k)}$, which is the summation of all individually calculated relevance components of a single decision (see Equation 3).

$$F(d_k) = \sum_{j=0}^{n} R(C_j) \quad (3)$$

Finally, we propose that the decision process ends up by searching among all the evaluated candidates for the individual decision that maximize the return criteria sought – $\mathbf{F(d_k)}$ at the same time it satisfies the expected validity according vector V.

B. Dealing with the Inverse Problem

A decision can also be viewed as a search problem where decision maker $\mathbf{m_k}$ knows a desired effect and would greatly benefit from discovering its conditioning factors which presents an Inverse Problem.

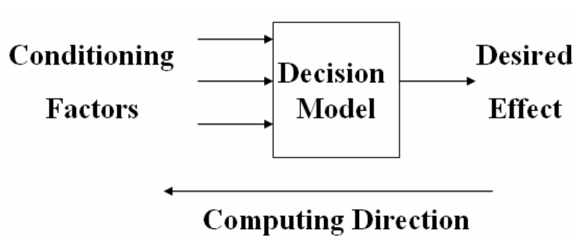

Fig. 3. Computing direction (from *Desired Effect* to *Conditioning Factors*)

The Inverse Problem can be described as a task where parameters of some model must be obtained from a previously known result or effect.

Figure 4, shows two mapping functions from set **C –** Conditionings to set **E** – Effects. In function h_1, there is a single mapping between each conditioning and effect. In function h_2, conditioning 1 and 2 lead to effect A. In this small example, there is no complexity in discovering which element either 1 or 2, most fits decision criteria. However this task reaches greater significance when dealing with a high dimensional space.

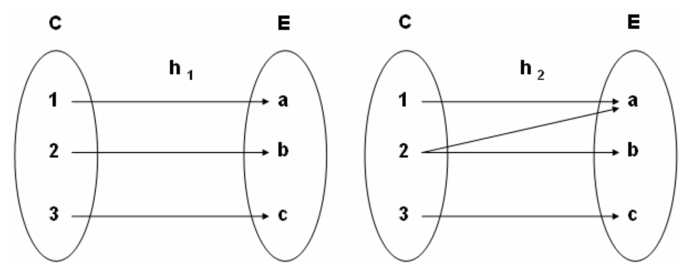

Fig. 4. Schematic view of a two mappings from set **C** - Conditionings to set **E –** Effects. The second mapping leads to Inverse Problem

When dealing with non-linear functions, as in most decision situations, the Inverse Problem becomes extremely hard to be solved. Moreover, the complexity of the solution increases according to the number of parameters which must be found.

In this work we propose a suitable combination of predictive and search modules, to explore the decision space. When appropriate, one or both modules can be composed of intelligent techniques. In the next section, this combination is presented as an effective and computationally inexpensive heuristic to explore the decision space, tackling elegantly with the inverse problem.

C. Hybrid Suite of AI Techniques for Decision Support

In previous works of the authors [5][6], prediction and selection were treated separately during a decision making process. As argued above, we should consider these aspects as inseparable for a good decision to be made.

In our approach for decision processes we make a strong distinction between *factors* and *indicators.* By *factors* we mean all aspects that may cause relevant impact on the decision; by *indicators* we mean ways to check how good or bad the results of the decision were [5].

According to this contributed approach, Figure 5 illustrates an overview of the proposed Hybrid Intelligent Decision Suite. It considers a decision as a whole (as opposed to other approaches mentioned before). The highlight of this framework is that it allows different intelligent techniques to be used in the two constituent modules of the suite and a closer integration between the predictive and search modules. So that, they can combine their abilities for achieving better decision support.

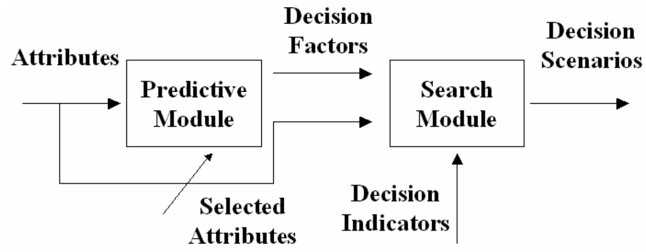

Fig. 5. Overview of the Hybrid Intelligent Suite for Decision Support

In the Figure, notice that some attributes can also be used, as input, in the search module. For this selection some technique such as Principal Component Analysis (PCA) and Independent Component Analysis (ICA) can be used.

IV. Applying HIDS to Cardiologic Diagnosis

In this example, HIDS was employed to implement a custom DSS conceived to assist medics on reducing patients cardiac risk levels. The various degrees of cardiologic disease data were extracted from the benchmark database Proben1 – Heart [7]. The predictive module of the HIDS uses an ANN to classify patients within five risk levels. Then, the search module generates scenarios using a FLC with a feedback control loop to the ANN. The generated scenarios helped medics to decide on treatments (i.e. actions upon decision factors). That is, searching the smallest difference between patient status (i.e. factors of predicted scenarios) and known safer states.

Details of the HIDS for the problem at hand are:

1. Training patterns of ANN (of the predictive module) is **X =** $\{I_1O_1, I_2O_2, ..., I_nO_n\}$, where $\mathbf{I_n}$, $\mathbf{O_n}$ are vectors obtained from the Proben1 database. The input vector is $\mathbf{I_n}$ = {age, sex, chest pain type, resting blood pressure, serum cholesterol, fasting blood sugar, resting electrocardiograph results, maximum heart rate achieved, exercise induced angina, ST depression induced by exercise relative to rest, the slope of the peak exercise ST segment, number of major vessels (0-3) colored by flourosopy, thal} and the output vector is $\mathbf{O_n}$= {diagnosis of heart disease – angiographic status};

2. Preprocessing of training data: training patterns were converted according to the following criteria: (i) measurable attributes were encoded between [0,1] and (ii) qualitative attributes were encoded using unary encoding. We used an extra binary digit to indicate whether the attribute is missing or not;

3. Predictive function $\mathbf{\Phi}$ maps patient information into risk levels ($\mathbf{O_n}$): healthy (0), increasingly sickness (1)(2)(3)and(4), and is given as $\mathbf{\Phi} (\mathbf{I_n}) = \mathbf{O_n}$;

4. Decision space $\mathbf{D_P}$ is composed by predicted attributes of components, each set relating to different treatments, for selection of the HIDS search module;

5. Each decision component is then represented by the modified tuple: ($\mathbf{I'_n}$,$\mathbf{O'_n}$);

6. Three functions were defined to evaluate the decision indicators: chest pain type – *cpt*, serum cholesterol – *sc* and maximum heart rate – *mhr*, represented here in (4) to (6):

$$f_{cpt}(cpt_i) = cpt_{final} - cpt_{initial} \tag{4}$$

$$f_{sc}(sc_i) = sc_{final} - sc_{initial} \tag{5}$$

$$f_{mhr}(mhr_i) = mhr_{final} - mhr_{initial} \tag{6}$$

7. For completing the decision making process, the medic must inform (based on his experience) weight and validity vectors: W = $\{w_{cpt}, w_{sc}, w_{mhr}\}$, V = {*Minimum cpt, Minimum sc, Maximum mhr*}. In this case, each weight is inversely proportional to its priority level. They are used to parameterize the search module by allowing the relevance of decision components to be calculated:

$$R(C_j) = \frac{f_{cpt}(cpt_i) * w_{cpt} + f_{sc}(sc_i) * w_{sc} + f_{mhr}(mhr_i) * w_{mhr}}{w_{cpt} + w_{sc} + w_{mhr}} \tag{7}$$

8. The decision making process ends when the most promising candidate treatment is selected. Equation (8) shows that decisions here have only one component.

$$F(d_k) = \frac{1}{R(C_j)} \tag{8}$$

All patients presented Asymptomatic chest pain, different Serum Cholesterol and Maximum Heart Rate. They also presented increasing cardiac risk levels. In this experiment, HIDS is required to assist a medic in finding suitable lines of treatment. It were used W = $\{w_{cpt} = 8, w_{sc} = 5, w_{mhr} = 5\}$, V = {*Minimum cpt = No pain, Minimum sc = 0.2, Maximum mhr = 0.8*}; refer to Table I.

TABLE I
Attributes of Patients Subject to Cardiologic Diagnosis

Patient	Risk Level	*Cpt*	*sc*	*mhr*
1	0.6371	Asymptomatic	0.4166	0.4666
2	0.7122	Asymptomatic	0.2916	0.1466
3	0.8095	Asymptomatic	0.7000	0.2000

V. Applying HIDS to automobile evaluation

In order to further test the framework presented in this work, another DSS using HIDS was conceived and implemented. In this case, the primary objective was to offer valuable information to a project manager about the impact of car setup in relation to their final price (in the perspective of candidate buyers). The database used was Auto Imports Database, contained in UCI Machine Learning Repository [8].

Based on the information available it was possible to offer some input such as (car) model number of doors, engine size, fuel type and a desired maximum prototype value. HIDS is then capable of locating suitable values for remaining parameters trying to match (approximate) the maximum desired price. The decision scenarios here are cars with different features which are categorized according to production manager preferences. Our approach to bypass the Inverse Problem is to explore decision space using a fuzzy logic controller coupled with an ANN.

Some details about this particular DSS based on HIDS are provided below:

1. Training patterns of ANN in predictive module is **X** = $\{I_1O_1, I_2O_2, ..., I_nO_n\}$, where $\mathbf{I_n}$, $\mathbf{O_n}$ are vectors obtained from the UCI database. The input vector is $\mathbf{I_n}$ = { Aspiration, Body Style, Bore, City Mpg, Compression Ratio, Curb Weight, Drive Wheels, Engine Location, Engine Size, Engine Type, Fuel System, Fuel Type, Height, Highway Mpg, Horse Power, Length, Num Cylinders, Num Doors, Peak Rpm, Stroke, Wheel Base, Width } and the output vector is $\mathbf{O_n}$= {Price};

2. Preprocessing of training data: training patterns were converted according to the following criteria: (i) measurable attributes were encoded between [0,1]; and (ii) qualitative attributes were encoded using unary encoding. All lines with missing attributes were removed;

3. Predictive function **Φ** maps car features into selling prices ($\mathbf{O_n}$): in this database, price is a continuous variable that ranges from 5118 to 45400 and is given by the expression $\mathbf{\Phi} (\mathbf{I_n}) = \mathbf{O_n}$;

4. Decision space $\mathbf{D_P}$ is composed by different possibilities of car setup, covering the concurrent lines of development for manager's project.

5. Each decision component is then represented by the modified tuple: $(\mathbf{I'_n}, \mathbf{O'_n})$;

6. To evaluate decision indicators, three functions were defined: city mpg – *mpg*, horse power – *hp* and peak rpm – *pr*. According to experiment requirements, decision scenarios should maximize *mpg* and *hp*, while minimizing *pr*. This heuristic is represented here in (9) to (11):

$$f_{mpg}(mpg_i) = 1 - (mpg_{\max} - mpg_{final}) \quad (9)$$

$$f_{hp}(hp_i) = 1 - (hp_{\max} - hp_{final}) \quad (10)$$

$$f_{pr}(pr_i) = 1 - (pr_{final} - pr_{\min}) \quad (11)$$

7. For completing the decision making process, the project manager must inform weight and validity vectors: W = $\{w_{mpg}, w_{hp}, w_{pr}\}$, V = { *Minimum hp, Maximum hp, Minimum mpg, Maximum mpg, Minimum pr, Maximum pr*}. In this case, each weight is directly proportional to its priority level. They are used to parameterize the search module by allowing the relevance of components to be calculated:

$$R(C_j) = \frac{f_{mpg}(mpg_i) * w_{mpg} + f_{hp}(hp_i) * w_{hp} + f_{pr}(pr_i) * w_{pr}}{w_{mpg} + w_{hp} + w_{pr}} \quad (12)$$

8. The decision making process ends when a possible project approximates closely the selected decision criteria. Equation (13) shows that decisions here have only one component.

$$F(d_k) = \frac{1}{R(C_j)} \quad (13)$$

Automobiles presented in Table II were extracted from UCI database. A decision objective was proposed for each of them: car 1 should have its price reduced to 12500.00 while car 2 should reach a price of 18000.00.

The experiment was performed trying to evaluate possible changes in configuration that allowed this significant price reduction.

TABLE II
Attributes of evaluated automobiles

Car	Price	mpg	hp	pr
1	13545.32	20.00	140.00	5000.00
2	19225.41	15.00	180.00	4500.00

The following weight vector and validity criteria were used: W = $\{w_{cpt} = 1, w_{sc} = 1, w_{mhr} = 1\}$, V = {*Minimum hp = 48, Maximum hp = 228, Minimum mpg=13, Maximum mpg = 49, Minimum pr = 4150, Maximum pr = 4150*}. According to W, there is no relevance distinction between attributes in this experiment.

VI. Results and discussion

A. Cardiologic Diagnosis

HIDS applied to cardiologic diagnosis presented results shown in Table III, as for most suitable lines of treatment, concerning *cpt*, *sc* and *mhr* model variables.

After evaluating the different approaches of treatment, in accordance to patient medical records and respecting previous experiences from the medic staff, it was possible to prioritize procedures and help doctors to make more informed decisions. If the best solution for the problem is not found, it is still possible to change some parameters and carry out new simulations very easily.

It was also shown that *cpt* has a high effect in risk level, so reducing patient chest pain is a very advisable measure. If patient does not present chest pain, it is advisable to improve his cardiac fitness by increasing his maximum heart rate (*mhr*). Serum Cholesterol (*sc*) had a slightly inferior impact in all cases for decreasing their risk level.

According to the weight vectors presented in section IV, *sc* and *mhr* had same relevance to decision, while *cpt* had an inferior relevance. The lines highlighted in Table III indicate the selected decisions for each of the patients.

TABLE III
DECISION SCENARIOS OBTAINED FOR EACH PATIENT

Patient	Risk Level	*cpt*	*sc*	*mhr*
1	**0.5535**	**Asymptomatic**	**0.4166**	**0.775**
1	0.5983	Asymptomatic	0.2030	0.4666
1	0.2567	No pain	0.4166	0.4666
2	**0.5266**	**Asymptomatic**	**0.2916**	**0.7740**
2	0.7048	Asymptomatic	0.2090	0.1466
2	0.4600	No pain	0.2916	0.1466
3	**0.7637**	**Asymptomatic**	**0.700**	**0.7966**
3	0.7777	Asymptomatic	0.2021	0.2000
3	0.6751	No pain	0.7000	0.2000

B. *Automobile Evaluation*

In Table IV results from experiments conducted with both cars are shown. The main goal was to find a car setup which allowed cost reduction with small perceived differences to potential customers.

TABLE IV
DECISION SCENARIOS OBTAINED FOR EACH AUTOMOBILE

Car	Desired Price	Calculated Price	mpg	hp	pr
1	12500.00	12497.09	27.61	140.00	5000.00
1	**12500.00**	**12500.81**	**20.00**	**134.00**	**5000.00**
1	12500.00	12502.81	20.00	140.00	4373.91
2	**18000.00**	**18000.08**	**26.10**	**180.00**	**4500.00**
2	18000.00	19214.57	15.00	180.00	4152.91
2	18000.00	18422.00	15.00	90.00	4500.00

For car 1, changes in *mpg*, *hp* and *pr* were equally effective in reducing price. However, reducing *hp* from 140 to 134, was enough to reach 12500.00 mark. For car 2, it was necessary a significant improvement in *mpg*, while other attributes had a poor impact in reducing price. Possibly, car 2 already had a considerably low price for its category.

After analyzing these results and considering all attributes with same relevance, the best decisions for this problem are highlighted in Table IV.

VII. Conclusion

In this work we proposed a decision suite – HIDS – and a simulation tool especially programmed for exemplifying the main ideas. The included simulations dealt with two problems: cardiologic diagnosis and automobile cost-benefit evaluation. The results obtained here were, for the first set of simulations, consistent reduction of estimated risk levels of patients and in the second set, effective suggestion of lines of development for new car models.

The possibility of multiple re-runs of the tool on the same decision problem can improve decision quality and accuracy, since this kind of system benefits on the skill of the decision maker who operate it.

Regarding the theoretical framework, it is worth mentioning that HIDS has been used successfully on other problem domain: decision making in agriculture – harvest. Case in which, another intelligent technique (*i.e.* genetic algorithms) acted as the engine of the search module [5].

Future works intend to improve the presented framework, adding other modules to provide extra-functionalities such as automatic evaluation of attribute impact for achieving good decisions. Another possibility is to couple other AI techniques to allow the suite to learn by itself suitable values for weight vectors and validity criteria. This could avoid time loss, might reduce the need for user inputs and would give extra support for decision makers.

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