A Study on Multi Criteria Decision Making Model: Interactive Genetic Algorithms Approach

Fang Cheng Hsu* Jiah-Shing Chen**

***Department of Information Management**
Tamsui Oxford University College.
Tamsui, Taipei, 25103, Taiwan
fanechi@jupiter.touc.edu.tw

****Department of Information Management**
National Central University,
Chung-Li 32054, Taiwan
jschen@im.mgt.ncu.edu.tw

ABSTRACT

Owing to the newly recognized nature of decision-making, the methodologies for supporting multiple criteria decision-making (MCDM) are emerging. In this paper, we propose an interactive genetic algorithms (IGA) approach to MCDM. This IGA-based approach has some unique characteristics that make it suitable to be a core technology for MCDM. However, the inefficiency problem of fitness assignment by the user in IGA needs to be improved to make it feasible for MCDM. Hence, we develop 3 concepts to improve the IGA performance, and integrate them into our IGA-based approach. To demonstrate the applicability of the IGA-based approach, a decision-making example on designing new product is presented.

1. INTRODUCTION

In classical decision models, an optimal solution is selected from a set of alternatives according to a single well-defined objective function. However, in real life, we regularly deal with decision problems with conflicting objectives. The goal of decision-making thus becomes finding some satisfactory solutions rather than selecting a single optimal solution. Owing to this newly recognized nature of decision making, the methodologies for supporting multiple criteria decision-making (MCDM) are emerging.

MCDM methodologies have been developed for more than forty years; nevertheless, those methodologies appear to be quite diversified due to many changes in decision concepts. Henig & Buchanan (1996) and Buchanan *et al.* (1998) have argued that prior methods for solving MCDM problems have largely been technical ones, with little emphasis on decision-making methodology. They reinvestigated the nature of decision-making and depicted a "good decision process" which is truly helpful for decision-makers to make their decisions.

A major goal of this study is to apply the unique characteristics of IGA to provide a workable decision-making model, which satisfies the essentials of the good decision process.

Another purpose of this study is to develop 3 concepts to improve the performance of IGA. Since IGA has brought up, improving chromosome evaluation procedure and decreasing evolution generations without sacrificing solution qualify have been major in GA community.

The rest of this paper is organized as follows. Section 2 discusses the difficulties in building a workable model, which satisfies the essentials of a " good decision making process." Furthermore, a description of why IGA is suitable for implementing the good decision process is also given. Section 3 investigates the problems of applying IGA. Section 4 describes an IGA-based model for supporting MCDM. Section 5 presents an example of decision-making on designing new product to demonstrate the applicability of the IGA-based model. Section 6 gives our concluding remarks.

2. A GOOD PROCESS OF DECISION-MAKING

The MCDM problem we are interested in is defined to be the problem of selecting the s (>=1) most preferred alternative(s) from S alternatives by K (>=1) decision-makers. An alternative A is composed of n attributes ($A = (a_1, a_2, \dots a_n)$). If attribute a_i has L_i levels then there are $S = L_1 * L_2 \dots * L_n$ alternatives.

Generally speaking, methods for MCDM problems can be classified into two categories: Multiple Objective Programming (MOP) and Multiple Attribute Decision-Making (MADM). In practice, MOP is suitable for decision problems with infinite, continuous alternatives and with a set of well-prepared objectives and/or constraints; on the other hand, MADM is suitable for decision problems with discrete alternatives and a set of prepared alternatives.

From the decision-making point of view, the MOP forces a decision-maker to start with a set of well-defined criteria, while the MADM asks the decision-maker to choose from a certain set of alternatives prepared by the analyst rather than the decision-maker. It is doubtful that either approach can bring good outcomes for the decision- making problems.

But what is a good decision-making process? To answer the question, Henig & Buchanan (1996) and Buchanan *et*

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al. (1998) proposed that a decision problem is comprised of two components: an objectively defined set of alternatives and subjectively defined criteria (Fig. 1). They believed that decision making is an interactive process, in which a decision-maker learns to understand his or her criteria by looking for attributes, then adds, combines or possibly reduces the number of criteria, and finally modifies the attributes and expands the set of alternatives accordingly. In other words, a decision-maker should play both the roles of an alternative generator and a criteria tourist.

We found that building a manipulative model based on the foregoing concept was confronted with two difficulties:

One is about searching capability. Usually, the numbers of alternatives and attributes are large in MCDM problems; making the search space beyond human capability. Therefore providing a system for a decision-maker to take on the role of an alternative generator in such a situation is becoming a big challenge.

The second one concerns with criteria establishment. When a problem's search space is large, guiding a decision-maker to learn to understand his preference through interactive process, and helping him to establish his criteria appropriately is another challenge.

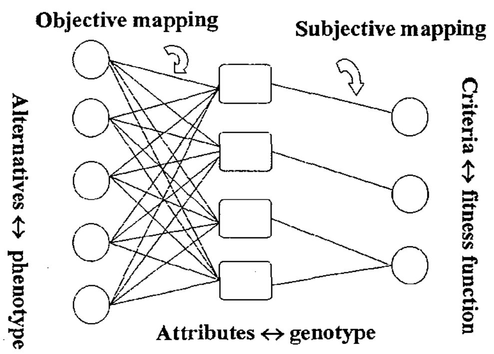

Figure 1. Alternatives-attributes-criteria relationship

Interestingly, the relationship among phenotype, genotype and fitness function in genetic algorithms corresponds to the relationship among alternatives, attributes and criteria (Fig. 1). When we try to apply IGA to help a decision-maker to play an alternative generator, we don't have to worry about the decision-maker's difficulties in searching a large search space due to the powerful search capability of genetic algorithms.

One specific feature of IGA is using decision-maker's preference as its fitness function, so that the decision-maker needs not to define clear, unchangeable criteria at the beginning of the decision-making process. In practice, a decision-maker can learn to understand his preference and then change his criteria in decision-making through interacting with IGA. Hence, we believe that applying interactive genetic algorithms in decision-making process matches with the essentials of a good decision process.

3. DIFFICULTIES IN APPLYING IGA

When applying IGA, a human is asked to interact with GA by evaluating chromosomes in all generations usually hundreds. Hence, how to reduce the participant's workload is becoming an interesting research issue.

Caldwell and Johnston (1991) have applied IGA on a criminal suspect search. Their system asked a witness to rate 20 faces on a nine-point scale in every generation. The problem with this strategy is that the witness must endure the lengthy process of fitness assignment.

Smith (1991) proposed another fitness assignment strategy, in which the participant picks up just a few chromosomes considered helpful for evolution outcome. Smith's assignment strategy is more efficient than Caldwell and Johnston' strategy, but the former is easier to fall into a local optimum than the latter.

After that, Nishio, etc., (1997) introduced two more strategies: "bias" and "fuzzy" fitness assignment strategies. The "bias" fitness assignment strategies can be considered as a special case of Smith's strategy. With "bias" strategy, the participant is asked to pick up the fittest chromosome only, and the system then assigns maximum fitness (1.0) to the picked chromosome, and some "bias" fitness (e.g., 0.1) to the other chromosomes. The "fuzzy" fitness assignment strategy is a refined version of the "bias" strategy. The major difference between "bias" and "fuzzy" fitness assignment strategy is that the value of bias is kept fixed over the evolution in "bias" assignment, whereas the value of bias is appropriately adjusted in the "fuzzy" fitness assignment strategy.

From the natures of interactive genetic algorithms, two challenges have to be conquered they can be used practically. One concerns how to improve the chromosome evaluation process; the other is how to reduce the number of evolution generations without sacrificing solution quality.

4. A CONCEPTUAL MODEL AND IGA PERFPRMANCE ENHANCEMENT

In this section, we begin with three concepts, which we hope to improve the performance of IGA. Then integrate all of them into an IGA-based conceptual model for supporting a decision-maker to make a "good" multiple criteria decision.

4.1 Three Concepts for Improving IGA Performance

a) Evaluation Procedure Enhancement

From the literatures discussed in section 3, we found that all endeavors for improving IGA performance were limited to provide a better fitness assignment strategy. The procedure for improving evaluating chromosomes was ignored.

Since there has exist a limitation of human capability on evaluating chromosome, the population size of an IGA is always small which is doubtless a negative factor on IGA performance. We believe that enlarging the population size of an IGA is helpful for preventing it from falling into a local optimum, and is advantageous for enhancing IGA performance. But increased the population size also lead increases the decision-maker's workload in fitness assignment.

To make IGA with a large population feasible, we propose a paging method, which divides a large population into several pages and displays them to the decision-maker one page at a time. Then the decision-maker selects the most preferred (or few of more favored) chromosome(s) per page. To help the decision-maker to effectively choose the satisfactory chromosomes from each page, a pair-wise comparison process borrowed from AHP (Satty, 1980) is provided.

The fitness of each chromosome can be determined by distance relationships among the chromosomes. The distance formula will be introduced in the following subsection.

b) Distance Relationship among Chromosomes

The paging method needs to operate in coordination with the "bias" fitness assignment strategy, although determining the value of bias for each chromosome is still a research issue (Nishio, etc., 1997). We propose a revised bias fitness assignment strategy based on a chromosomes distances to those picked ones. Similar to bias strategy, a picked chromosome is assigned a higher fitness (e.g. 1.0) while an unpicked chromosome is assigned a bias according to its distance to picked chromosomes.

The distance between any two chromosomes refers to the Euclidean distance of all attributes. Ideally, when a chromosome encoded, we hope to provide a mapping between genotype and phenotype with an identical order. But in practice, some of attributes might be hard to meet the identical requirement. To appropriately deal with these attributes, we integrate a concept of "absolute distance" into the Euclidean distance equation. Assume that a chromosome is composed of n attributes, where m of them have the identical order between genotype and phenotype, and (n-m) of them don't. Then, for any two chromosome

$$A = (a_1, a_2, \ldots, a_m, a_{m+1}, \ldots, a_n) \text{ and}$$
$$B = (b_1, b_2, \ldots, b_m, b_{m+1}, \ldots, b_n)$$

The distance between them

$$d(A,B) = [\sum_{1}^{m} (a_i - b_i)^2 + \sum_{m+1}^{n} (a_j \otimes b_j)^2]^{1/2} \text{ where}$$
$$(a_j \otimes b_j) = 0, \text{ when } a_j = b_j;$$
$$(a_j \otimes b_j = 1, \text{ when } a_j \neq b_j)$$

Suppose a decision-maker picks up s preferred chromosomes ($P_{i=1\ldots s}$), and leaves out of t (=S-s) unpicked chromosomes ($U_{j=1\ldots t}$). Then, the fitness for each chromosome is given as:

$P_{i=1\ldots s} = 1.0$,

$U_{j=1\ldots t} = 1 - \{\text{Min}\,[d(U_j, P_i)] / \text{Max}\,[d(U_{j=1\ldots t}, P_{i=1\ldots s})]\}$

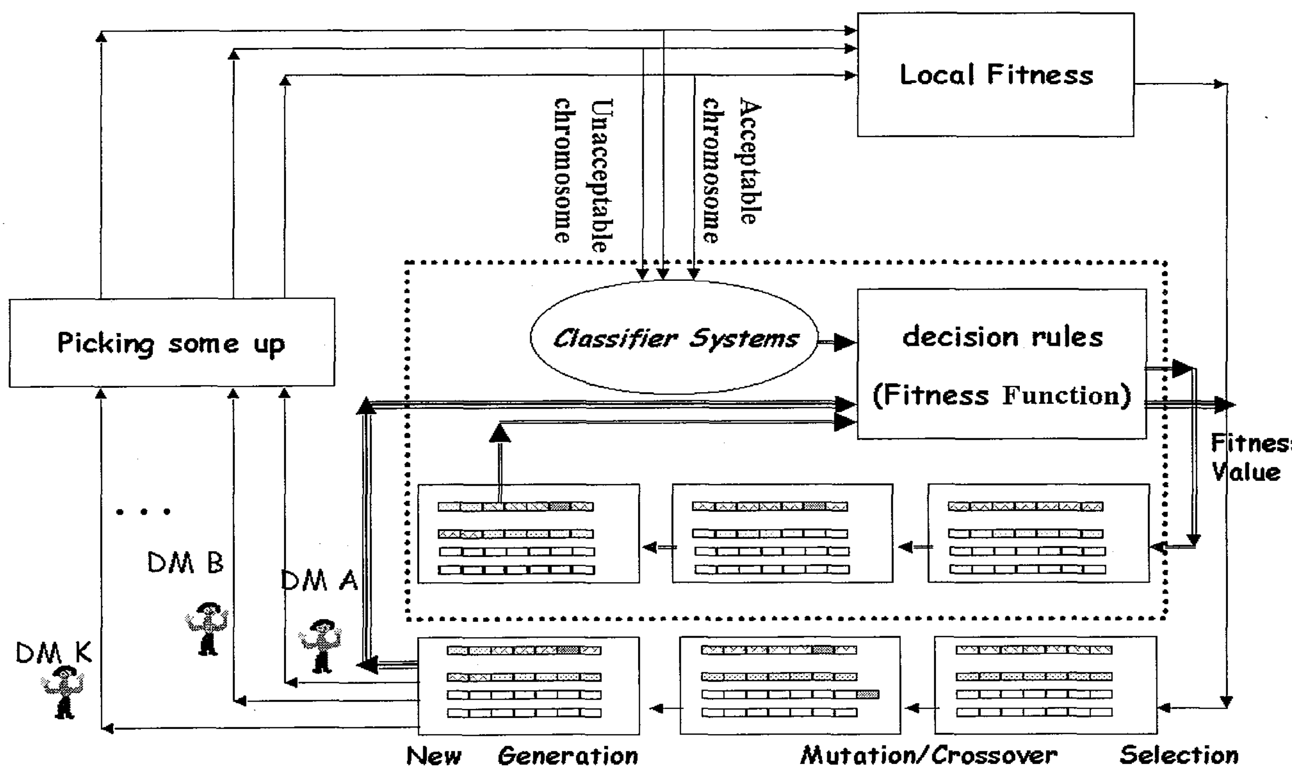

Figure 2. An IGA-Based MCDM Model

c) Learning The Subjective Fitness Function of A Decision-Maker

There is another way to enhance the IGA's performance. If we can dynamically learn a set of decision rules (or preferences) of a decision-maker with a classifier system to mimic the decision-maker's subjective fitness function, the IGA will be operated unattendedly just as a GA. This will dramatically reduce the running time usually required in IGA.

In the duration of running IGA (30 generations, for instance), the decision-maker can offer extra information to a classifier system, such as acceptable or unacceptable chromosomes, instead of just picked or unpacked decisions. After collecting sufficient information as an environment, a set of decision rules of the decision-maker can be learned.

4.2 An IGA-Based Multiple Criteria Decision-Making Model

Figure 2 is a conceptual model of our IGA-based model. A, …, K represent a group of decision-makers, each of them can make an individual decision or a group decision via a cooperation mechanism. In each individual sub-system, the decision-maker picks a few alternatives based on his experience and/or preference in every generation. Then the system calculates the distance among the picked alternatives and other alternatives, and then assigns fitness to all of the alternatives according to the formula distance in section 4.2.

On the other hand, a decision-maker can select a few chromosomes that are acceptable to him to the classifier subsystem during the whole evolution process.

To help a decision-maker to be a competent alternative generator, we must look for a set of attributes, which can cover what a decision-maker desires to find. It is not an easy job, because elements in the set of attributes could be dynamically changed in the decision-making process.

Theoretically, for solving the above-mentioned problems, we can include all possible attributes in the attribute set to cover all possible alternatives. However, it is could result in the search cost unlimited increasing. With classical methodologies, the important attributes were selected through certain procedures, and then the decision-making is completed based on those selected attributes. A major problem of using classical methodologies is that a few seemingly unimportant but actually key attributes might be missed.

To use the IGA-based model, we must try our best to analyse the problem at hand based on past experience or theory guidance so that we can find enough attributes to cover the decision-maker's satisfactory solutions. After that, the decision-maker selects some attributes as the "dominant attributes" and leaves the others as "recessive attributes". In addition, we attach a "control bit" to each attribute. An attribute is dominant when its control bit equal to 1 and is recessive otherwise (Figure 3).

Having the control bits, the model has a mechanism to dynamically change a recessive attribute into a dominant attribute and vice versa. We only need to set the control bit to 0 for each recessive attribute and 1 for each dominant attribute in the initial population. Then the dominant attribute is always dominant; the recessive attribute is always recessive unless a mutation happens.

Since the attribute set can be changed dynamically, the model permits the criteria of decision-maker to be unclear at the beginning of decision-making. When an attribute emerges from the recessive attribute set, the decision-maker can decide whether the attribute should be integrated into his criteria or not.

In practice, we must provide an appropriate interface for a decision-maker to help him evaluate chromosomes and revise his preferences in the evaluation process.

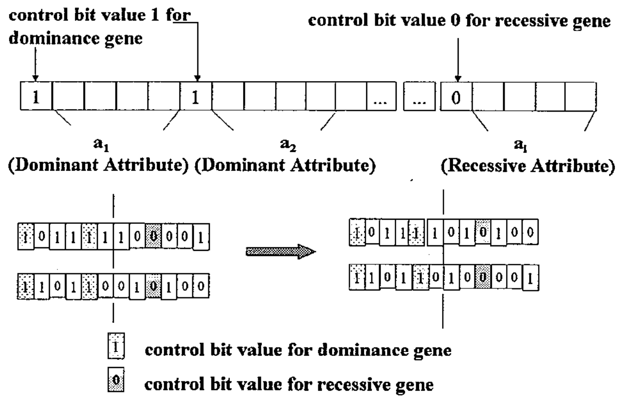

Figure 3. Control bits for dominant/recessive attributes

5. AN EXAMPLE OF NEW PRODUCT DESIGN

From the marketing point of view, a product can be regarded as a set of attributes. In other words, the construct of a product can be completely described by an attribute set (Crawford, 1991). The most important factor a customer cares is whether or not new functions and/or new idea are integrated into a new product whereas whether or not a new technology is adopted is not so much important.

In this section, we use cartoon facial mask design as an example to illustrate how the proposed model can help a decision-maker make his decision with a good decision-making process.

Suppose that attributes and attribute levels for facial mask have been accumulated where the attribute set has 12 attributes (nose, ear, mouth, chin, eye, eyebrow, hairstyle, beard, eyeglasses, mole, earrings, wrinkle) and each attribute has 16 attribute levels. A new attribute can be added to the attribute set whenever necessary.

Various attributes and corresponding attribute levels are then encoded into genotypes and phenotypes (Figure 4). An order relationship between genotype and phenotype must be taken into account carefully.

A decision-maker is asked to select some important attributes (in this example, nose, ear, mouth, chin, eye, eyebrow, and hairstyle) as "dominant attributes" while the others (beard, eyeglasses, mole, earrings, and wrinkle) are treated as "recessive attributes". After that, the decision-maker can start the following interactive evolution procedure.

1). The system generate an initial population of 32 facial masks at random, and display it to the decision-maker one page (8 facial masks) at a time using a interface such as the one in Figure 5.

2). The decision-maker picks up the most preferred (or few of more favored) facial mask(s) per page. To help the decision-maker effectively choose the satisfactory facial mask from each page, we provide him a pair-wise comparison process. The fitness of each facial mask can then be set according to the distance formula and fitness formula in section 4.2.

   In the meantime, if any good enough facial mask emerges during the evolution process, the decision-maker can mark it as an acceptable one; the other facial masks, of course, are served as non-acceptable. The chromosome structure of decision rules and examples are showed in Table 1.

3). According to the fitness of these facial masks, genetic algorithms perform the selection, crossover or mutation operations, and then generate a new population.

4). Repeat steps (2) to (3) until the optimal facial mask emerges or the maximum number of generations is reached. At this time, numerous of acceptable and unacceptable facial masks have been collected for the classifier system.

5). All of the information about acceptable and unacceptable facial masks is used by a classifier system to learn a set of decision rules of the decision-maker.

6). Finally, a simple GA will proceed with the decision rules learned by the classifier system (step 5) as a fitness function until a set of optimal facial masks is found.

After accomplishing the above procedure, the decision-maker obtains a set of alternatives. In addition, the decision-maker must have understood his preference and must have set up his criteria effectively by interacting with the IGA-model. It is believed that the alternatives and the criteria via the proposed model satisfy the requirements of a good decision process.

Because of the existence of recessive attributes (beard, eyeglasses, mole, earrings, and wrinkle, in this example), a facial mask with beard (or eyeglasses, mole, earrings, wrinkle) might appear via mutation operator in step 3.

Any recessive attribute can become a dominant attribute if the mutated dominant attribute is in the decision-maker's favor.

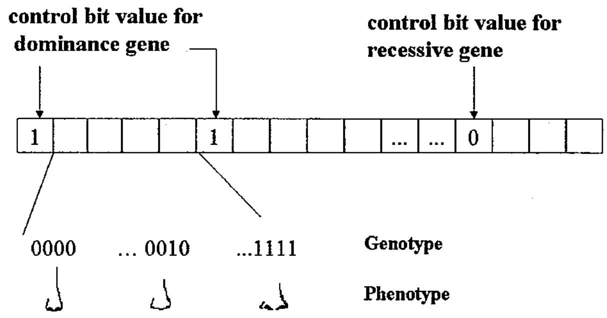

Figure 4. Genotypes and phenotypes of facial mask

Figure 5. A interface of IGA-based model

Table 1. decision rules representation

Bit 1-4	Nose, 0000 = don't care, 0001 = nose A,… 1111 = nose O
Bit 5-8	Ear, 0000 = don't care, 0001 = ear A, …… 1111 = ear O
Bit 9-12	Mouth, 0000 = don't care, 0001 = mouth A, … 1111 = mouth O
…	…
Bit 45-48	Wrinkle, 0000 = don't care, 0001 = Wrinkle A, … 1111 = Wrinkle O
Bit 49	Decision, 0 = acceptable, 1 = Non-acceptable
Example	
Rule 1: Genotype: 111# 0001 0011 0000 0000 … 0000 00#1 1 Phenotype: A facial mask is **acceptable** if (Nose = Nose N or O) and (Ear = Ear A) and (Month = Mouth c) and (Wrinkle = Wrinkle A or C)	

We developed a prototype to test the feasibility of the proposed IGA-based model. Although neither the classifier system nor the dominant/recessive attributes mechanism was included yet, some of the initial test results showed that the model performs as we expected.

6. CONCLUSION

Based on our study and practical implementation, we believe that interactive genetic algorithms can be integrated into decision support systems to help decision-makers cope with unstructured problems (Simon, 1960; Gorry and Scott Morton, 1971). Besides, interactive genetic algorithms can help a decision-maker simultaneously find out several different alternatives with equal effectiveness. This distinguishing job is almost impossible for other models.

How to enhance the performance of interactive genetic algorithms is still an open issue. We argued that this challenge should be conquered before they can be used practically. The three concepts suggested in the paper are believed to be helpful for IGA-based systems. In addition, the dominant/recessive attribute mechanism also provides a new direction for IGA applications.

In conclusion, the proposed IGA-based model points out a new direction for supporting multiple criteria decision-making and attempts on improving IGA performance might help the applications of IGAs on various other domains.

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