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Decision Theoretic Conflict Resolution in Rule-based Expert System

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Abstract

Techniques from decision analysis and expert system have both been extensively used in the development of computerized decision aids, although each discipline uses different approaches in knowledge (information or input) acquisition, representation, and problem solving methodology. From the perspective of many types of practical decision aiding applications, both normative decision aids and expert system technology have significant limitations. Many research efforts have been exerted toward complementing the one's deficiency with the other's possible techniques or vice versa.

In this paper, among many possible complementary techniques for better decision aiding between decision analysis and expert system, we focus on the using prescriptive methodology of decision analysis which incorporates user's preference knowledge for conflict resolution in rule based expert system.

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1. Introduction

Techniques from the disciplines of artificial intelligence (AI) and decision analysis (DA) have both been extensively used in the development of computerized decision aids. Expert system (ES), one of methods emulating human decision making, is a computer program that solves problems that required significant human expertise by using explicitly represented domain knowledge and computational decision procedures (Kastner and Hong, 1984). In normative DA, decision aids have been developed that use decision models as prescriptive problem representations to help guide users through the decision making process. Both ES and DA, providing systematic methods for problem solving and decision making, have conceptual basic denominators in view of objectives (decision aiding), delivery vehicle (the computer), conceptual basis (graphs, networks).

Unfortunately, from the perspective of many types of practical decision aiding applications, both normative decision aids and expert system technology have significant limitations. Particularly, in expert system development, there is a lack of established techniques for problem structuring and knowledge engineering. This usually leads to time consuming rule based development efforts with limited success in domains where the knowledge required to solve problems is not already well established (Davis, 1982). Further, the current generation of expert systems do not explicitly consider preference, which plays key role in DA and when preference are (indirectly) addressed, they are the preferences of the expert rather than the user's preferences adjusted to the current problem solving environment (White, 1990). Normative decision analysis, on the other hand, is usually built around prescriptive and rigid problem structure called a decision analysis model. This model, in turn, may not be compatible with the evolutionary approach to system development, which is characteristic of AI (Lehner, et.al., 1985).

So many efforts have been exerted toward complementing the deficiency of ES with DA's possible techniques or vice versa. The detailed part of researches for complementation will be described in following section. In this paper, among many possible complementary techniques for better decision aiding between DA and ES, we focus on the possibility of using DA's prescriptive methodology (prioritize or rank alternatives or options in prescriptive manner) which incorporates user's preference knowledge for conflict resolution in rule based expert system. A cycle of a production system can be viewed as having three phases: matching, conflict resolution, and action. During inference, it is possible to identify the set of rules that matches the context. If this occurs during matching process in production system, some approaches should be applied to resolve conflicts (Bar and Feigenbaum, 1981; Davis and King, 1977; Hayes-Roth, et.al., 1977).

Metarules useful in conflict resolution are often directly related to the multiple, conflicting and noncommensurate objectives associated with problem domain. However, it is perceived that the use of metarules for conflict resolution and in its current forms, has three key drawbacks:

1) Metarule use in rule selection is not tailored to the specific user (as opposed to the domain expert, whose domain expertise, preferences, etc. were used to construct the system) and the current situation.

2) Use of metarules in rule selection does not take into account objectives tradeoffs.

3) Metarules do not permit efficient representations of expert knowledge when many objectives or decision contexts must be taken into account.

We propose DA based techniques applicable in some problem domains to resolve conflicts in rule based expert system, trying to integrate two disciplines for finding synergy. Further, group consideration in conflict resolution will be discussed for better consensus of rule selection.

The rest of this paper is organized as follows. Section 2 reviews a number of approaches in viewpoint of decision theoretic expert system. Section 3 suggests the possible use of decision analysis techniques for conflict resolution in expert system and application is included in Section 4.

2. Research Background

In view of ES's applications, ES can be largely divided into two categories:

analytic and synthetic. Analytic ES deals with valuation of the alternatives, e.g., prediction, classification, diagnosis. On the other hand, synthetic ES focuses on the constructing one or more feasible options, e.g., generation of alternatives, design, configuration, and planning. Early ES researchers have more concerns on the automated probabilistic reasoning for diagnosis under uncertainty. For reduction of probability calculation, two simplifying assumptions, mutually exclusiveness and conditional independence on the probabilities are adopted for tractability. Many numerous medical diagnostic problems have been dealt successfully (Szolovits and Pauker, 1978). However, due to the unwarranted simplifying assumptions and intrinsic restricted problem domain, the Bayesian reasoning method lost its standing basis.

Concern with the restrictive assumptions of the simplified probabilistic scheme coupled with the perception that a combinatoric explosion would threaten any attempt to move beyond these assumptions or to larger domains led to disenchantment with the approach (Horvitz, et.al., 1988).

A key feature of the new expert system paradigm was the application of the production rule architecture to real world application. Production rules had appeal as providing a general and flexible scheme for representing expert knowledge in a declarative and modular form (Buchanan and Shortiffe, 1984). Above all, the two best known attempts to develop representations of uncertainty (we call ES dealing with uncertainty as likelihood knowledge based ES) as an extension of deterministic rule based expert system were the MYCIN (propose appropriate drug treatment in the area of blood and meningitis infection) and Prospector (work as an economic geologist, assessing the likelihood of the occurrence of particular ore deposits, given data concerning geological features).

Researchers have attempted to develop richer knowledge representations that are based on probability and decision theory in a principled way and yet are capable of expressing, in a flexible and tractable manner, a wider range of both qualitative and quantitative knowledge. Much of this work has centered on the use of graphs and networks to represent uncertain relationships, including belief networks and influence diagrams. Influence diagrams are a potentially more parsimonious graphical knowledge representation language that represents the decision basis (alternatives, states, preferences, and relationship). Influence diagrams formally describes a decision basis, yet have a human oriented qualitative structure that facilitates knowledge acquisition and communication. Belief networks (sometimes called causal networks or Bayesian networks) focus on the specialization of influence diagram that contains only chance nodes. Under several assumptions, this approach to representation and calculation allows a full specification of the probability of any combination of events with smaller elicitation of probabilities (Matzkevich and Abramson, 1995). Belief network is versatile, so it may be used either to predict what will happen or to infer causes from observed effects. Though both influence diagram and belief network have more expressive representation capability of domain knowledge and explanation capability, differently from the past decision theoretic expert system used in diagnosis and prediction, they still have several difficulties in eliciting a priori probability information from the users.

Apart from likelihood knowledge based ES, there have been other approaches to use ES for constructing utility functions in DA applications (we call ES embedding user's preferential knowledge as preferential knowledge based ES). Farquhar (1987) examines applications in the construction of evaluation functions for intelligent computer systems with the intent of demonstrating the usefulness of utility theory for these AI based research activities. He reports on three basic multiattribute utility theory (MAUT) approaches for modifying evaluation functions in intelligent systems. Lehner, et.al. (1985) outlines an approach which systematically exploits both the problem structuring techniques of DA and the incrementally modifiable software architectures found in AI. Keeney (1988) notes that many AI based decision aids treat preferences implicitly and heuristically and hence violate the premise that preferences should be prominent in decision aid development since preferences are the driving force for making decisions. He remarks that implicit representation of preference does not permit an investigation of how preference can affect changes in suggested actions. He then provides suggestions for knowledge engineers to explicitly structure preferences in ESs and hence to integrate DA into ESs. As a method incorporating DA's prescriptive technique in ES's conflict resolution, White and Sykes (1986) suggest the possibility of utilizing user preference guided approach to conflict resolution and in design problem such as fossil fuel boiler design and computer aided design, alternative designs created by production rule should be evaluated by employing user preference to personalize the search for improved design (Brown and White, 1987; Syskes and White, 1991).

The prescriptive DA's method which takes into account user's preferences will be described in next section.

3. Transforming Conflict Resolution Problem Into Multiattribute Decision Making

3.1. Single User Case in Conflict Resolution

In this part, we briefly introduce DA's key concept and techniques that will be used as conflict resolution method in rule-based expert system. In multicriteria single decision making, one usually considers a set of alternatives (options or candidates), which is valued by a family of criteria (objectives). Assuming any two given combinations elicited from decision maker (DM) of three pieces of information (alternatives, attributes, utility scores) as shown in Figure 1, many researches to infer the information about the unknown one parameter have been done under different types of assessed information from decision maker (e.g., exact estimate, ordinal ranking, incomplete, etc.).

	Attributes(1,...,n), w
Alternatives (1,...,m), a	Utility Scores of Alternative i on Attribute j, u

Figure 1. The framework of multiattribute decision making

Under additive independence assumption, if exact values about attribute weights and utility score are specified, the expect utility of an alternative, $a \in A$ can be denoted by

$$EU(a) = \sum_{i=1}^{n} w_i u_i(a) = \mathbf{wu}(a)$$

where w is tradeoff weight among attributes, usually assumed to be sum to one (Keeney and Raiffa, 1976). By comparing the magnitude of each alternatives' expected values, we can rank most preferred alternative(s) in viewpoint of decision maker.

As mentioned in literature (White, et.al., 1984; Kahneman, et.al., 1983; Weber, 1987), the assessment of precise utility scores and tradeoff weights can be time consuming and stressful and hence can represent a significant barrier to the acceptability of any MAUT-based decision making procedure. So natural language statements about attribute weights (e.g., attribute i is twice important as much as attribute j) and utility scores are more appropriate assessment of preferences, though they do not sometimes provide sufficient information for precise determination of alternatives ranking. The type of natural language statements for preferential knowledge that we suggest for tradeoff weight between objectives and utility of alternatives on objective is linear inequality forms. The linear inequalities in our consideration consist of 5 forms which are illustrated in the case of tradeoff weights between objectives as follows: 1) A weak ranking: $\{w_i \geq w_j\}$, 2) A strict ranking: $\{w_i - w_j \geq \alpha_i\}$, 3) A ranking with multiples: $\{w_i \geq \alpha_i w_j\}$, 4) An interval form: $\{\alpha_i \geq w_i \leq \alpha_i + \varepsilon_i\}$, 5) A ranking of differences: $\{w_i - w_j \geq w_l - w_m\}, for\ j \neq l \neq m.$

When information about attribute weights and utility scores is specified incompletely, we can construct preference order of alternatives through pairwise comparison between alternatives (Sage and White, 1984; Park and Kim, 1997). Pairwise dominance of an alternative over another indicates that the expect value of the dominant alternative is larger than that of the dominated alternative for all the relevant information that DM specifies. If following inequality (3.1) holds

$$Min[EU(a') - EU(a)] = \sum_{i=1}^{n} w_i[u_i(a') - u_i(a)] \geq 0 \qquad (3.1)$$

then we can say alternative a′ dominates alternative a.

Now we are in a position that conflict resolution problem in rule-based expert system can be viewed as a multiattribute decision making problem depicted in following Figure 2.

	Conflicting Objectives
Conflicting Rules	User's preference about rules on each objectives

Figure 2. A scheme of conflict resolution

In Figure 2, conflicting rules occur during matching stage of production cycle and it can be thought that conflicting objectives replace the role played by metarules, which are often directly related to the multiple and conflicting objectives associated with problem domain. For example, consider the following spill-over crisis management rules (Hayes-Roth, et.al., 1983; White, 1990).

R1 If the spill is sulfuric acid, then use an anion-exchanger.

R2 If the spill is sulfuric acid, then use acetic acid.

R3 Use rules that employ cheap materials before those that employ more expensive materials.

R4 Use less hazardous methods before more hazardous methods.

Clearly, metarules R3 and R4 are directly related to objectives "minimize cost" and "maximize safety", respectively. Further, though it has been determined that a spill has been discovered and the spilled material is sulfuric acid, there should be more concerns about the characteristics of spill (e.g., proximity to humans, wild life, property, etc.), the user's attitude toward risk, or budgetary constraints before concluding R1 or R2 as an action rule. Of course, it is possible to include aforementioned situation as rules or metarules but it increases the size of rule base in explosive way and hence difficult to manage.

What can be identified by pairwise dominance suggested in (3.1), is the set of all nondominated rules in the conflict set. Let the rules in all the conflicting rule set, A be ordered by the following relation: rule a' is at least as preferred as rule a if and only if $\mathbf{wu(a') \geq wu(a)}$ for all $w \in W$ and $u \in U$, where W is the set of all possible tradeoff weight vectors and U is the set of all utility score arrays $u = \{u_i(a)\}$. A rule

$a \in A$ is said to be nondominated if and only if there is no rule $a' \in A$ such that $\mathbf{wu(a') \geq wu(a)}$, for all $w \in W$ and $u \in U$.

Once the set of nondominated rules has been selected, then either the user can select his/her most preferred rule from the set of nondominated rules or the user must provide the system with a more precise description of preferential knowledge so that the number of rules in the nondominated set can be reduced.

3.2. Group Consideration in Conflict Resolution

The increasing complexity of the socio-economic environment makes it less and less possible for single decision maker to consider all relevant aspects of problem domain. In decisions affecting and pervading the important influence, such as spill over crisis management, group members who have different perception and preferences about problem domain need to be involved for better consensus of conflict resolution in rule based expert system. Further, if possibly different decision power in reaching final group decision can be adopted, it is more reasonable rule selection process which takes into account group members' different recognition and attitude toward current situation.

If the group members share the same conflicting rule set and objectives related with conflicting rules, the transformation of rule selection problem into group decision making problem can be depicted in following Figure 3.

	Conflicting Objectives
Conflicting Rules	Group 1's preference about rules

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	Conflicting Objectives
Conflicting Rules	Group K's preference about rules

Figure 3. A scheme of group's conflict resolution

So far only a few studies have employed incomplete preference model in group settings (Salo, 1995). As an extension of multiattribute single decision making situation, when each group member specifies preferential knowledge about attribute weights and utility scores incompletely, the detailed process in reaching group's aggregated rule selection can be found in Kim and Ahn (1997a, 1997b). For example, for any competing rules r1 and r2, group prefers r1 to r2 if and only if $V(r_1,r_2) \geq 0$,

$$V(r_1,r_2) = Min\sum_k p^k \sum_i w_i^k \{u_i^k(r_1) - u_i^k(r_2)\} \geq 0$$
$$s.t. \quad P,W,U.$$

where $p^k \in P$ is the group member k's importance weight in participating at conflict resolution. By solving a series of linear programs, we can find out most preferred rule with which group members are satisfied.

An interactive algorithm applicable to the conflict resolution problem based on the above model for rule selection can be outlined by following 4 steps:

1) Assessment of P, W, U.

2) Interactive inconsistency checking with users because linear inequality constraints can cause infesibility.

3) Solving pairwise dominance problem between rules by individual group members.

4) Aggregation of individual dominance results among conflict rules, using possible different group member's importance weight.

4. Application

This application examines the application of multi-objective linear goal programming (MOLGP) in military budget planning where there exist multiple (sometimes) conflicting objectives to be considered (Kim, et.al., 1997). The basic idea of goal programming is to establish a specific numerical goal for each of the objectives, formulate an objective function for each objective, and then seek a solution that minimizes the (weighed) sum of deviations of these objective functions from their respective goals. Specifically, in a typical model, some of the goals will be hard (i.e., they absolutely must be satisfied) and some will be soft (i.e., some deviation is tolerable). It is sometimes uncertain which constraints or objectives should be hard or soft. In this paper, we are considering three mathematical models which differ by user's emphasis on the quantity of weapon system procured or available amount of budget.

4.1. Problem Description

With given considerations such as the annual available budget, the total annual effectiveness index to be achieved and the military industry's ability to supply weapon systems and components, we aim to find the annual procurement amount for the next five years above the desirable aspiration level for each weapon system in accordance with three types of preemptive priority levels. Each weapon system is classified into three categories according to its procurement priority. The weapon systems are prioritized as the A type which is extremely important, the B type which is important, and the C type which is of minor important. The terminology is defined as follows:

1) aspiration level : an aspiration level is employed in order to convert an objective into a goal. It represents a target (or threshold) level for the given objective - a level that is desired and/or acceptable. When one employs aspiration levels, he or she is implicitly using the notion of satisficing;

2) procurement unit cost : the purchasing price of each weapon system incorporating the annual deflation rate which is calculated automatically by entering historical procurement data;

3) operating/maintenance unit cost : the cost used to operate and fix each weapon system during a given year incorporating the annual deflation rate;

4) effectiveness index : this index is prior knowledge obtained through war game simulation at Operation Analysis Department in the Korea Ministry of National Defense. This index is measured against similar North Korean weapon systems and is limited to fire weapon systems;

5) annual industry supply capability : the lower and upper bound that industry can supply, with regard to the military screening plan;

6) deflator : under particularly military environments, the fluctuating price rates obtained by transforming the nominal price into the real price, we use two types of deflator depending on purchasing location; domestic and foreign deflator.

We have four assumptions for model building: the planning horizon is five years, the cost is made at the point of procurement, each weapon system is classified by a priority level and has a desirable aspiration level. Instead of an inflation rate which reflect the fluctuating price rates, we use the deflator which has the specific value according to weapon system categories.

4.2. Optimization Model Formulation

Based on the criteria (see appendix A), we suggest three models for military budget optimization. Although MOLGP is a solving procedure we use, some difficulties exist in determining what the objectives and rigid constraints are. To resolve this problem, we have developed a rule based expert system for supporting model selection process. Through interaction with the user, our system suggests the most suitable model which is determined according to the characteristics of each model in Table 1. Three models can be classified according to the different goals in achieving the aspiration level based on the priorities of weapon systems, minimization of procurement cost, and maximum achievement of weapon systems requirement. The detailed model formulation can be found in appendix B.

Table 1. The three types of MOLGP models

	POM	BOM	ROM
Utilization Goal	allocate more than AL by priority	achieve the least AL at the minimum cost	achieve the maximum AL with total budget
Objectives	more than AL for type A&B and near AL for type C	AL for type A&B at minimum cost and near AL for type C	maximum allocation of weapon system at given budget and max AL by weight
Constraints	APC, EFI, AOC, ISC, APD	AL, EFI, AOC, ISC, APD	EFI, AOC, ISC, APD

4.3. Model Selection Expert System

The model selection expert system as shown in Figure 4 is used to help decide which of the three mathematical models (POM, BOM, ROM), interactively asks the necessary questions needed to reach a conclusion. If the user has sufficient knowledge or experience about the three models, he can skip the model selection step; otherwise, through interactive dialogue based on the model selection criteria such as understandability of model, budget boundary, difficulty of prioritization, and importance of requirement, the expert system suggests a more suitable model.

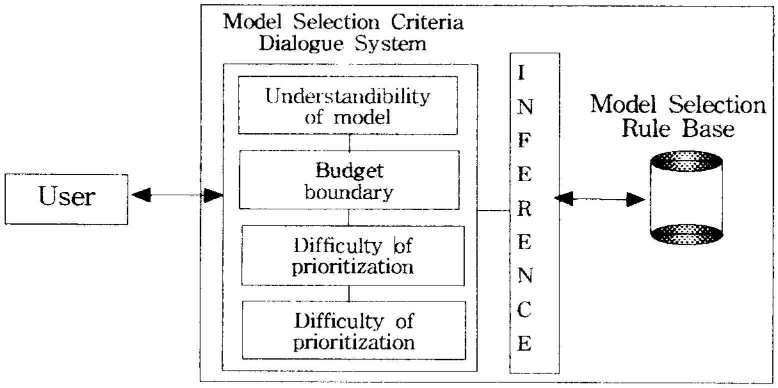

Figure 4. Model selection expert system

In model selection stage, there may exist two models to be matched according to user's input facts. For example, if achievement more than objective requirement is required or there exists difficulty and uncertainty in determining priority level, then the two models (POM or ROM) are suggested. We suppose that there are three competing rules, R1, R2, and R3 which suggest two mathematical model POM and ROM, respectively and through analysis of counterpart's strategy or tactic, the user recognizes the following three conflicting criteria which is dependent on evolution of situation, so it is difficult to be included in predetermined production form : firstly, in future 2 years, the counterpart is planning his power index (effectiveness index) maximized through buying more modern weapon systems and secondly, the model is preferred to buy weapon systems least influenced by changes of defense budget, and finally, it is difficult to reserve capable staffs to operate new modern weapon systems with high priority or the military system will be rearranged and hence many seniors will be dropped out, etc.

To resolve conflicting rules under 3 criteria, such as safety, economical consideration, and situational change, we can transform the conflict resolution problem into imprecise multiattribute decision problem which takes account of user's perception toward various criteria. For example, the preference information in Table 2 is gathered from the single staff.

Table 2. Incomplete preference information among conflicting rues

	Effectiveness	Economy	Environment
R1	$U_{EF}(R_1) \geq U_{EF}(R_2)$	$U_{EC}(R_1) \geq U_{EC}(R_2) + U_{EC}(R_3)$	$U_{EN}(R_3) \leq 0.5$
R2	$U_{EF}(R_3) \geq U_{EF}(R_2)$	$U_{EC}(R_3) \geq 2U_{EC}(R_2)$	$U_{EN}(R_1) - U_{EN}(R_3) \geq U_{EN}(R_2)$
R3	$U_{EF}(R_2) \leq 0.4$		$U_{EN}(R_3) \geq U_{EN}(R_2)$

Further, assume that there exists the tradeoff weights, between criteria, which means that the user considers that the importance of efficiency is more important than any other competing objectives. Using DA's prescriptive methodology to solve this problem under incompletely specified information, we can find out the most preferred rule among R1, R2, and R3, reflecting user's preferences. Further, if group of staffs is involved to determine which model should be applied, we can gather each group member's preferences, assuming possibly different importance weights between staffs. Applying the methodology suggested in Section 3, will produce group's aggregated preferred rule.

5. Concluding Remarks

Despite their different perspectives, expert system and the disciplines of decision science have common roots and strive for similar goals, decision aiding. Many researches have been reported , trying to integrate seemingly two different disciplines for finding synergy, although each has its own generic characteristics.

We have proposed an approach to resolve conflict set in the process of matching of production cycle. The prescriptive approach of decision analysis is based on preferential knowledge progressively acquired from the user in the context of the specific problem situation. The representation of preferential knowledge is a type of natural language described by linear inequality forms. Further, group members who have different perception and preferences about problem domain need to be considered for better consensus of conflict resolution, especially in decisions affecting the important influences. We think that the conflict resolution in rule based expert system of incorporating user's preferences in some specific problem domain, will enhance not only the system' s capability but also its acceptability.

Appendices

A. Multiple Criteria

In order to solve the national military budget optimization problem, we must establish the following goals and considerations. The considerations are classified into objectives (soft goals) or constraints (rigid goals) in accordance with the accomplished goal.

1) Aspiration Level (AL)

The priority levels A, B, and C, and the total five-year amount of each weapon system for each priority to be achieved are the aspiration level . It is considered into objectives (soft goals) in our formulation.

$$\sum_{m} X_{ijklm} \leq A_{ijklm}, \text{ for each priority } l = \text{A, B, C} \qquad (1)$$

Army, navy, air, and common weapon systems are represented by i. Functions of weapon systems indexed as j consist of mobile, armored, and the like. Types of weapon systems, k, are troop, fire, and common respectively.

2) Annual Procurement Cost (APC)

The annual procurement cost should not exceed the given available budget each year.

$$\sum_i \sum_j \sum_k \sum_l C_{ijklm} \bullet X_{ijklm} \le B_m, \text{ for each } m = 1,2,\mathrm{K},5 \qquad (2)$$

where, Cijklm is a unit procurement cost of weapon system ijkl at year m, and Bm is the available budget at year m. The procurement cost at year m+1, Cijkl(m+1), is calculated by following Cijklm × (1+i), where i is a deflator.

3) Effectiveness Index (EFI)

The unit effectiveness of a weapon system multiplied by the quantity of purchased weapon system determines the total effectiveness index.

$$\sum_i \sum_j \sum_k \sum_l E_{ijklm} \bullet X_{ijklm} \ge TE_m, \text{ for each } m = 1,2,\mathrm{K},5 \qquad (3)$$

where, Eijklm is the unit effectiveness index of weapon system ijkl at year m, and TEm is the total desirable effectiveness index at year m.

4) Annual Operating Cost (AOC)

The cumulative operating cost for any given year should not exceed the given available operating cost. The annual operating cost at year m+1, Oijkl(m+1), is calculated by following Oijklm × (1+i).

$$\sum_i \sum_j \sum_k \sum_l O_{ijklm} \bullet (X_{ijkl(m-4)} + X_{ijkl(m-3)} + X_{ijkl(m-2)} + X_{ijkl(m-1)} + X_{ijklm}) \le OC_m,$$
$$\text{for each } m = 1,2,\mathrm{K},5 \qquad (4)$$

where Oijklm is a unit operating cost of weapon system ijkl at year m, and OCm is the total operating budget at year m.

5) Industry Supply Capability (ISC)

The number of weapon systems which will be procured should fall between the lower and upper bounds which industry can supply.

$$L_{ijklm} \le X_{ijklm} \le U_{ijklm}, \text{ for k = facility, fire equipment} \qquad (5)$$

where L is lower bounds, and U is upper bounds of industry supply capability.

6) Allowable Percentage Deviation (APD)

For stable budget utilization, the weapon systems should be purchased within the allowable percentage deviation.

$$(1 - p_{ijkl})X_{ijkl(m+1)} \le X_{ijklm} \le (1 + p_{ijkl})X_{ijkl(m+1)} \qquad (6)$$

where pijkl is an allowable percentage deviation from the previous year production quantity.

B. Three MOLGP Models

POM : Priority Oriented Model

The POM is used to allocate a higher aspiration level according to the weapon system priorities. Therefore, the goals of a POM are the sum of unwanted deviation, that is, shortage procurement, for priority level A, B, and C of each weapon system. Then objectives are represented in formula (1) and constraints (2) are added into the constraints of a POM in Table 1.

$$\textit{lexico.}\ \min\ \{\sum_{i\in A} w_i\eta_i, \sum_{j\in B} w_j\eta_j, \sum_{k\in C} w_k\eta_k\} \tag{1}$$

$$\textit{subject to}\quad \sum_m X_{ijklm} + \eta_l - \rho_l = A_{ijkl},\ \text{for each priority } l = \text{A, B, C} \tag{2}$$

The algorithm used for solving this model is based on the sequential linear goal programming (SLGP). So unwanted deviations are minimized because we buy the most important weapon systems first, due to a lack of budget.

BOM : Budget Oriented Model

The utilization goal of a BOM is to achieve the minimum aspiration level at a minimal cost as in the objectives in (3). The first two goals of a BOM for weapon systems with priorities A, and B are to minimize the procurement cost and then those resulting values are included in the constraints of the next formula to maintain the values attained in the previous formula. The final goal for priority C is to achieve the aspiration level with the remaining budget.

$$\begin{aligned} &\textit{Minimize}\ \sum_i\sum_j\sum_k\sum_l\sum_m C_{ijkA_lm} \bullet X_{ijkA_lm},\ \text{for priority A variables} \\ &\textit{Minimize}\ \sum_i\sum_j\sum_k\sum_l\sum_m C_{ijkB_lm} \bullet X_{ijkB_lm},\ \text{for priority B variables} \\ &\textit{Minimize}\ \sum_{i\in C} w_i(\eta_i + \rho_i),\ \text{for priority C variables} \end{aligned} \tag{3}$$

The solution technique is the combination of a SLGP and a LP. The first two steps will reveal the solution satisfying the given aspiration level with minimum cost for priority levels A, and B. In doing that, the optimal values of the first formula are reflected in the constraints of the second formula and we then seek to minimize the cost for procuring the priority B weapon systems as in the first step. In the third step, we apply the SLGP algorithm to the priority C variables in order to procure as close as possible the aspiration level with the remaining budget.

ROM : Requirement Oriented Model

The ROM is designed to achieve the maximum procurement above the aspiration level by utilizing as much of the budget as possible. The SLGP's goals of a ROM are the sum of an unwanted deviation, that is, over and under the usage of the budget, for all weapon systems. The ROM objectives are represented in formula (4) and constraints (5) are added into the constraints of ROM in Table 1.

$$lexico.\ \min \{\sum_{p} w_p(\eta_p+\rho_p), \sum_{i\in A} w_i(\eta_i+\rho_i), \sum_{j\in B} w_j(\eta_j+\rho_j), \sum_{k\in C} w_k(\eta_k+\rho_j)\} \tag{4}$$

$$subject\ to\quad \sum_{i}\sum_{j}\sum_{k}\sum_{l} C_{ijklm} \bullet X_{ijklm} + \eta_p - \rho_p \le B_m,\ \text{for each } m = 1,2,\Lambda\ ,5$$

$$subject\ to\quad \sum_{m} X_{ijklm} + \eta_p - \rho_p = A_{ijkl},\ \text{for all weapon systems} \tag{5}$$

The first goal is to totally utilize the budget and allocate the maximum number of weapon systems. The amount of used budget in the first step is considered as constraints in the second step. Then we will discover the optimal procurement amount using weighted sums of undesirable deviation variables.

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