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A New MCDM Approach to Solve Public Sector Planning Problems

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Abstract. An interactive multiple criteria decision making method is developed to aid decision makers in public sector planning and management. The method integrates machine learning algorithms along with multiobjective optimization and modeling-to-generate-alternatives procedures into decision analysis. The implicit preferences of the decision maker are elicited through screening of several alternatives. The alternatives are selected from Pareto front and near Pareto front regions that are identified first in the procedure. The decision maker's selections are input to the machine learning algorithms to generate decision rules, which are then incorporated into the analysis to generate more alternatives satisfying the decision rules. The method is illustrated using a municipal solid waste management planning problem.

Keywords. MCDM, interactive methods, association rule mining, preference elicitation methods

I INTRODUCTION

Many public sector planning and management problems still pose challenges and complexities due to their computational requirements, multiple criteria nature, and sociological impacts. Especially the environmental control, management and policy problems typically require the consideration of numerous conflicting criteria including cost, public health, social acceptability, political feasibility, equity and environmental performance such as emissions, energy consumption and impact.

Multiple Criteria Decision Making (MCDM) methods are designed to help decision makers (DMs) in searching for the best compromise solution. The extensive use of MCDM methods in public decision making applications has been limited by the complexities involved in eliciting the preferences of the decision maker (DM). In the traditional MCDM methods, the preference elicitation techniques include pair-wise comparisons and/or ranking of alternatives to obtain utility functions of a DM [1, 2] or to utilize outranking approaches [3]. As number of alternatives to be compared increases, the combinations of pair-wise comparisons increase as well. Unfortunately, this situation results in an increase in cognitive load imposed on the DM. Thus, the likelihood of making inconsistent or irrational decisions increases.

Recently, to elicit the DM's preferences easily, more and more nonclassical techniques are being utilized and seen in the literature. One of the preference modeling approaches is the decision rule approach [4]. The preferences can be modeled in the form of *"if..., then..."* structure. This structure is called a decision rule. Initially, the concept of the decision rules in MCDM literature was first introduced by [5] through the rough set theory. The theory is based on inductive thinking and analyzes the logical relations among the selected alternatives. Some applications include, but not limited to, the generation of the decision rules to be utilized in manufacturing process control applications [6, 7].

Machine learning is a well-known computer science discipline that is concerned with the development of the algorithms and the techniques to allow computers to "learn". In general terms, there are two types of learning and reasoning, namely inductive and deductive. The machine learning techniques utilize inductive learning and reasoning concepts around data or examples to extract unknown and/or hidden patterns and trends. [8]

More specifically, data mining and knowledge discovery field was formed to develop specific algorithms for finding meaningful and useful patterns in large databases. The patterns can be represented in the form of association rules [9]. Most of the algorithms are designed to relate attributes or features of each data entry with the rest of the data set. This field combines methods from statistics, information retrieval, machine learning and pattern recognition. The use of data mining and knowledge discovery methods promises effective applications to public as well as private multiple criteria decision problems.

One way to represent the trends and the patterns in a data set is to generate a decision tree. Consequently, each branch in the decision tree would represent a decision rule. Algorithms are designed to prune the decision tree effectively to generate the most meaningful list of the decision rules. These rules are then incorporated into models that would predict the value of a new data entry [10].

References [11] and [12] looked at the customer interactions to discover association rules for the purchasing behaviors of the customers. The preference information of the DM, which is represented by the decision rules of the *"if..., then..."* structure, are incorporated into the decision making process. For example, if a DM is frequently selecting an attribute during the decision making process, then the machine learning algorithm will create a decision rule to include that attribute into the model.

During the decision making process, the applicability of the resultant decision vector of solutions from the Pareto front region is often left to be scrutinized at the end of the search process. Identification of the final solution should, however, consider not only its performance in the objective space, but also the values of the decision variables that constitute the final solution. The examination of decision space would help evaluate subjective or unquantifiable issues such as practicability and feasibility. Further, some objectives and criteria cannot be captured via mathematical modeling due to insufficient mathematical representation, incomplete information, or qualitative nature of the objective. Most public sector planning decisions are compounded by these complexities as they involve consideration of political feasibility, sociological concerns, equity among different interest groups, and cost and benefits of each action. In addition to the complexities in the preference elicitation techniques, the applicability of the MCDM methods in public sector planning is limited by the complexities while considering the qualitative objectives.

In a multiobjective problem when additional objectives are introduced, the original best compromise solution is no longer noninferior, and the new best compromise solution would lie in the inferior region of the original objective space [13]. The best compromise solution on the Pareto front may deem inadequate to address the unmodeled issues, and therefore consideration of near noninferior solutions that have maximally different decision variable values may be needed.

The modeling-to-generate-alternatives (MGA) method [14] is used to generate alternative solutions on and near the Pareto front region. These alternative solutions are selected from maximally different regions in the decision space while ensuring them to be similar within a small deviation from the best compromise solution in the objective space. As these alternatives are likely to represent distinct solution characteristics, they are expected to perform differently with respect to unmodeled or qualitative objectives that a DM may consider during the decision making process.

An interactive MCDM method is developed to bridge the gap in existing methods. The method incorporates search in the Pareto front along with the search in the decision space. At each iteration, the objective values and the values of the corresponding decisions variables of the solution are examined simultaneously. Utilization of machine learning algorithms, more specifically data mining algorithms is being investigated to enable easy extraction of the DM's preference information. Based on what solutions are selected by the DM as acceptable or not, the relations and the associations are constructed among the objectives and the decision variables.

Next section describes the new MCDM method. In section 3, the results from an application of the new MCDM method to a real public sector planning case study are presented.

II METHODOLOGY

An interactive MCDM method is developed to aid decision makers involved with public sector planning and management problems. The method integrates data mining algorithms along with multiobjective optimization and MGA procedures into decision analysis.

The method searches for the best compromise solution by exploring selective solutions from Pareto front while the DM's preferences are elicited and incorporated into the analysis. The utilization of data mining algorithms is being investigated to enable easy extraction of the preference information. Based on the preference to accept or not accept each alternative solution, the relations and the associations are constructed among the objectives and the decision variables of the problem.

The method is decomposed into two phases. In the first phase of the procedure, the analyst and the DM assess the preferences on the Pareto front. In the second phase of the procedure, the preferences in the decision space are assessed while the preferences in the objective space are still reflected and preserved at each iteration. The iterations continue until the best compromise solution is attained.

The tradeoffs among conflicting objectives and the payoff matrix are generated in the first phase. An ideal point is identified from the payoff matrix. Many methods have been developed to generate the Pareto front region or to find the best compromise solution on the Pareto front region [15]. Our method focuses on finding a solution or a region on the Pareto front that is close to the aspiration levels (e.g. ideal point). Methods such as the Tchebycheff method [16] and goal programming [17] are available to find the solution that best meets the specified aspiration levels. While the approach described in this paper is flexible to accommodate any of these methods, the description and the results are based on a constraint method-based implementation to generate the Pareto front region. Based on the aspiration levels of the DM, a region or a point on the Pareto front is found for further investigation.

In the next phase, the investigation includes the decision space. From the region or the point on the Pareto front that is close to the aspiration levels, a collection of solutions are presented to the DM. The values of the decision variables and the objectives of the solution/s are analyzed by the DM. If there are explicit preferences on the values of the decision variables and the objectives, they are then incorporated as constraints into the multiobjective optimization model to find new solutions.

Next, distinct solutions within the inferior region of the decision space are generated by employing MGA methods by relaxing the objective values of the point on the noninferior region. These distinct solutions would lie close to each other in the objective space; however, the values of the decision variables will be maximally different than those in the original solution. The number of MGA solutions to be generated is dictated by the uniqueness of the last MGA solution generated. Unless the solutions start to look similar to each other, more MGA solutions will be generated.

The MGA solutions and the noninferior solution/s form a solution set. The DM and the analyst examine the values of the decision variables and the objective values of the solution in the set. The DM categorizes the solutions as preferred or not preferred. The selection information is processed by the data mining algorithms. The algorithm analyzes the trends and the hidden patterns in the set of solutions to generate decision rules. Consequently, the decision rules would help us discover the implicit preferences of the DM. The applicability of the decision rules are validated at each iteration by the DM, and irrelevant rules are discarded. The satisfactory decision rules are incorporated into the original multiobjective optimization model as constraints. The model is solved again to obtain an updated solution with an updated decision vector that is reflective of the decision rules.

In some cases, the algorithms may yield inapplicable or irrational decision rules. In this case, the analyst generates additional MGA solutions to generate more decision rules. The iterations continue until a satisfactory solution is attained.

At any point in the decision making process, any new preference information explicitly stated by the DM can be incorporated into the analysis. The ultimate goal in each iteration is to analyze distinct alternative solutions that would help the DM converge to the best compromise solution.

III ILLUSTRATIVE EXAMPLE

The MCDM procedure was applied to a real public sector planning case study. A municipal solid waste management planning case study was conducted for the State of Delaware. The goal of this case study was to generate and to analyze alternative solid waste management (SWM) strategies. A SWM strategy includes means to collect, transport, separate, treat and finally dispose MSW in a cost- and environmentally-effective way. The problem was represented in a solid waste management-life cycle inventory (SWM-LCI) model [18-21]. The model includes (1) LCI-based process models for each waste processing technology (referred to as SWM unit operations), (2) a linear programming based SWM system model that embeds waste-item specific mass flow equations, (3) an interface for the interaction with CPLEX®, and (4) a graphical user interface. A variety of technology choices were considered to collect waste, to recover the recyclables and to treat the waste. Specifically, the decisions include the selection of collection options to transport waste from generation to next destination, the selection of alternative waste treatment technologies such as composting, waste-to-energy, the selection of recycling facilities, total capacity of and the itemized mass flows through these facilities.

The evaluation of the SWM strategies is based on several objectives, including cost, energy consumption, environmental emissions and waste diversion from landfills. For demonstration purposes, only two objectives, (1) minimizing the total cost of the strategy and (2) minimizing the total greenhouse gas equivalents (GHE) emissions of the strategy, were considered.

The State of Delaware has three counties. In the planning case study, each county was modeled and analyzed separately as a Multi-Objective Linear Programming (MOLP) model. In this illustration, we focused on the decision making process for only one of counties in the state, i.e. New Castle County.

Fig. 1 presents the tradeoff between cost and GHE emissions. The noninferior region, generated by constraint method, was analyzed. The DM selected a region on the Pareto front that reflected his preferences. This area of interest is shown in Fig. 1. The noninferior solution with a cost of $43 million/yr and net annual GHE offset (i.e., the avoided GHE emissions) of 8,200 tons was shown to the DM. The values of the objectives and the decision variables were analyzed in detail. Given the feedback from the DM, this solution was found unsatisfactory. Next, MGA solutions were generated. The objective values of the MGA solutions were close to each other and located within the area of interest shown in Fig. 1; however, each solution had distinct values of decision variables. Each solution reported the item specific mass flow through the unit operations of a SWM system. Table 1 summarizes the facilities utilized in the Pareto front and MGA solutions. The corresponding cost and GHE emissions are given in Table 2. In addition to the GHE emissions, SWM-LCI model can report environmental emissions and energy consumption; some of the emissions and energy consumption values are in given in Table 2 as well.

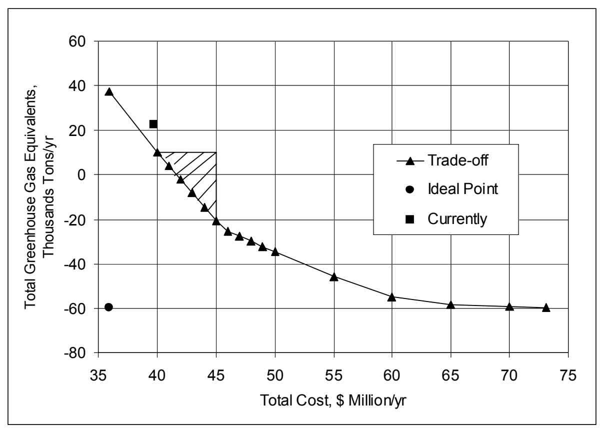

Fig. 1. Noninferior trade-off between cost and greenhouse gas emissions

TABLE 1
.UTILIZATION OF WASTE PROCESSING FACILITIES IN PARETO FRONT AND NEAR PARETO FRONT STRATEGIES

	Pareto front Solution	Alternative SWM Strategies											
		1	2	3	4	5	6	7	8	9	10	11	12
Mixed Waste Transfer (Mixed-TR)	1	1	-	-	1	-	-	-	-	-	-	-	-
Commingled Transfer (Comm-TR)	-	-	-	-	-	-	-	-	1	-	-	-	1
Pre-Sorted Transfer (Presorted-TR)	-	1	1	-	1	1	-	1	-	1	-	1	1
Mixed Waste Separation (Mixed-MRF)	-	-	1	1	-	-	-	-	1	-	1	1	1
Presorted Separation (Presorted-MRF)	1	1	1	1	1	1	1	1	1	1	1	1	1
Commingled Separation (Comm-MRF)	-	-	-	-	-	-	-	-	1	-	-	1	1
Composting	-	-	-	-	-	-	-	-	-	1	-	1	-
Waste-to-energy	1	1	1	1	1	1	1	1	1	1	1	1	1
Landfill	1	1	1	1	1	1	1	1	1	1	1	1	1
Ash-landfill	1	1	1	1	1	1	1	1	1	1	1	1	1
Preferred	NO	NO	YES	YES	NO	NO	NO	NO	YES	NO	YES	YES	YES

TABLE 2
COST AND ENVIRONMENTAL EMISSIONS OF THE PARETO FRONT AND NEAR PARETO FRONT STRATEGIES

	Cost	Greenhouse Gas Equivalents	Energy Consumption	Total Particulate Matter	Nitrogen Oxides	Sulfur Oxides	Preferred
	\$/year	tons/year	MBTU/year	lbs/year	lbs/year	lbs/year	
Least GHE	4.30E+07	-8.20E+03	-1.30E+06	-3.30E+05	-4.10E+05	-1.80E+06	NO
1	4.30E+07	-5.00E+03	-1.10E+06	-2.90E+05	-3.60E+05	-1.60E+06	NO
2	4.30E+07	-5.00E+03	-1.20E+06	-3.00E+05	-3.70E+05	-1.70E+06	YES
3	4.50E+07	-5.00E+03	-1.40E+06	-3.00E+05	-5.40E+05	-1.70E+06	YES
4	4.30E+07	0.00E+00	-1.30E+06	-3.20E+05	-4.60E+05	-1.60E+06	NO
5	4.30E+07	0.00E+00	-1.10E+06	-2.80E+05	-3.60E+05	-1.60E+06	NO
6	4.30E+07	0.00E+00	-1.10E+06	-2.70E+05	-3.20E+05	-1.50E+06	NO
7	4.50E+07	0.00E+00	-1.40E+06	-2.90E+05	-5.20E+05	-1.60E+06	NO
8	4.50E+07	0.00E+00	-1.60E+06	-3.60E+05	-5.20E+05	-1.70E+06	YES
9	4.50E+07	0.00E+00	-1.20E+06	-2.80E+05	-3.20E+05	-1.60E+06	NO
10	4.50E+07	1.00E+04	-1.40E+06	-3.10E+05	-6.00E+05	-1.60E+06	YES
11	4.50E+07	1.00E+04	-1.20E+06	-3.00E+05	-3.40E+05	-1.60E+06	YES
12	4.50E+07	1.00E+04	-1.40E+06	-3.20E+05	-6.00E+05	-1.60E+06	YES

The analysis of the solutions, first, focused on the selection of facilities. For each solution, the DM was asked to state explicit preferences on the selection of the facilities. Then, the DM decided whether each solution is preferable or not. Next, analysis focused on the selection of capacities of each facility. The division of the problem into sub-problems eased the selection process, thus the DM did not feel overwhelmed with the choices.

To test and validate the algorithms, the DM implicitly selected solutions with commingled and mixed waste material recovery facilities (MRF) as preferable. Based on this input, last row in Table 1 and last column in Table 2 were generated.

WEKA, a data-mining-software [10], was used to generate the decision rules. Within the WEKA, there are many association rule mining and clustering algorithms. Two association rule mining algorithms: Apriori [22-24] and Tertius [25] algorithms were tested and reported in this paper. The information in the Table 1 was input to the association rule mining algorithms embedded in WEKA. The decision rules were generated from each algorithm. Tables 3 and 4 summarize the decision rules generated from Apriori and Tertius algorithms, respectively.

The algorithms verified the DM's implicit preferences. For example, rule #1 in Table 4 says that when mixed waste material recovery facility (MRF) is not utilized, the solution is not preferable, and this rule has a confidence value of 99.41% with zero counter instances. Similarly, regarding the preference on the utilization of the commingled MRF, Rules #5, 7, 13 in Table 4 verified that if the commingled MRF is not in the solution, then the solution is not preferred. In addition, Rules #5 and 8 in Table 3 verified that if neither commingled MRF nor mixed waste MRF is in the solution, then the solution is not preferred. Similarly, Rules #16 and 19 in Table 4 revealed that solution is not preferred when the mixed waste transfer station is not in the solution.

In addition, some feasibility conditions within the multiobjective linear programming (MOLP) model were generated as decision rules. For example, the commingled transfer station can be utilized only in the presence of the commingled MRF. This feasibility condition was captured in rule #1 in Table 3.

The decision rules were generated using data set in Table 1 that has only binary values. One drawback with association rule mining was the handling of the numeric attributes. In the SWM planning problem, all of the mass flows through the facilities, cost and environmental emission of the strategy had real values. To work with the association rule mining, the data had to be preprocessed so that the numerical attributes were discretized before running the algorithms. Unfortunately, these results were not very promising. Thus, another data mining algorithm was tried out.

Clustering is the partitioning of a data set into smaller data subsets so that each cluster has more common traits. K-means [26] is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. K-means algorithm embedded in the WEKA was utilized. Clusters were formed based on the preferred solutions and their emission and energy consumption values. The results from the clustering set are described in Table 5. Cluster '0' corresponding to the preferred solution set has a mean GHE value of 2,857 tons/yr with the standard deviation of 6,986 tons/yr.

The information gathered from the association rule mining and the clustering was incorporated into the MOLP model to generate a Pareto front strategy. Following constraints were added to the MOLP model:

(1) Total cost should be less than or equal to $43Million/yr, (2) total GHE emissions should be less than or equal to 2857 tons/yr, and (3) a commingled MRF should present in the solution. Thus, the amount of waste processed at the commingled MRF was constrained to be at least 5,000 tons/yr which represents the size of a reasonable mid-size facility.

Table 6 summarizes the waste flows through the SWM unit operations in the resultant strategy. The corresponding cost and emission values are given in Table 7.

The DM analyzed this solution and decided to cease the iterations as this strategy was selected to be the best compromise solution.

TABLE 3
ASSOCIATION RULESET FROM APRIORI ALGORITHM

Rule	IF	a		THEN	b	c
1	Comm-MRF=0	10	==>	Comm-TR=0	10	1
4	Mixed-MRF=0	7	==>	Comm-TR =0 Comm-MRF =0	7	1
5	Preferred=NO	7	==>	Comm-TR =0 Mixed-MRF =0 Comm-MRF =0	7	1
6	Comm-TR =0 Mixed-MRF =0	7	==>	Comm-MRF =0 Preferred=NO	7	1
7	Comm-TR =0 Preferred=NO	7	==>	Mixed-MRF =0 Comm-MRF =0	7	1
8	Mixed-MRF =0 Comm-MRF =0	7	==>	Comm-TR =0 Preferred=NO	7	1

a: the support of the rule, the number of items covered by its premise
b: the number of items for which the decision part of the rule holds.
c: confidence value: b/a

TABLE 4
ASSOCIATION RULESET FROM TERTIUS ALGORITHM

Rules	a	b	IF		THEN
1	0.9941	0	Mixed-MRF=0	==>	Preferred=NO
2	0.9941	0	Preferred=NO	==>	Mixed-MRF=0
3	0.6658	0	Comm-TR=0 and Compost=0	==>	Comm-MRF=0
5	0.5476	0.0769	Preferred=YES	==>	Presorted-TR=0 or Comm-MRF=1
7	0.5444	0	Preferred=NO	==>	Comm-MRF=0
10	0.5244	0	Comm-MRF=0	==>	Comm-TR=0
12	0.5160	0.2308	Mixed-TR =0	==>	Compost=1 or Preferred=YES
13	0.5160	0.2308	Comm-MRF =0	==>	Preferred=NO
16	0.4845	0	Preferred=YES	==>	Mixed-TR=0
19	0.4643	0.3077	Mixed-TR=0	==>	Preferred=YES

a. confirmation value; b. frequency of counter-instances

TABLE 5
CLUSTERING THE CONTINUOUS ATTRIBUTES VIA K-MEANS ALGORITHM

Cluster Centroids:

		Energy	Greenhouse Gas Equivalents	Total Particulate Matter	Nitrogen Oxides	Sulfur Oxides	Preferred
		MBTU/year	tons/year	lbs/year	lbs/year	lbs/year	
Cluster 0	Mean	-1,359,215	2,857	-310,711	-470,730	-1,625,107	YES
	Standard Deviation	128,153	6,986	24,788	123,430	69,938	N/A
Cluster 1	Mean	-1,209,003	-2,201	-296,300	-403,726	-1,623,275	NO
	Standard Deviation	111,628	3,557	22,102	76,160	76,817	N/A

Clustered Instances:

	# of items	% of coverage
Cluster 0	7	54%
Cluster 1	6	46%

TABLE 6
RESULTANT BEST COMPROMISE SWM STRATEGY – MASS FLOWS THROUGH THE FACILITIES

Sector	Unit Process	Best Compromise SWM Strategy
Residential 1	Residuals Collection	139,150
Residential 2	Residuals Collection	15,499
Residential 1	Recyclable Drop-Off Collection	10,870
Residential 2	Recyclable Drop-Off Collection	1,211
Multifamily 1	Recyclable Drop-Off Collection	557
Multifamily 1	Commingled Collection	5,000
Multifamily 1	Residuals Collection	37,700
Commercial 1	Residuals Collection	176,085
	Mixed Waste Separation	15,499
	Presorted Separation	12,637
	Commingled Separation	5,000
	Waste-to-energy	98,520
	Landfill	268,805
	Ash-landfill	13,161

TABLE 7
RESULTANT BEST COMPROMISE SWM STRATEGY – COST AND EMISSION VALUES

Cost/LCI Parameter	Units	Best Compromise SWM Strategy
Cost	$/year	43,000,000
Greenhouse Equivalents	tons GHE/year	786
Energy Consumption	MBTU/year	-1,194,707
Total Particulate Matter	lbs/year	-297,616
Nitrogen Oxides	lbs/year	-301,835
Sulfur Oxides	lbs/year	-1,568,404

IV CONCLUDING REMARKS

The new MCDM methodology searches for the best compromise solution in both objective and decision spaces. The solutions from the region of interest are investigated and analyzed while the DM makes selections among the solutions. Machine learning algorithms utilize the selection information to create decision rules that captures the relationships between the traits of the solutions, such values of the decision variables and the objectives, and the preference information reflected by the DM's selections. The decision rules ultimately reflect the DM's implicit preferences and are used to constrain the decision space further to converge to a solution reflective of the DM's preferences in both objective space and decision space.

Both association rule mining and clustering algorithms verified that the DM preferred a solution with commingled and mixed waste MRF. Some of the feasibility conditions of the LP model were verified. Furthermore, clustering analysis helped us define statistically the region on the Pareto front and near Pareto front that DM preferred the most.

In addition, the new MCDM method was illustrated via a MSW planning case study conducted for the State of

Delaware. The results presented in this paper represent the decisions for only one county of the state. Currently, the method has been tested on the application to the rest of the state.

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