Robust Contingency Plans for Transportation Investment Planning

Nabil Kartam, Gwo-Hshiung Tzeng, and Junn-Yuan Teng

***Abstract*— A multistage decision process for transportation investment planning is described. Most transportation investment problems inherently involve multiple criteria and uncertainty. To deal with the variations arising from changes in external environments, robust contingency plans should be integrated in the planning process—not after plans are developed—to account for uncertainty. With the proposed decision process, a multiple criteria decision making (MCDM) method is first used to select a set of good potential designs (or potential solutions). Corresponding optimal contingency plans for each design under uncertainty are then prepared. Robustness considerations are used in making the final selection among contingency plans. To demonstrate the proposed decision making process, a scenario approach is applied to develop a multistage decision making process for transportation investment planning problems. Finally, an example of regional transportation investment is presented to illustrate the method.**

I. Introduction

TRANSPORTATION plays an important role in national economic development. Therefore, transportation investment decisions are critical to a national economy. Since transportation investment is constrained by budget, manpower, equipment, and other limited resources, we are facing multistage decision problems in transportation investment programs.

Most conventional investment methods optimize the solution for a single objective such as "Maximal Profit" or "Minimal Cost"; some others use cost-benefit analysis to rank transportation investment projects. Since the introduction of "Efficient Vector" [18] and "Vector Maximization" [19] methods to derive the optimal conditions for "Efficient Solutions," significant progress has been made in solving multiobjective problems. Applications of multiobjective decision making in public investment problems began in the 1960s [22], [24]. Since then, research on multiobjective public investment decision analysis has been increasing [4], [5], [10], [23], [25], [31], [32]. In transportation, Hill [13] and Keeney [16] are forerunners in the application of multiobjective programming in transportation investment problems.

Due to uncertainty about the future, a previous transportation investment plan may have to be adjusted by increasing the financial budget or other resources, otherwise the quality of investment will be downgraded. To mitigate or avoid influence of uncertainty on multistage transportation investment decisions, the robustness of each alternative project has to be considered in each stage of the investment planning, which may not be the optimality for the solution [29]. To insure beneficial results in each stage of the whole investment plan, contingency plans are required to cope with risk and uncertainty. Although some researchers have tried to set up robust decisions [7], [9], [29], [28], and optimal contingency plans [20], the decision concept has not been integrated and applied in transportation investment problems. This paper describes the concept of robust contingency plans and demonstrates the proposed decision process with an example in transportation investment planning.

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II. Uncertainty and Robustness

Traditional decision situations can be classified into three areas: certainty, risk, and uncertainty [21]. To deal with risk, the probability can be measured by risk discounting or certainty equivalents. However, to deal with uncertainty, the probability of possible outcomes cannot be measured, and the decision quality is difficult to control. For long-term investment planning in transportation, it is impossible to gather complete information. Hence, uncertainty exists in every investment planning stage.

The Laplace Rule, Maximin Rule, Maxmax Rule, Hurwicz Rule, and Minmax Regret Rule are traditional methods used to deal with uncertainty in single criterion decision problems [6]. Recent decision making methods tend to focus on multicriteria problems including logic of decision theory, game theory, fuzzy theory, and catastrophe theory [7], [12], [38].

Robustness, a measure of the useful flexibility maintained by a decision, has characteristics that make it a suitable criterion for sequential decision making under conditions of uncertainty. It handles the uncertainty of the environment, not by imposing a probabilistic structure, but by stressing the importance of flexibility (flexibility can be defined as the future uncertainties that the decision maker faces and solves). It makes explicit the distinction between committed decisions and planned solutions. It reflects the sequential nature of decision making by placing less emphasis on the plan, but more on the continuous process of planning [29]. Therefore, robustness is a way of trading off flexibility against expected value, and is adopted in this paper as the criterion for making robust decisions in each decision stage. Robust decisions are defined as those system elements which are resistant to any change of contingencies, no matter which constellation of the

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environment will happen. The decision for these elements will not have to be regretted.

In most cases, transportation investment planning is a discrete multicriteria decision problem: A given set of investment alternatives is evaluated with respect to a set of criteria at the planning horizon. Solving a discrete multicriteria decision problem entails choosing the best subset of alternatives, i.e., nondominated alternatives, from the finite set of feasible alternatives at the planning horizon. In long-term transportation investment planning, the planning horizon can be divided into a number of decision stages; multicriteria evaluation is applied in each stage. A transportation investment plan includes a set of decisions to be implemented in future stages. Each decision involves the mix of various resources consumed. Throughout the planning horizon, the implementation of some decisions will influence the feasibility of other decisions and require the modification of subsequent decisions.

III. Multistage Multicriteria Decision Problems

A. Single-Stage versus Multistage Decision Process

A decision process is either single stage or multistage. A single-stage decision process is often used in short-term or medium-term decisions, which involves static uncertainty and assumes the current decision will not be affected by future events. A multistage decision process considers extensive factors, not only the influence of each stage to the following stages, but also the environmental factors. This type of decision process involves dynamic uncertainty and is appropriate for long-term planning.

B. Development of Multistage Multicriteria Decision Problems

A multistage multicriteria decision problem is a serial decision problem. Multicriteria decision making (MCDM) methods such as ELECTRE [2], [14], [35] goal programming [3], concordance analysis [26], surrogate worth trade-off (SWT) method [11], or multiple criteria and multiple constraints (MC^2) [20], [37] can be used to search for nondominated alternatives in each stage, and the earlier decisions will affect later ones.

In the multistage multicriteria decision process [38], it is assumed that available resources in each stage can be forecast. Based on resources available in each stage and resources used in the previous stage, various alternatives can be formulated. Then, many MCDM methods as mentioned previously can be applied. It is assumed in this paper that evaluation criteria used in each stage of the multistage decision process are the same, that each stage uses h criteria. Since transportation investment planning is a long term process, it is necessary for consistency to apply the same criteria in each stage.

C. Determination of Criteria Weights for the Initial Stage—The Entropy Method

In long-term investment planning for transportation, data obtained at the initial stage are more accurate allowing for a reduction in the uncertainty. Therefore, the weights for criteria can be derived from the evaluation scores of each alternative. With this concept, information theory has provided useful basic evaluation methods, especially the entropy concept, which plays a key role in the initial stage evaluation. In this paper, entropy is used as a tool to measure the expected information content of the alternative impacts for each criterion. Alternative impact matrix and preference weights for criteria can be considered as serial of information. They are very important to the evaluation of various alternatives. Based on the entropy concept, a diversification factor can be derived to identify the significant differences among alternatives [26], [39], [40].

If the impact matrix C_1 for m_1 alternatives and h_0 criteria in the initial stage is:

$$C_1 = \begin{bmatrix} C_{11}(d_{11}) \cdots C_{1g}(d_{11}) \cdots C_{1h}(d_{11}) \\ \vdots \\ C_{11}(d_{1m_1}) \cdots C_{1g}(d_{1m_1}) \cdots C_{1h}(d_{1m_1}) \end{bmatrix} \quad (1)$$

where C_{tg} is the gth evaluation criterion used in t stage, and d_{tj} is the decision variable in t stage, i.e., feasible alternative for transportation investment. Then the project outcome P_{jg} for the jth alternative under gth criterion can be normalized and defined as

$$P_{jg} = \frac{C_{1g}(d_{1j})}{\sum_{j=1}^{m_1} C_{1g}(d_{1j})}, \quad \forall g. \quad (2)$$

Therefore, the expected information value can be derived from the alternative impact matrix for criterion g, which can be approximated with the entropy value [14], [36]. The entropy value E_g of the set of alternative impact $(P_{1g}, P_{2g}, \cdots, P_{m_1 g})$ for criterion g is:

$$E_g = -k \sum_{j=1}^{m_1} P_{jg} \ln P_{jg}, \quad \forall g \quad (3)$$

where k is Boltzman's constant, which equals

$$k = (\ln m_1)^{-1} \quad (4)$$

which guarantees that

$$0 \le E_g \le 1. \quad (5)$$

The degree of diversification f_g of the information provided by the alternative evaluation value of criterion g can be defined as

$$f_g = 1 - E_g, \quad \forall g. \quad (6)$$

If the decision maker has no reason to prefer one criterion over another, the principle of insufficient reason [33] suggests that each one should be equally preferred. Then, the best weight set we can expect, instead of the equal weights, is

$$w_{1g} = f_g \Big/ \sum_{g=1}^{h} f_g, \quad \forall g. \quad (7)$$

This objective weight set will be used to set the criteria preference of decision makers in future stages.

IV. Robust Contingency Planning

Robust analysis provides strategic planning with a method to insure potential alternatives with flexibility in the future. So far, many researchers have tried to develop decision methods to define robustness and flexibility [1], [9], [15], [28], [29]. However, none of these has been applied in transportation investment planning. The contingency plan is the set of actions that should be taken under various uncertainty in the future. This uncertainty situation will be changed when the external environment changes; the change in external environment will also influence the decision maker's preference, and thus affect the feasible alternatives.

A. Measurement of Future Decision-Making Preferences

In long-term transportation investment planning, each decision stage is affected by the economic development element (e_t) of that time as well as by investment decision-making result of the previous stage; furthermore the preference of the decision maker (or the decision-making agency) will be affected. Therefore, predicting the preference of the decision maker has become an important issue among multistage investment decision problems.

Among multistage multicriteria decision problems, the preference of the decision maker will be reflected in the changes of relative importance of the evaluation criteria; in other words, the decision maker exercises different kinds of weights for various levels of economic development. Evaluation criteria can be categorized into two types: one is benefit criteria, and the other is cost criteria. The weight of the former criteria will be gradually stressed as economy regresses, while the weight of the latter criteria will be enhanced as economy prospers. For instance, when economic development lapses, the decision maker will be more concerned about economic criteria so as to achieve the goal of attaining affluence. On the other hand, when economic development reaches a certain level, the decision maker will be concerned about environmental protection so as to pursue a higher quality of life. The weights of h criteria can be grouped into two categories: π_1 and π_2, π_1 is the weight summation of h_1 benefit criteria, while π_2 is the weight summation of h_2 cost criteria.

Therefore,

$$\pi_1 + \pi_2 = \sum_{i=1}^{h_1} w_{1i}^1 + \sum_{j=1}^{h_2} w_{1j}^2 = 1 \tag{8}$$

and

$$h_1 + h_2 = h \tag{9}$$

where π_1 and π_2 have the characteristics of trade-off, meaning that when π_1 is increased by one, one unit of π_2 will be deducted. When π_1 approaches 1, π_2 will be very much near 0, and vice versa. As economic development improves, cost criteria will be given a higher degree of emphasis and the value of π_2 becomes greater. On the other hand, if economic development continues to regress, the importance of benefit criteria will be stressed and the value of π_1 becomes greater.

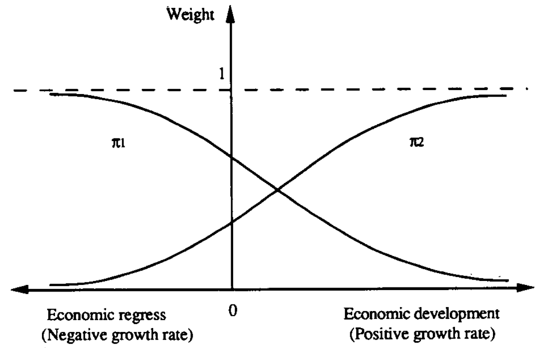

Fig. 1. The characteristics of π_1 and π_2 trade off.

The trade-off and weight summation of these two types of criteria π_1 and π_2 are illustrated in Fig. 1.

According to the characteristics of π_1 and π_2, as long as the preference of the decision maker toward different economic development or regression is grasped, the preference curve of π_1 and π_2 can thus be estimated. From the features of π_1 and π_2, we conclude that the curve is of logistic nature that is

$$\pi_1 = \frac{1}{1 + e^{a-by}} \tag{10}$$

$$\pi_2 = \frac{1}{1 + e^{-a+by}} \tag{11}$$

where, y of the equation denotes economic development.

Since $\pi_1 + \pi_2 = 1$ once π_1 is known, the value of (π_2) can be found. Thus, from the π_1 curve the values of π_1^s and π_2^s under s situation can be disclosed.

B. Variation of the Criterion Weight

Since we have used the same h criteria in each of the multistage decisions in this paper, we will not deal with the influence of variations among different criteria weights in each stage. The choice of criteria (attributes) should consider the following characteristics [17]:

1) Completeness: all important issues should be covered as much as possible.
2) Operationality: the choice of criteria should be meaningful to decision makers.
3) Decomposability: the chosen criteria should be amenable to top–down breakdown to simplify the complex evaluation process.
4) Nonredundancy: the chosen criteria should be independent and avoid the redundancy in the estimation of potential impacts.
5) Minimum size: the chosen criteria should be chosen to simplify the decision problem.

Aside from considering the initial objective weight, the relative importance of benefit criteria and cost criteria of every stage in the future can also be subjectively judged by the decision maker so as to produce levels of importance for multiple criteria. This will help to rectify changes of criteria importance due to longer periods of the planning horizon. If the subjective weights ratio (λ_{tg}^i) of benefit criterion $(i = 1)$

and cost criterion ($i = 2$) in t stage are

$$\lambda_t^i = (\lambda_{t1}^i, \cdots, \lambda_{tg}^i, \cdots, \lambda_{th_i}^i)^T, \quad i = 1, 2. \tag{12}$$

the compromise weight ratio (u_{tg}^i) ratio after rectification is

$$u_t^i = (u_{t1}^i, \cdots, u_{tg}^i, \cdots, u_{th_i}^i)^T, \quad i = 1, 2 \tag{13}$$

where

$$u_{tg}^i = (\lambda_{tg}^i w_{1g} \Bigg/ \left(\sum_{j=1}^{h_i} \lambda_{tj}^i \cdot w_{1j} \right), \quad i = 1, 2 \tag{14}$$

and

$$0 \leq u_{tg}^i \leq 1, \quad i = 1, 2. \tag{15}$$

From the two criteria preference curves of the decision maker, the values π_1^s and π_2^s under any economic development in every stage can be obtained. Through the compromise weight of every type of criteria, values of π_1^s and π_2^s can be distributed to every type of criteria. That is, the weight for the gth criterion in t stage and s situation can be calculated as follows:

$$w_{tg}^s = \pi_1^s x u_{tg}^1, \qquad g = 1, 2, \cdots, h_1 \qquad t = 2, 3, \cdots n \tag{16}$$

$$w_{tg}^s = \pi_2^s x u_{tg}^2, \qquad g = 1, 2, \cdots, h_2 \qquad t = 2, 3, \cdots n \tag{17}$$

Therefore, the weight vector of h criteria under s situation in t stage is

$$W_t^s = (w_{t1}^s, \cdots, w_{th_1}^s, w_{t(h_1+1)}^s, \cdots, w_{th}^s). \tag{18}$$

C. Preparation of Robust Contingency Plan

In the multistage multicriteria decision processes for transportation investments, each stage includes about 5–10 years. Each stage has different feasible alternatives. Given the same criterion, the change of criterion's weight will influence the nondominated alternatives, i.e., under different future influencing variables, there are different nondominated alternatives. Therefore, a robust decision approach will integrate sensitivity analysis and scenario analysis [7], and be applied in the preparation of contingency plans. A scenario is the definition of long-term changes of certain sets of variables or parameters. A set of scenarios may be seen as a wide and consistent description of possible future developments of the described system, spanning a range of uncertainty, where it is assumed that the future development lies within this range of uncertainty.

There are two general scenario approaches. They are the exploratory scenario approach and anticipatory scenario approach [30]. The former is designed to explore alternative futures, in a set of trend-seeking scenarios, by examining events that are logically necessary for a possible future by parameterizing the principal components of the system under study. Its starting point is the present. The latter is concerned with the conceptualization of feasible and desirable futures. Unlike the exploratory scenario that proceeds from the present to the future, anticipatory scenarios follow the inverse path by starting with the future and working backward to the present to discover what alternatives and actions are necessary to attain these futures.

Scenario analysis is a potentially powerful instrument for representing the type of uncertainty encountered in transportation planning. In this paper, we will use exploratory scenario approach to describe the possible decisions (i.e., combination of nondominated alternatives) under various influencing variables in a future stage.

It is thus supposed that q_t changes are effected on current state variables (S_t) in t stage because of the influences of current environmental variables and previous state variables (i.e. $S_t = f(S_{t-1}, e_t)$). As a result, the decision maker will formulate q sets of preference toward the weights of h criteria. According to the weights of q sets and the evaluation matrix of feasible alternatives, different sets of nondominated alternatives in t stage and s situation $\hat{D}_t^s$ of q_t sets can be obtained through MCDM evaluation methods:

$$\hat{D}_t^s = \{\hat{d}_{t1}^s, \hat{d}_{t2}^s, \cdots, \hat{d}_{tk}^s, \cdots, \hat{d}_{tP_ts}^s\}, \quad s = 1, 2, \cdots, q_t \tag{19}$$

and

$$P_{ts} \geq 1$$

where, P_{ts} is the obtained numbers of the nondominated alternatives under s situation in t stage.

This paper applies the ELECTRE I model [2], [14] to proceed with nondominated alternatives selection under every situation. The mathematical model of ELECTRE I is illustrated in Appendix I.

P_{ts} nondominated alternatives obtained under every situation in every stage can be formed into combinatorial alternatives $\hat{A}_t^s$ for implementation with resource available after current stage has been satisfied:

$$\hat{A}_t^s = \{A_{t1}^s, A_{t2}^s, \cdots, A_{t\alpha}^s, \cdots, A_{t\phi_{ts}}^s\} \tag{20}$$

$$A_{t\alpha}^s = \{\hat{d}_t^s | \hat{d}_t^s \varepsilon \hat{D}_t^s\}$$

where $A_{t\alpha}^s$ is the αth combinatorial alternative in t stage and s situation.

$$\phi_{ts} \geq 1, \quad S = 1, 2, \cdots, q_{ts}$$

where ϕ_{ts} is the number of combinatorial alternatives in t stage and s situation.

For instance, under situation 3 ($s = 3$) in stage 2 ($t = 2$), five nondominated alternatives $\hat{D}_2^3 = \{a_1, a_2, a_5, a_7, a_{10}\}$ will be obtained from twelve feasible alternatives $D_2 = \{a_1, a_2, \cdots, a_{12}\}$, and there are four sets of workable combinatorial alternatives (i.e., $\phi_{23} = 4$) with resource available after satisfying current s situation:

$$\hat{A}_2^3 = \{A_{21}^3, A_{22}^3, A_{23}^3, A_{24}^3\}$$

where

$$A_{21}^3 = \{a_1, a_5, a_7\}$$
$$A_{22}^3 = \{a_2, a_5, a_{10}\}$$
$$A_{23}^3 = \{a_1, a_2\}$$
$$A_{24}^3 = \{a_5, a_7, a_{10}\}.$$

Every set of combinatorial alternatives are all current workable decisions which are known as possible decisions. So, decision-making issues in t stages require robust decisions matchable to $(t+1)$ and $(t-1)$ periods.

In this paper, the first stage (initial stage), with the shorter planning horizon and higher certainty, will be less affected by environmental variables because after implementation, the investment construction time might have already passed its planning horizon. Because of less exposure to environmental variables, the changeability is low and it will be handled as $(q_1 = 1)$ situation. After the set of nondominated alternatives $\hat{D}_1$ has been obtained according to h criteria with ELECTRE I model, its possible decisions total ϕ_1 with resources available after satisfying the first stage:

$$\hat{A}_1 = \{A_{11}, A_{12}, \cdots, A_{1\phi_1}\}$$

To ask for a robust decision for the first stage, this paper employs a permutation method [27] to find robust combinatorial alternative A_1^{rob}. Since the permutation method can evaluate ranking of ϕ_1 possible decisions, if it combines with entropy method the best decision-making robust combinatorial alternatives A_1^{rob} [26] will come out. As for the mathematical model of the permutation method, it is illustrated in Appendix B.

Suppose we take the transportation investment decision problem for an example. Stage 2 and stage 3 are influenced by environmental variables, and each will have three possible situations of changes (i.e., $q_2 = q_3 = 3$). According to h criteria, various sets of nondominated alternatives $\hat{D}_t^s$ can be attained; each set can get ϕ_{ts} set of possible decisions A_t^s with resource available after satisfying the current stage. Thus, the robust decision method of tristage decision-making issues can be used for scenario analysis to acquire suitable decision-making methods for previous and later stages (as illustrated in Fig. 2).

In considering transportation investment decision-making issues for the nth stage, the decision maker needs to find decisions of robustness from possible decisions of every stage for possible changes of situations. The first-stage robust decision is the best combinatorial alternatives obtained using permutation and entropy methods; as for other stages under every different situation, possible decisions of upmost robustness have to be determined. If under q_t situation in t stage $(t > 1)$ there will be V_t possible decisions, that is

$$V_t = \sum_{s=1}^{q_t} \phi_{ts}, \quad t = 2, 3, \cdots, n. \tag{21}$$

Possible decisions (as indicated in (20)) under every different situation can be denoted by $N_t (t > 1)$:

$$\begin{aligned} N_t &= \hat{A}_t^1 U \hat{A}_t^2 U \cdots U \hat{A}_t^{q_t} \\ &= A_{t1}^1 U \cdots U A_{t\phi_{11}}^1 U A_{t1}^2 U \cdots U A_{t\phi_{1s}}^s \end{aligned} \tag{22}$$

where $A_{t\alpha}^s$ robustness of V_t possible decisions in N_t is indicated in robust index $r_t(A_{t\beta}^s)$ and defined as

$$r_t(A_{t\beta}^s) = n(G_{t\beta}^s)/n(G) \tag{23}$$

$$(A_{t\beta}^s) \varepsilon N_t, \quad \beta = 1, 2, \cdots, \nu_t$$

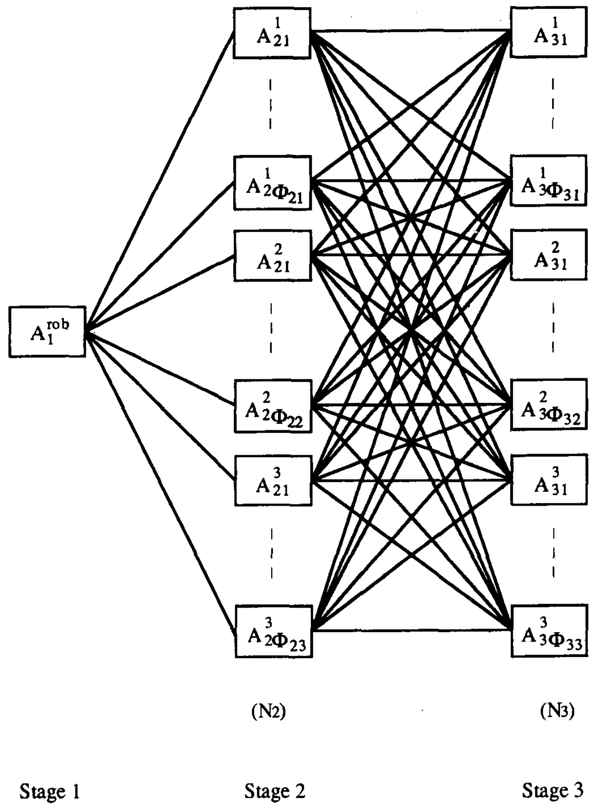

Fig. 2. Scenario of three-stage decision process.

where G is the set of potential good designs from all possible decisions in n stage, e.g., $\{A_1^{\text{rob}}, A_{21}^2, A_{31}^3\}$ are potential good designs in Fig. 2, $G_{t\beta}^s$ is a subset of G, and $n(G)$ is the number of potential good designs out of all possible decisions.

Thus, the robust decision under s situation in t stage is to select combinatorial alternatives of greatest robust index value under such a situation, which is decided accordingly:

$$A_{ts}^{\text{rob}} = \{\max_{\beta} [r_t(A_{t\beta}^s)] | A_{t\beta \varepsilon N_t}\} \tag{24}$$

where A_{ts}^{rob} indicates the most robust combinatorial alternatives under s situation in t stage.

V. Illustrative Example

A. Problem Description

The local authorities of XYZ regions intend to prepare investment plans for traffic and transportation so as to promote regional development. Thus, they formulated a tristage transportation investment alternatives for 12 years. Those alternatives include constructing new road systems, widening and renovating existing road systems, improving the management of the mass transportation system, and building parking lots and cargo distribution centers. After the planning and analysis of the decision-making agency, feasible investment alternatives for each stage can thus be formulated as follows.

$$D_1 = \{a_1, a_2, \cdots, a_{15}\}$$
$$D_2 = \{b_1, b_2, \cdots, b_{10}\}$$
$$D_3 = \{c_1, c_2, \cdots, c_{12}.\}$$

The local authorities of XYZ regions are to evaluate feasible investment alternatives for every stage and select the best option. In case of the influence of future uncertainty, it is hoped that consideration of investment planning for the three stages can be combined so as to come up with a contingency plan of robustness.

B. Evaluation of Criteria and Weight

Among the tristage transportation investment decision-making issues of XYZ regions, similar evaluation criteria are available to evaluate in every stage (e.g., $h_1 = h_2 = h_3 = h$); these criteria are categorized as benefit and cost criteria. After they are discussed and analyzed by the decision-making agency, seven criteria are selected respectively: promoting industrial development ($C1$),) increasing job opportunities ($C2$), raising personal income ($C3$), improving reasonable population distribution ($C4$), evaluating the service level for mass transportation ($C5$), reducing air pollution ($C6$), and avoiding ecological destruction ($C7$). The three former criteria are benefit criteria, whose weights increase as the economy regresses; the latter four are of cost criteria whose weights increase as the economy prospers. The objective weights of the seven criteria found through entropy method in the initial period are

$$W_1 = (0.220, 0.158, 0.185, 0.114, 0.142, 0.106, 0.075)^T.$$

If the initial economic development is used as the base (i.e., economic growth rate is set at 0%), then the respective weight summation of benefit and cost criteria are $\pi_1 = 0.563$ and $\pi_2 = 0.437$. Under different economic developments, the decision-making agency retains various preferences toward the values of π_1 and π_2, and after inquiries, functions of π_1 and π_2 obtained are as follows:

$$\pi_1 = \frac{1}{1 + e^{-0.253+6.747y}}$$
$$\pi_2 = \frac{1}{1 + e^{0.253-6.747y}}.$$

Employing the second stage, the decision-making agency predicted two situations for economic development. One is to maintain economic growth initially (economic growth rate 0%, $s = 1$), while the second stage will outgrow the first by 3%. In stage three, three situations are predicted: one is to maintain initial development (economic growth rate is 0%, $s = 1$), the second is to outgrow the first by 5% ($s = 2$) and the third is to outgrow the first by 10% ($s = 3$).

According to preference functions of π_1 and π_2, values of π_1 and π_2 under different situations in every stage can be attained. Then with compromise weights of these type of criteria, values of π_1^s and π_2^s can be distributed onto each criterion.

TABLE I
SETS OF NONDOMINATED ALTERNATIVES IN DIFFERENT SITUATION OF EACH STAGE

Stages	$s = 1$	$s = 2$	$s = 3$
1	$(a_2, a_6, a_7, a_{10}, a_{12})$	—	—
2	(b_1, b_5, b_7, b_9)	(b_1, b_2, b_5, b_8)	—
3	$(c_3, c_5, c_6, c_8, c_9)$	(c_2, c_5, c_7, c_8)	$(c_1, c_2, c_5, c_9, c_{12})$

As far as the third stage is concerned, the decision-making agency's subjective weights toward the three benefit criteria C_1, C_2, C_3) and four criteria (C_4, C_5, C_6, C_7) are respectively as follows:

$$\lambda_3^1 = (0.2, 0.4, 0.4)$$
$$\lambda_3^2 = (0.2, 0.3, 0.3, 0.2).$$

Then the compromise weight of the second and third stages can be found according to (14):

$$u_3^1 = (0.243, 0.349, 0.408)$$
$$u_3^2 = (0.203, 0.380, 0.283, 0.134).$$

Thus, under the third situation of the third stage ($y = 10\%$),, the weight summation of benefit criteria $\pi_1 = 0.396$ can be found through the preference matrix of π_1 and π_2, while the weight summation of cost criteria is $\pi_2 = 0.604$, and through (16) and (17), weights of the seven criteria under the third situation of the third stage can be obtained:

$$W_{\text{stage}=3}^{\text{situation}=3} = (0.096, 0.138, 0.162, 0.122, 0.230, 0.171, 0.081).$$

C. Decisions of Nondominated Alternatives

Various sets of nondominated alternatives can be acquired after using ELECTRE I model to evaluate the economic development of the three stages, they are shown on Table I.

D. Possible Decision Formulation

Due to the constraint of resources available under different situations in every stage, not all of the nondominated alternatives can be implemented. Some sets of nondominated alternatives can satisfy the constraint of these resources available. These are sets of combinatorial alternatives. Every possible decision can be obtained from resources available under situations of the three stages, and they are illustrated on Table II.

E. Robust Contingency Plan

Of the four possible decisions ($A_{11}^1, A_{12}^1, A_{13}^1, A_{14}^1$) in the first stage, $A_{13}^1, A_{11}^1, A_{14}^1, A_{12}^1$) rank the best among 4! (24) sets after calculation by the permutation method and thus the possible decision A_{13}^1 is selected as the decision of robustness. As for possible decisions of the three situations in other two stages when integrated with robust decision A_{13}^1 in the initial stage, altogether 42 sets of potential good designs can be obtained by the decision-making agency through scenario analysis. They are illustrated on Table III.

The robust index (as illustrated on Table IV) of possible decisions in stage two and stage three can be found through

TABLE II
POSSIBLE DECISION IN DIFFERENT SITUATION OF EACH STAGE

Stages	$s=1$	$s=2$	$s=3$
1	$A_{11}^1=(a_2,a_7,a_9)$ $A_{12}^1=(a_2,a_{10},a_{12})$ $A_{13}^1=(a_2,a_6,a_7,a_{12})$ $A_{14}^1=(a_6,a_7,a_{10},a_{12})$	—	—
2	$A_{21}^1=(b_1,b_9)$ $A_{22}^1=(b_5,b_7,b_9)$ $A_{23}^1=(b_1,b_7,b_9)$	$A_{21}^2=(b_1,b_2,b_5)$ $A_{22}^2=(b_2,b_5,b_8)$ $A_{23}^2=(b_1,b_8)$	—
3	$A_{31}^1=(c_3,c_6,c_8)$ $A_{32}^1=(c_3,c_5,c_9)$ $A_{33}^1=(c_3,c_6,c_9)$ $A_{34}^3=(c_5,c_9,c_{12})$ $A_{35}^1=(c_6,c_8,c_9)$	$A_{31}^2=(c_2,c_5,c_8)$ $A_{32}^2=(c_5,c_7,c_8)$	$A_{31}^3=(c_1,c_2,c_{12})$ $A_{32}^3=(c_1,c_5,c_{12})$ $A_{33}^3=(c_2,c_9,c_{12})$ $A_{34}^1=(c_5,c_8,c_9)$

TABLE III
POTENTIAL GOOD DESIGNS FOR THREE STAGE DECISIONS

Sets	Potential Good Designs	Sets	Potential Good Designs
1	$A_{13}^1-A_{21}^1-A_{31}^1$	22	$A_{13}^1-A_{21}^2-A_{31}^1$
2	$A_{13}^1-A_{21}^1-A_{32}^1$	23	$A_{13}^1-A_{21}^2-A_{33}^1$
3	$A_{13}^1-A_{21}^1-A_{33}^1$	24	$A_{13}^1-A_{21}^2-A_{34}^1$
4	$A_{13}^1-A_{21}^1-A_{35}^1$	25	$A_{13}^1-A_{21}^2-A_{35}^1$
5	$A_{13}^1-A_{21}^1-A_{31}^2$	26	$A_{13}^1-A_{21}^2-A_{31}^2$
6	$A_{13}^1-A_{21}^1-A_{31}^3$	27	$A_{13}^1-A_{21}^2-A_{32}^2$
7	$A_{13}^1-A_{21}^1-A_{34}^3$	28	$A_{13}^1-A_{21}^2-A_{32}^3$
8	$A_{13}^1-A_{22}^1-A_{31}^1$	29	$A_{13}^1-A_{21}^2-A_{33}^3$
9	$A_{13}^1-A_{22}^1-A_{33}^1$	30	$A_{13}^1-A_{22}^2-A_{35}^1$
10	$A_{13}^1-A_{22}^1-A_{32}^2$	31	$A_{13}^1-A_{22}^2-A_{31}^2$
11	$A_{13}^1-A_{22}^1-A_{32}^3$	32	$A_{13}^1-A_{22}^2-A_{32}^3$
12	$A_{13}^1-A_{22}^1-A_{33}^3$	33	$A_{13}^1-A_{22}^2-A_{33}^3$
13	$A_{13}^1-A_{23}^1-A_{31}^1$	34	$A_{13}^1-A_{22}^2-A_{34}^3$
14	$A_{13}^1-A_{23}^1-A_{32}^1$	35	$A_{13}^1-A_{23}^2-A_{31}^1$
15	$A_{13}^1-A_{23}^1-A_{33}^1$	36	$A_{13}^1-A_{23}^2-A_{33}^1$
16	$A_{13}^1-A_{23}^1-A_{35}^1$	37	$A_{13}^1-A_{23}^2-A_{34}^1$
17	$A_{13}^1-A_{23}^1-A_{31}^2$	38	$A_{13}^1-A_{23}^2-A_{35}^1$
18	$A_{13}^1-A_{23}^1-A_{32}^2$	39	$A_{13}^1-A_{23}^2-A_{31}^2$
19	$A_{13}^1-A_{23}^1-A_{31}^3$	40	$A_{13}^1-A_{23}^2-A_{32}^3$
20	$A_{13}^1-A_{23}^1-A_{32}^3$	41	$A_{13}^1-A_{23}^2-A_{33}^3$
21	$A_{13}^1-A_{23}^1-A_{33}^3$	42	$A_{13}^1-A_{23}^2-A_{34}^3$

(23). Higher flexibility is indicated as the robust index goes higher. As a result, contingency plans of robustness can be achieved according to the decision environment of various situations in every stage. Its results are shown in Table V.

From the tristage transportation investment planning and decision making of XYZ regions, initial planning has to put forth contingency plans to cope with economic development changes in the future and adjust to possible changes of the decision environment. Few changes are seen in the initial stages once decisions are made and implemented, so only one robust possible decision $A_{13}^1=(a_2,a_6,a_7,a_{12})$, would be enough and the use of both entropy and permutation methods is good for this purpose. During the second stage investment planning, $A_{23}^1=(b_1,b_2,b_3)$ decisions can be employed if economic development is maintained as in the initial level; yet if economic development should increase by 3%, either $A_{21}^2=(b_1,b_2,b_5)$ or $A_{23}^2=(b_1,b_8)$ can be employed for it. As for the

TABLE IV
ROBUST INDEX OF POSSIBLE DECISIONS

	$t=2$		$t=3$	
	Possible Decisions $(A_{2\beta}^s)$	Robust Index $[r_2(A_{2\beta}^s)]$	Possible Decisions $(A_{3\beta}^s)$	Robust Index $[r_3(A_{3\beta}^s)]$
$s=1$	A_{21}^1	0.167	A_{31}^1	0.119*
	A_{22}^1	0.119	A_{32}^1	0.048
	A_{23}^1	0.214*	A_{33}^1	0.119*
			A_{34}^1	0.048
			A_{35}^1	0.119*
$s=2$	A_{21}^2	0.190*	A_{31}^2	0.119*
	A_{22}^2	0.119	A_{32}^2	0.071
	A_{23}^2	0.190*		
$s=3$	—	—	A_{31}^3	0.048
			A_{32}^3	0.119*
			A_{33}^3	0.119*
			A_{34}^3	0.071

TABLE V
ROBUST CONTINGENCY PLANS

	Situations		
Stages	$s=1$	$s=2$	$s=3$
$t=1$	A_{13}^1	—	—
$t=2$	A_{23}^1	A_{21}^2 A_{23}^2	—
$t=3$	A_{31}^1 A_{33}^1 A_{35}^1	A_{31}^2	A_{32}^3 A_{33}^3

third stage investment planning, either $A_{31}^1=(c_3,c_6,c_8)$ or $A_{33}^1=(c_3,c_6,c_9)$ or $A_{35}^1=(c_6,c_8,c_9)$ can be selected for the purpose of maintaining economic development as at the initial stage, or if the growth rate should outgrow the initial stage by 5%, $A_{31}^2=(c_2,c_5,c_8)$ can be considered. Furthermore, if predicted economic growth rate should rise by 10% above the initial stage, either $A_{32}^3=(c_1,c_5,c_{12})$ or $A_{33}^3=(c_2,c_9,c_12)$ should be employed.

VI. CONCLUSION

The traditional optimization planning models are deterministic models. Their basic assumption is that various future situations can be well-controlled. However, due to the uncertainty of decision environment, the optimized planning alternative may not be the real optimal alternative in the future. Since large-scale transportation investment planning deals with long time periods and extensive areas, it needs a robust contingency plan in each stage in order to mitigate the effects of uncertainty. Although many methods are able to deal with uncertainty in transportation investment, we have found no method that has integrated both robustness and contingency plans. In this paper, the multicriteria decision method ELECTRE I was applied in each stage to search for nondominated alternatives. In the first stage, the Entropy method was suitable for computing objective weights for criteria from the expected information values. Selected evaluation criteria can be categorized as benefit criteria and cost criteria. The decision makers vary their weights toward these two criteria according to different economic development in every stage.

Meanwhile, the decision makers will provide their subjective views on the importance of each type of criterion. This paper combines levels of objective and subjective importance, and distributes weight summations of benefit criteria and cost criteria among every criterion. Thus, the weight evaluation criteria under every kind of situation in every stage can be achieved. Robust decisions in the first stage can be generated by the multicriteria permutation method. In other stages, based on the set of possible decision in different situations, potential good designs are found by means of the scenario approach. Meanwhile, the robustness indices of possible decisions in each stage are generated and used to prepare contingency plans for different situations in each stage. A key question for further research is how to deal with situations where different criteria are used for evaluation in each stage.

Appendix I
Brief Description of ELECTRE I Method

ELECTRE I is a discrete method [2], [14]. The algorithm is to search for a "kernel," which is a nondominated solution. The condition of the "kernel" is based on the assumption of intransitive ordering of alternatives and the following formula: Alternative k is preferred to alternative $l (k > l)$ if and only if

$$c(k,l) \geq p$$

and

$$d(k,l) \leq q$$

where p and q are determined by decision makers. $c(k,l)$ and $d(k,l)$ are defined as

$$c(k,l) = \frac{\sum_{g\epsilon k_g > l_g} W_g + 1/2 \sum_{g\epsilon k_g = l_g} W_g}{\sum_g W_g}$$

$$d(k,l) = \max_{g\epsilon kg < l_g} \frac{k_g(f/s) - l_g(\overline{f}/s)}{K(s)}$$

where $c(k,l)$ is the concord index, $d(k,l)$ is the discord index, W_g is the gth criterion weight, $k_g > l_g$ is the $k > l$ at gth criterion, $k_g = l_g$ is the alternative k and l have no difference $(k = l)$ at gth criterion, $k_g < l_g$ is the alternative k is inferior to alternative l at gth criterion, $k_g(f/s) - l_g(\overline{f}/s)$ is the discomfort caused by going from level $(\overline{f}/s)$ to level (f/s) of criterion g, and $K(s)$ is the total range of scale.

Appendix II
Brief Description of Permutation Method

The permutation method uses Jacquet-Lagreze's successive permutation of all possible rankings of alternatives. With m alternatives, $m!$ permutation rankings are available. The method will identify the best ordering of the alternative rankings, then the dominating alternative.

Suppose a number of alternatives $(d_j, j = 1, 2, \cdots, m)$ have to be evaluated according to a certain number of criteria $(c_g; d_j = 1, 2, \cdots, h)$. The problem can be stated in an evaluation matrix (or impact matrix) E :

$$E = [C_g(d_j)]_{m \times h}$$

where $C_g(d_j)$ is evaluation score of jth alternative to gth criterion.

Assume that a set of weights $W_g (g = 1, 2, \cdots, h), \sum_g W_g = 1$ to be given to the set of corresponding criteria. The weight for each criterion can be derived by the entropy method.

If in the ranking the partial ranking $d_k \geq d_l$ appears, the fact that $C_g(d_k) \geq C_g(d_l)$ will be rated $W_g, C_g(d_k) < C_g(d_l)$ being rated—W_g. The evaluation criterion of chosen hypothesis is the algebraic sum of Wg's corresponding to the element by element consistency. Consider the sth permutation:

$$P_s = (\cdots, d_k, \cdots, d_l, \cdots), \quad s = 1, 2, \cdots, m!$$

where d_k is ranked higher than d_l. Then the evaluation criterion of P_s, R_s, is given by

$$R_s = \sum_{g\epsilon C_{kl}} W_g - \sum_{g\epsilon D_{kl}} W_g, \quad s = 1, 2, \cdots, m!$$

where C_{kl} denotes the concordance set which is the subset of all criteria for which $C_d(d_k) \geq C_g(d_l), D_{kl}$ denotes the discordance set which is the subset of all criteria for which $C_g(d_k) < C_g(d_l)$. The sets of C_{kl} and D_{kl} are defined as

$$C_{kl} = \{g | C_g(d_k) \geq C_g(d_l); \quad k, l = 1, 2, \cdots, m, \quad k \neq l\}$$
$$D_{kl} = \{g | C_g(d_k) < C_g(d_l); \quad k, l = 1, 2, \cdots, m, \quad k \neq l\}.$$

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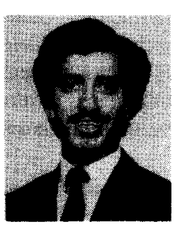

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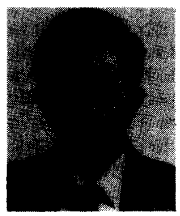

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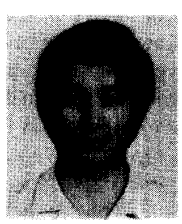

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