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RESEARCH ARTICLE

Incorporated Dempster-Shafer Theory, MACONT, and e-STEP Method (DSM-eSTEP) for Multicriteria Tradeoff Analysis in Transportation Budget Allocation

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ABSTRACT This study introduces a multicriteria tradeoff analysis method based on Dempster-Shafer (DS) theory in conjunction with the Mixed Aggregation by Comprehensive Normalization Technique (MACONT) and the e-STEP method, termed DSM-eSTEP method, to assist transportation agencies in making optimal investment decisions under alternative budget allocation scenarios. Specifically, the DS evidence theory is employed to develop belief functions from preferences of multiple transportation performance criteria revealed by transportation decision-makers. The belief functions are transformed to probability functions using the pignistic transformation technique, leading to a set of initial weights that could reflect the priorities of decision-makers on the performance criteria. To enhance the robustness of relative weights assigned, the MACONT technique and the entropy measure are employed to derive refined weights via context-dependent adjustments. Having established the refined weights of transportation performance measures, the multi-objective budget allocation formulation according to various tradeoff scenarios could be converted to a linear programming model readily solvable for optimality. An empirical study is conducted for optimal budget allocation of 233 highway bridge and pavement preservation projects proposed for a U.S. state-maintained urban Interstate highway network. Cross comparisons of budget allocation results are made between the proposed method and the widely used compromise programming (CP) method. It shows that the proposed DSM-eSTEP method could generate efficient investment outcomes and slightly outperform the CP method.

INDEX TERMS Dempster-Shafer theory, e-STEP method, multicriteria, transportation, budget allocation.

I. INTRODUCTION

The surface transportation system in the United States comprises more than four million miles of public roads, including over 48.5 thousand miles of Interstate highways and approximately 550 thousand road bridges, that constitutes one of the most valuable assets owned by the public sector [1]. These facilities are the nation's backbone in the way to support the economy and people's daily lives. Over the years, extensive efforts have been made by state and local transportation agencies to preserve the conditions of transportation facilities and sustain performance levels of system usage concerning user costs, mobility, safety, and environmental impacts. Economic prosperity has led to steady increases in people travel and goods movement, entailing accelerated deterioration in facility conditions and degradation in system usage performance levels. This poses tremendous challenges to transportation decision-makers to make truly optimal decisions in allocating limited budgets to preserve facility conditions and sustain system usage performance.

On the other hand, transportation funding is primarily generated from fuel taxes, vehicle and motor carrier registration fees, and tolls. With the use of more fuel-efficient

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vehicles and a higher market penetration rate biofuel and battery-operated vehicles, it becomes extremely challenging to upkeep the revenue stream at the current level. This has enlarged the gap of transportation funding between what is available and actually needed over time. Meanwhile, the higher public expectation for more efficient and safer travel and goods delivery urges transportation agencies to employ the state-of-the art approaches to help achieve optimal budgets allocation [2], [3], [4].

A. CURRENT PRACTICE OF TRANSPORTATION BUDGET ALLOCATION

Transportation budget allocation approaches at the state level vary greatly in sophistication and analytic capability. Historically, state transportation agencies have employed legacy-driven, fix-it-first, partial optimization, and performance-based approaches for budget allocation [5].

The legacy-driven approach involves allocating transportation funds to achieve an agency's transportation system management goals, which are primarily determined by the existing structure of various system management programs. The amount or share of funding allocated to each program is often based on historical practice. This approach is popular in many U.S. states, such as Kansas, Louisiana, and Mississippi, but lacks adaptability when new issues arise [6], [7], [8].

The fix-it-first approach prioritizes funding for facility preservation, leaving minimal funding for other transportation system management goals. Some states using this approach include Colorado, Georgia, South Carolina, and Virginia [9], [10], [11], [12].

Other states, such as Arizona, Michigan, North Carolina, and Ohio, have incorporated optimization techniques into transportation investment decisions to better align with holistic considerations of various system management goals and priority settings [13], [14], [15], [16].

In the last two decades, many states have adopted a performance-based budget allocation approach that holistically addresses the preservation of different types of transportation facilities and performance of different aspects of system usage, including user costs, mobility, safety, environmental impacts, and economic development. Budgets are typically designated to different management programs, with multi-year budgets allocated within individual programs or across multiple programs to achieve maximized performance gains for the entire transportation system. Exemplary states that have adopted this approach include Florida, Utah, Virginia, and Washington. The main difference between the performance-based approach and the previously mentioned approaches is that the decision outcomes are mainly derived from data-driven analytical methods and models [17], [18], [19].

B. MOTIVATION

Transportation budget allocation is a highly intricate decision-making process that involves multiple performance criteria, impacting both transportation agencies and system users. The primary objective of transportation agencies is to minimize costs related to facility construction, maintenance, and repair, while simultaneously ensuring the highest level of facility condition preservation. On the other hand, transportation users aim to reduce vehicle operating costs, maximize travel time savings, and avoid accidents. Additionally, both parties are concerned about mitigating the environmental impact caused by motor vehicle usage, particularly concerning vehicle air emissions. However, achieving these transportation system performance goals becomes challenging due to their conflicting nature, necessitating careful consideration of trade-offs during the decision-making process.

The process of budget allocation for transportation further faces several constraints. A fundamental constraint lies in the availability of budgets for a given multi-year analysis period for various management programs associated with facility preservation and system usage.

As a result, the transportation budget allocation problem falls into the category of multicriteria decision-making (MCDM) problems. MCDM methods involve utilizing preferences to guide the selection of investment projects proposed for possible implementation under budget and other constraints through weighting, scaling, amalgamation steps, coupled with optimization techniques. However, in order for these methods and models to be useful in support of budget allocation by transportation agencies, they must meet certain analytical conditions.

First, MCDM methods must be coherent, well-structured, and robust enough to address multiple categories of system management goals holistically, to ensure achieving truly global optimality in terms of maximized overall returns on investments to the entire transportation system. Second, they need to incorporate the capability of tradeoff analysis as one of the key features in the decision-making process by evaluating the impacts of various investment levels and allocation strategies on the overall system performance, as well as the extent to which one performance goal/criterion can be exchanged for another. Unfortunately, these analytical capabilities are largely absent in current practice.

To address this limitation, a new MCDM tradeoff analysis method is proposed for optimal transportation budget allocation. The proposed method consists of a model formulation along with solution algorithms. In addition, a computational experiment is conducted for model application to demonstrate its applicability.

The remainder of this paper is organized as follows: Section II provides a brief literature review of MCDM methods and solution techniques developed for transportation budget allocation over the years. Section III offers background information on the methods and techniques used in the proposed method. Section IV elaborates on the proposed method and model formulation along with solution algorithms. Section V presents a computational experiment for the model application. Finally, Section VI provides a study summary and draws conclusion.

II. RELATED WORK

The MCDM methods for transportation budget allocation can be broadly classified into two groups: multi-attribute decision-making (MADM) methods and multi-objective decision-making (MODM) methods [20], [21]. From a practical viewpoint, the MADM methods conduct decision-making analysis for a relatively small set of alternatives using qualitative criteria, measures, or attributes. Alternatively, MODM generally deals with quantitative criteria or measures.

Along with the methods and models, a variety of solution techniques have been developed mainly based on two approaches: exact algorithms and heuristic algorithms [22], [23]. In general, the exact solution approach transforms a multi-attribute or multi-objective optimization formulation into a single-attribute or single-objective optimization model that is readily solvable for optimality. Conversely, the heuristic approach uses straightforward "rules of thumb" that are established based on past experiences. They are normally cognitive tools to help decision-makers quickly proclaim good enough judgments.

Table 1 summarizes notable MCDM methods and models along with solution techniques developed over the years for transportation budget allocation. It can be seen that the methods developed based on the MADM approach have the advantage of being straightforward for applications. However, they normally require a greater deal of effort from the decision-makers to express their preferences towards multiple performance criteria and the set of investment alternatives proposed for possible implementation. Therefore, it makes them hard to be scaled up to simultaneously handle extensive performance criteria and be applied to multiple levels of transportation agencies involving a large number of investment alternatives. On the contrary, the MODM methods could readily deal with the scale-up issues and budget allocation tasks involving a large number of alternatives.

When using the exact solution approach to solve the multi-attribute decision-making or multi-objective optimization problem, the weighting component is essential for converting the multi-attribute or multi-objective formulation to a single attribute or objective model. Therefore, the quality of methods for weighting analysis will influence the solution quality. At present, relative weights of multi-attribute or multi-objective functions are generally determined based on the preferences of performance measures expressed by the decision-makers by assuming the presence of full and completed information on them. This is not always the case.

On the other hand, the use of heuristic techniques to derive near-optimal solutions for budget allocation is advantageous in that it reduces the requirements in computational power for large problem instances. However, the pre-defined "rules of thumb" are hard to determine and may not be applied across the transportation agencies at different levels. In contrast, the exact algorithms using mathematical programming models could generate optimal solutions but typically require significantly more effort in data preparation and computational resources when dealing with large-scale problems. In some cases, it might not be practical to generate decision outcomes in a timely manner if the number of alternatives or performance criteria is too large.

With an effort to improve the weighting process and solution technique for multicriteria transportation budget allocation with tradeoffs, the current study introduces a new weighting procedure that establishes initial weights of performance criteria and refines them based on additional information made available. For deriving the initial weights, the Dempster-Shafer (DS) evidence theory is employed to construct degrees of belief profile assigned by decision-makers to all elements of the power set created for the performance criteria. Then, the degrees of belief profile are transformed into probabilities using the pignistic transformation technique that are treated as initial weights for the performance criteria. Further, context-dependent adjustments are performed to derive refined weights for the performance criteria. These adjustments are achieved by implementing the Mixed Aggregation by Comprehensive Normalization Technique (MACONT) technique alongside entropy measures of the e-STEP method [38], [39].

With relative weights in place, the multi-objective optimization formulation can be converted to a linear programming model solvable for optimality [40]. For this reason, the proposed method is termed the DSM-eSTEP tradeoff analysis method that provides a promising framework for allocating transportation budgets in a fair and transparent manner.

III. BACKGROUND

This section first elaborates on fundamental elements of the DS theory, including basic belief assignment (BBA), belief function (Bel), plausibility function (Pl), and DS rule of evidence combination for constructing the degrees of belief profile. It then presents the background of the pignistic transformation technique for converting degrees of belief profile to probabilities that are treated as relative weights of multiple performance criteria. Lastly, the MACONT technique for calculating, normalizing, and synthesizing values of different performance criteria into a single value is discussed.

A. DEMPSTER-SHAFER EVIDENCE THEORY

The DS evidence theory is considered an extension of the Bayesian theory that can effectively handle incomplete information or information under risk and uncertainty through multiple aggregation operations for greater control of the decision-maker's judgments [41]. It was first introduced by Dempster [42] in 1976 and further developed by Shafer [43]. Over the last several decades, the DS theory has been widely applied for decision analysis for cases under risk, uncertainty, or lack of information. The primary fields of applications include multidimensional data generation and fusion [44], multi-source information

TABLE 1. Notable studies on different MCDM methods in transportation resource allocation.

Category	Application	Cost component	Model	Decision variable	Objective function	Solution algorithm	Experiment
I. Studies using MADM							
[24]	Bridges	- Program budget	Multiple attribute utility theory (MAUT)	Number of bridges considered for budget allocation	- Maximize bridge condition preservation - Maximize effectiveness of investment - Minimize bridge deficiency	Monte Carlo simulation	Sub-network consisting of 11 bridges
[25]	Transit	- Attainment cost - Operation cost - Maintenance cost	Analytic Hierarchy Process (AHP)	Selection of alternative-fuel buses	Maximization of 11 bus performance criteria	Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)	Selection pool of alternative-fuel buses for the Taiwan urban areas.
[26]	Highways	- Program budget - Construction time	AHP	Selection of transportation construction projects	- Maximize project benefits - Maximize construction quality - Minimize construction costs	Mathematical model applying log-normalization and multiplicative exponential weighting	Hypothetical experiment with 7 projects and 10 performance criteria
[27]	Highways	- Labor hours - Facility hours - Quantity of material	Resource-constrained project scheduling	Project portfolio scheduling	- Minimize make-span - Minimize costs	High-level petri nets, activity-based costing, and TOPSIS	Hypothetical experiment of 2 projects and 4 performance criteria
[28]	Highways	- Project time - Project costs	Goal programming	Selection of project scheduling alternatives	Maximize construction quality	Goal programming model solver	Patterson problems for evaluating project scheduling algorithms
[29]	Highways	- Funding - Equipment - Maintenance types	Nadir compromise programming	Selection of maintenance projects	Maximize weighted average performance after maintenance	Genetic algorithm	Hypothetical experiment of a highway network consists of 4 types of facilities
II. Studies using MODM							
[30]	Transit	Route construction costs	Hybrid multicriteria decision-making method	Selection of monorail route alternatives	Maximize project benefits in terms of economic, social impact, engineering, and environmental impact	Analytic network process and TOPSIS	6 alternatives of monorail routes proposed for Ankara, Turkey
[31]	Highways	Program budget	Pareto frontiers	Selection of asset program portfolio	Maximize project benefits in terms of performance criteria	Generic algorithm	Hypothetical experiment of 4 projects and 3 performance criteria
[32]	Highways	Program budget	Chance-constrained multidimensional Knapsack model	Selection of transportation projects considered for budget allocation	Maximize project benefits in terms of performance criteria	Heuristic algorithm	10-year data of transportation improvement projects and available budget proposed by Indiana DOT.
[33]	Highways	Investment cost	Composite modeling assessment (COSIMA)	Selection of transportation projects considered for budget allocation	Maximize project benefits in terms of performance criteria	Combination of Cost-benefit analysis (CBA), The simple multi-attribute rating technique (SMART), and AHP	Hypothetical experiment of 4 projects and 4 performance criteria
[34]	Highways	Program budget	Applied Multicriteria Ideal Rehabilitation Model (AMIR)	Selection of rehabilitation projects considered for budget allocation	Maximize the improvement factor of rehabilitation projects	Theory of inventive problem solving (TRIZ)	Hypothetical experiment of 4 transportation assets and 64 rehabilitation criteria
[35]	Highways	Program budget	Fuzzy multicriteria grade classification model	Selection of transportation infrastructure projects considered for budget allocation	Maximize project benefits in terms of performance criteria	Fuzzy project ranking technique	Hypothetical experiment composed of 22 projects under 5 assets, and 19 performance criteria
[36]	Tollways	Program budget	Surrogate worth tradeoff	Selection of transportation projects considered for budget allocation	Maximize project benefits in terms of performance criteria	Lagrange relaxation and ε-constraint	6 major toll highway capital investment
[37]	Highways	Program budget	Herfindah-Hirschman Index and Compromise programming	Selection of transportation projects considered for budget allocation	Maximize project benefits in terms of performance criteria	Minimax algorithm and ε-constraint	235 candidate projects proposed for rural Interstate highway improvement program
[38]	Tollways	Program budget	e-STEP method	Selection of transportation projects considered for budget allocation	Maximize project benefits in terms of performance criteria	Mathematical model applying minimax algorithm	6 major toll highway capital investment for Chicago regional highway network

fusion [45], [46], [47], [48], [49], [50], [51], [52], [53], adaptive multi-agent trust analysis [54], artificial intelligence [55], [56], [57], [58], [59], data mining [60], quantum computing and decision-making [61], [62], risk and uncertainty assessment [63], [64], [65], [66], [67], [68], [69], fuzzy measures and cognitive maps [70], [71], [72], [73], portfolio optimization [74], automatic disease detection [75], [76] epidemic decision support system [77], visual recognition [78], image forgery detection [79], multispectral pedestrian detection [80], vehicle route planning [81], robot navigation systems [82], [83], [84], civil infrastructure construction and management [85], [86], and climatic and natural hazards management [87], [88].

Some notable applications of the DS theory in MCDM problems are seen in studies of Chen and Rao [89], Fang et al. [90], Hamid et al. [91], Hua et al. [92], Le et al. [93], Ma and An [94], Merigo et al. [95], Rong [96], Tang et al. [97], Wang et al. [98], Wu and Liao [99], and Zhong et al. [100], [101].

There are three essential elements in the DS theory, namely, the basic belief assignment function (BBA), the Belief function (Bel) and Plausibility function (Pl), and the rule of combined evidence.

1) BASIC BELIEF ASSIGNMENT

It is assumed that there exists a set of hypotheses K that represents a finite nonempty set with mutually exclusive and exhaustive elements. In the context of multicriteria decision-making (MCDM), K can be referred to as a set of performance criteria. For instance, if K performance criteria are considered for a transportation budget allocation problem, the set of hypotheses called as the frame of discernment can be expressed as $K = \{K_1, K_2, \ldots, K_K\}$. The power set of discernment $\mathcal{X}$ is defined as a set that contains all possible propositions of the subsets of K, with a total of 2K elements covering all possible ways that decision makers can combine their judgments on the K performance criteria. It can be expressed as follows:

$$\{\phi, \{K_1\}, \{K_2\}, \ldots \{K_K\}, \{K_1, K_2\}, \ldots, \{K_1, K_2, \ldots, K_K\}\} \tag{1}$$

where ϕ is the null set.

A basic belief assignment (BBA) is defined as a normalized mass function n in the interval [0,1] assigned for each possible proposition in 2^K, and satisfies the following conditions:

$$m{:}\boldsymbol{\chi} \rightarrow [0, 1], \tag{2}$$

$$n(\phi) = 0, \text{ and} \tag{3}$$

$$\sum\nolimits_{C\subset\boldsymbol{\chi}} m(A) = 1 \tag{4}$$

where A is a subset in χ with non-zero mass value.

Specifically, the BBAs are regarded as levels of priorities/importance that a decision-maker assigns to any performance criterion or any combination of performance criteria in χ.

2) BELIEF AND PLAUSIBILITY FUNCTION

From the basic belief assignment, the upper and lower bounds of an interval can be defined. This interval contains the precise probability of a set of interest (in the classical sense) and is bounded by two nonadditive continuous measures called Belief and Plausibility.

The lower bound Belief for a set A is defined as the sum of all the basic probability assignments of the proper subsets (B) of the set of interest (A) ($B \subseteq A$), which can be calculated by:

$$Bel(A) = \sum\nolimits_{B|B\subset A} m(B) \tag{5}$$

The upper bound, Plausibility, measures the sum of all the basic probability assignments of the sets (B) that intersect the set of interest (A) ($B \cap A \neq \emptyset$). Formally, for all sets A that are elements of the power set ($A \in \boldsymbol{\chi}$), which yields:

$$Pl(A) = \sum\nolimits_{B|B\cap A=\emptyset} m(B) \tag{6}$$

3) RULE OF COMBINED EVIDENCE

In the multicriteria decision analysis process, such as the process of transportation decision making, it is rarely the case where a decision outcome is achieved based on a single assessment of multiple performance criteria. Normally, multiple rounds of judgments on performance criteria from a collection of decision-makers are performed. Therefore, it is essential to have a rigorous method to aggregate diverse opinions of decision makers on individual performance criteria. The purpose of aggregation of information is to meaningfully summarize and simplify a corpus of data whether the data is coming from a single source or multiple sources. As robust as its basic belief assignment method, the DS rule of combined evidence provides a flexible means of consolidating the BBAs regardless of the level of certainty that each decision maker maintains with the belief assignment.

Given two basic belief assignments n_i and n_j associated with two sources i and j, the information can be treated as two sets of evidence from the decision makers. The combined evidence of subset C in $\boldsymbol{\chi}$ using orthogonal rule of the DS theory can be defined as:

$$m(C) = (m_i \oplus m_j)(C) = \begin{cases} \dfrac{\sum_{A\cap B=C} m_i(A)\, m_j(B)}{1-M}, & C \neq \phi \\ 0, & C = \phi \end{cases} \tag{7}$$

where A, B, and $C \in \boldsymbol{\chi}$; $m_i(A)$ and $m_j(B)$ are two BBAs determined on proposition A by source i and on proposition B by source j, respectively; $M = \sum_{A\cap B=\phi} m_i(A)\, m_j(B)$ represents basic belief mass associated with conflict, which is determined by summing up the products of the BBAs of all sets where the intersection is null; and ϕ is the null set.

In the general case where multiple sources of evidence are available, the combined evidence of C is calculated by:

$$(m_1 \oplus m_2 \oplus \ldots \oplus m_m)(C) = \begin{cases} \dfrac{\sum_{A_1 \cap \ldots \cap A_m = C} m_1(A_1)\, m_2(A_2) \ldots m_m(A_m)}{1 - M}, & l \neq \phi \\ 0, & l = \phi \end{cases} \tag{8}$$

where $M = \sum_{A_1 \cap \ldots \cap A_m = \phi} m_1(A_1)\, m_2(A_2) \ldots m_m(A_m)$; m is number of sources of information.

B. PIGNISTIC POSSIBILITY-PROBABILITY TRANSFORMATION

The results obtained by the DS combining evidence from different sources of information are the utility values for the subsets in $\boldsymbol{\chi}$, where the elements in one subset are different to those of others. It is also called the belief function of propositions in $\boldsymbol{\chi}$. Since determining relative weights of multiple performance criteria is concerned with a probability measure for a single element in $\boldsymbol{\chi}$, meaning that the probability measure for individual performance criteria, there is a need for a transferable belief model offering appropriate and fair inference with a probability measure for singletons. The pignistic probability transformation, as proposed by Smets [102], employs the principle of insufficient reason to convert degrees of belief to probabilities. This enables the integration of uncertainty measures into probabilistic or risk-based analytical frameworks, which can be more easily combined, updated, and used in decision-making models [39]. The formulation of pignistic transformation is defined as:

$$P(K_p) = \sum_{C \subseteq \boldsymbol{\chi}, K_p \in C} \frac{1}{|C|} n(C) \tag{9}$$

where $P(K_p)$ is the pignistic probability of performance criteria K_p in $\mathbf{K}$; and $|C|$ is the number of single elements in subset C that contains K_p, in $\boldsymbol{\chi}$.

By performing the above calculation, $P(K_p)$ transfers the positive mass of belief of each nonspecific element into individual elements according to the cardinal number of subsets [39].

C. MIXED AGGREGATION NORMALIZATION

Typically, the impacts of an investment alternative under various performance criteria such as agency costs, mobility, and safety are measured in non-commensurable units. In order to make cross comparisons among the investment alternatives on an equal basis, the impacts must be transformed to a commensurable unit. In most cases, this transformation is often accomplished by a single normalization technique. However, this treatment is likely to cause deviations between the normalized and original data [39]. In recent years, research has been conducted to address this discrepancy issue of normalized data. Liao and Wu [103] developed a double normalization technique and introduced an adjustment coefficient to the normalized value. Wen et al. [39] introduced an MACONT Method to perform and synthesize three normalized performance values into a single normalized value to reflect the deviations of the original data set. This normalization technique is executed in the following steps.

First, a decision matrix is formed from the information of itemized impacts or benefits associated with individual performance criteria for each investment alternative as below:

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1k} & \cdots & a_{1K} \\ a_{21} & a_{22} & \cdots & a_{2k} & \cdots & a_{2K} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nk} & \cdots & a_{iK} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{Nk} & \cdots & a_{NK} \end{bmatrix} \tag{10}$$

where a_{nk} is the level of impacts or benefits of the n^{th} investment alternative concerning performance criterion k.

Next, three normalization operations are executed on the derived decision matrix. The normalization techniques used in this step are linear sum-based normalization, ratio-based normalization, and linear max-min normalization, and can be calculated by:

$$\acute{a}^1_{nk} = \frac{a_{nk}}{\sum_{n=1}^{N} a_{nk}} \tag{11}$$

$$\acute{a}^2_{nk} = \frac{a_{nk}}{\max_n a_{nk}} \tag{12}$$

$$\acute{a}^3_{nk} = \frac{a_{nk} - \min_n a_{nk}}{\max_n a_{nk} - \min_n a_{nk}} \tag{13}$$

where $\acute{a}^1_{nk}, \acute{a}^2_{nk}, \acute{a}^3_{nk}$ are the normalized values of the level of impacts or benefits of the n^{th} investment alternative relating to criterion k derived from the execution of linear sum-based normalization, ratio-based normalization, and linear max-min normalization, respectively; $\min_n a_{nk}$ is the smallest value of impacts or benefits associated with performance criterion k among all N investment alternatives; $\max_n a_{nk}$ is the largest value of impacts or benefits associated with performance criterion k among all N investment alternatives.

Finally, after the three normalization operations are done, two balance coefficients, β and μ, are introduced to integrate the normalized values of impacts or benefits. The purpose of these coefficients is to give decision-makers control over the aggregated normalized values of impacts or benefits. The integration equation is of the following specification:

$$\acute{a}_{nk} = \beta \acute{a}^1_{nk} + \mu \acute{a}^2_{nk} + (1 - \beta - \mu) \acute{a}^3_{nk} \tag{14}$$

where $\acute{a}_{nk}$ is the aggregated normalized value of the impacts or benefits of the n^{th} investment alternative related to performance criterion k; $0 \leq \beta, \gamma, \mu \leq 1$ and can be determined by decision-makers.

Besides the benefit of minimizing the discrepancy between the normalized and original data, the MACONT technique, as shown in Equation (13), also allows decision-makers to have control over the final normalized values of impacts or benefits. For example, if the decision-makers want to focus on the benefits associated with individual performance criteria of the investment alternatives, the value of β can be assigned larger; if the purpose is to highlight the best performer among the investment alternatives, then a higher value of μ should be assigned. Conversely, if the decision-makers want to the magnitude of impacts between the best and worst performers, both coefficients should be kept at small values to emphasize the importance of $\acute{a}_{nk}^{3}$ [39].

Owing to the flexibility in normalizing the impacts or benefits of investment alternatives under various performance criteria, MACONT technique is employed in conjunction with the entropy measures for context-dependent adjustments to the initial weights of performance criteria [40].

IV. PROPOSED METHOD

This section presents a model formulation for transportation budget allocation involving multiple performance criteria, followed by a procedure to derive the optimal solution via tradeoff analysis.

A. MODEL FORMULATION

1) DECISION VARIABLES

The decision of budget allocation to a candidate project for possible investment is a zero/one binary choice process, meaning rejection or selection of the project for actual investment. In reality, the decision can either be concerned with each project separately or multiple projects under the same contract package collectively. Correspondingly, the decision variables can be denoted as:

$$x_n = \begin{cases} 1 \; \textit{if project or contract is selected} \\ 0 \; \textit{otherwise} \end{cases} \tag{15}$$

where x_n indicates the n^{th} project/contract in the list of candidate projects $X = \{x_1, x_2, \ldots, x_n, \ldots, x_N\}$, $n = 1, 2, \ldots, N$.

2) OBJECTIVE FUNCTIONS

The optimization of transportation budget allocation involving K performance criteria can be formulated as maximization of overall benefits or minimization of total costs. Without loss of generality, all the objective functions are expressed in maximization form as below:

$$Maximize \{F_1(x), F_2(x), \ldots, F_K(x)\} \tag{16}$$

where $F = \{F_k(x) \,|k = 1, 2, \ldots, K$ is a set of objective functions correspond to K performance criteria used as the basis of investment decision-making.

3) CONSTRAINTS

The constraints for transportation budget allocation genrally include but are not limited to constraints of thr available budget, and lower and upper bounds of number of projects that could be implemented together. The feasible region S_N that is bounded by the constraints is specified by:

$$R_N = \begin{cases} \sum_{n=1}^{N} (c_n . x_n) \leq B, \quad n = 1, 2, \ldots, N \\ L_N \leq \sum_{n=1}^{N} x_n \leq U_N \end{cases} \tag{17}$$

where c_n is cost of investment associated with the n^{th} candidate project; B is total available budget; and L_N and U_N are lower and upper bounds of number of projects allowed to be simultaneously implemented.

B. MODEL EXECUTION PROCEDURE

Fig. 1 illustrates the model execution procedure that includes three main components: i) initial weight estimation, ii) context-dependent adjustments, and iii) model execution. Detailed descriptions follow.

1) INITIAL WEIGHTS OF PERFORMANCE CRITERIA

The purpose of this component is to establish initial relative weights for transportation performance criteria. The following steps are executed:

Step 1.1 Identifying the set of K performance criteria and constructing a power set of discernment $\boldsymbol{\chi}$. With K performance criteria, the frame of discernment can be denoted as $\boldsymbol{K} = \{K_p\}\,(p = 1, 2, \ldots, K)$. Accordingly, the power set of discernment can be constructed by Equation (1) as:

$$\boldsymbol{\chi} = \{\phi, \{K_1\}, \{K_2\}, \ldots \{K_K\}, \{K_1, K_2\}, \ldots, \{K_1, K_2, \ldots, K_K\}\}.$$

Step 1.2 Selecting a list of M decision makers that represents different stakeholder groups, $DM = \{m_i\}\,(i = 1, 2, \ldots, M)$. Each decision maker m_i assigns degrees of belief to all elements of the power set following the conditions of BBA in Equations (2) - (4), denoted as $m_i(a_i)\,(i = 1, 2, \ldots, M)\,; a_i \in \boldsymbol{\chi}$. Establish belief and plausibility function as in Equations (5) and (6) to derive lower and upper bound for each BBA and generate a collection of BBAs.

Step 1.3 Performing the DS rule of combining evidence as Equation (8) on the obtained collection of BBAs to create degrees of belief profile in $\boldsymbol{\chi}$.

Step 1.4 Applying pignistic probability transformation as Equation (9) to convert degrees of belief profile to probabilities corresponding to the performance criteria, $P(K_p)\,(p = 1, 2, \ldots, K)$.The derived probabilities can be used as initial weights w_p^I of performance criteria to convert the multi-objective optimization formulation to a linear programming model readily solvable for optimality, and can be expressed as below:

$$w_p^I = P(K_p) \tag{18}$$

where $\sum_{p=1}^{K} w_p^I = 1$; and $p = 1, 2, \ldots, K$.

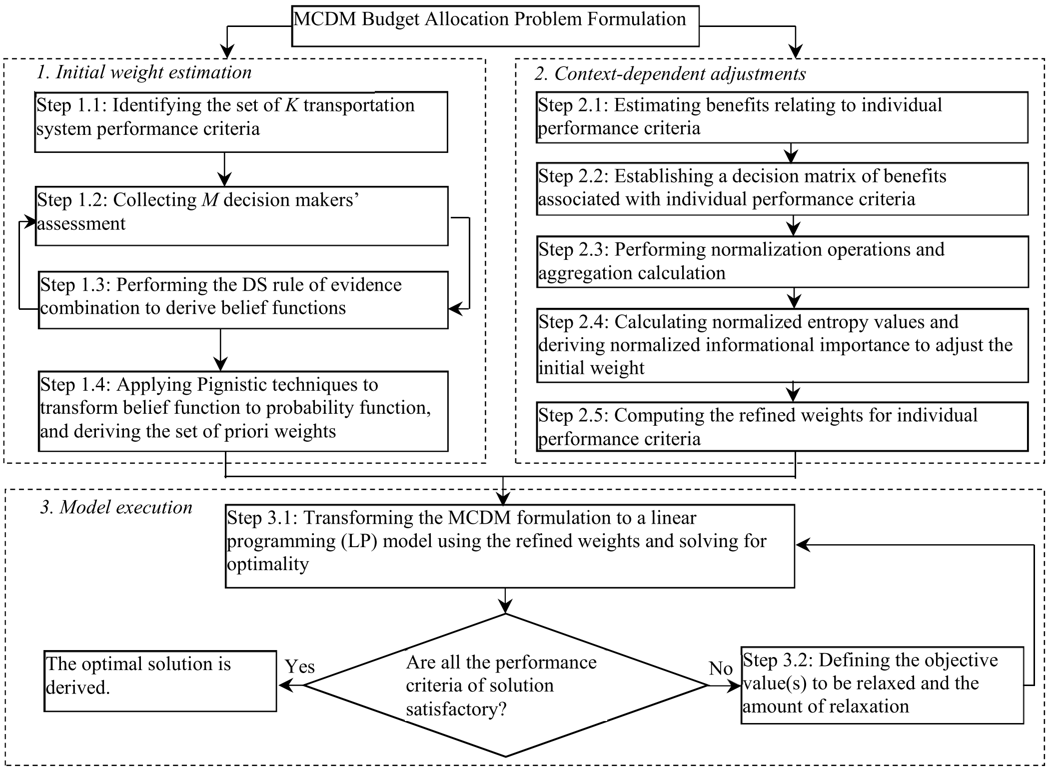

FIGURE 1. The iterative model execution process for transportation budget allocation.

2) CONTEXT-DEPENDENT ADJUSTMENTS AND REFINED WEIGHTS

For a multi-objective optimization problem, one unit increase in the weight assigned to a performance criterion does not necessarily lead to increase in benefits estimated by the performance criterion proportionally. It might even result in a greater extent of decrease in benefits assessed by other performance criteria. As an example, we consider two performance criteria regarding transportation agency benefits of facility life-cycle agency cost reductions and transportation user benefits of travel time savings. If one unit increase in the weight of performance criterion for assessing agency benefits could bring up one million dollars of agency benefits, the one unit decrease in the weight of performance criterion for evaluating user benefits could potentially lead to a greater level of losses. If a decision maker prioritizes agency benefits over user benefits, the set of weights could satisfy the decision maker's expectation, but the overall benefits could be worse off. Therefore, it is necessary to calculate the context-dependent adjustments for initial weights derived using the DS evidence theory to establish the refined weights that reflect decision makers' preference and incorporate additional information that affects the relative importance of different performance criteria.

The context-dependent adjustments are computed follow the MACONT technique [39] and entropy measures used by the e-STEP method introduced by Benayounet al. [40]. Specifically, a decision matrix is developed for multiple objective functions. Next, normalization operations are executed on the decision matrix. Then, the MACONT technique is employed to establish the normalized matrices. Finally, the entropy measures on the mixed aggregated normalized values are computed to derive context-dependent adjustments to the initial weights. The calculation steps are presented as follows:

Step 2.1 Estimating project benefits relating to individual performance criteria.

Step 2.2 Establishing a decision matrix of impacts or benefits of each candidate project. The columns of the decision matrix represent the number of performance criteria, whereas the rows represent the number of candidate projects proposed for possible implementation.

Step 2.3 Performing three sets of normalization operations on the decision matrix using Equations (11)–(13) and computing mixed values by aggregating three normalized matrices.

Step 2.4 Calculating the normalized entropy value $e(d_k)$ of the k^{th} performance criterion by:

$$e(d_k) = -\frac{1}{ln\ K} \sum_{n=1}^{N} \left[\left(\frac{\acute{a}_{nk}}{\sum_{n=1}^{N} \acute{a}_{nk}} \right) \cdot ln \left(\frac{\acute{a}_{nk}}{\sum_{n=1}^{N} \acute{a}_{nk}} \right) \right] \tag{19}$$

where $\acute{a}_{nk}$ is the aggregated normalized value of impacts or benefits of the n^{th} candidate project relating to criterion k; $0 \leq \acute{a}_{nk} \leq 1$;

$0 \leq e(d_k) \leq 1; k = 1, 2, \ldots, K$; and $n = 1, 2, \ldots$, N.

Naturally, the larger the normalized entropy value $e(d_k)$ is, the less information is conveyed. Therefore, the reverse value $(1 - e(d_k))$ should be used for the context-dependent adjustment to the initial weight of the k^{th} performance criterion. The normalized information importance for the adjustment to the k^{th} performance criterion can be determined by:

$$\alpha_k = \frac{(1 - e(d_k))}{\sum_{k=1}^{K} (1 - e(d_k))}, \quad k = 1, 2, \ldots, K. \tag{20}$$

Step 2.5 Establishing refined weights of performance criteria by synthesizing the initial weights with the context- dependent adjustments derived in Step 2.4 as follow:

$$w_k = \frac{w_k^I \times \alpha_k}{\sum_{\mathrm{k}=1}^{K} \left(w_k^I \times \alpha_k\right)} \tag{21}$$

where $\mathrm{k} = 1, 2, \ldots, K$.

3) ITERATIVE MODEL EXECUTION

In presence of the refined weights of performance criteria, the multi-objective optimization formulation can be converted to a linear programming model with the objective of minimizing the Chebyshev distance [104], defined as the maximum weighted relative distance between the ideal and actual objective function values of respective performance criteria. This model formulation is of the following specification:

$$Minimize \left\{ L_\infty = Max \left| w_k . \left(\frac{F_k^* - F_k(x)}{F_k^*} \right) \right| \right\} \tag{22}$$

Subject to

$$X \in R_N \tag{23}$$

The above model can be iteratively solved with constraints updated based on new information becoming available. In cases where not all the optimal values of the objective functions $\mathrm{F_p(X)}$ are satisfactory, the decision maker could relax $\Delta \mathrm{F_p}$ amount of a satisfactory objective function $\mathrm{F_p}$ to improve the unsatisfactory objective function(s) in the subsequent iteration. In general, the feasible region of the constraints in the t^{th} iteration is expressed as:

$$R_N^t = \begin{cases} R_N^{t-1} \\ F_p(X) \geq F_p\left(X^{t-1}\right) - \Delta F_p \\ F_k(X) \geq F_k\left(X^{t-1}\right), \quad k \neq p \end{cases} \tag{24}$$

C. MODEL SOLUTION TOOLS

The model execution for determining initial weights follows Steps 1.1 to 1.4 is coded in Python programming environment. The same program is used to derive context-dependent adjustments as Steps 2.1 to 2.5. The linear programming model as Expressions (22) and (23) is handled using the MS Excel Solver plugin capable of solving large-scale linear programming models. For each iteration of model execution, its feasible region is updated using Equation (24).

V. EMPIRICAL STUDY

A. DATA COLLECTION AND PROCESSING

Two datasets are used for the current experimental study. The first set of data is solicited from questionnaire surveys to help establish the initial weights [105]. The second set of data is on projects proposed for improving an U.S. state-maintained urban Interstate highway system to help derive the refined weights and executing the proposed optimization model for budget allocation [106]. In the multi-objective optimization formulation, five performance criteria including highway agency costs, vehicle operating costs, travel time, vehicle crashes, and vehicle air emissions are used as the basis of allocating available budget to various candidate projects. In this respect, a frame of discernment corresponding to the above five performance criteria can be constructed, which is denoted as $\boldsymbol{K} = \{\boldsymbol{K_1}, \boldsymbol{K_2}, \boldsymbol{K_3}, \boldsymbol{K_4}, \boldsymbol{K_5}\}$. To derive initial weights for the performance criteria, two questionnaire surveys are administered for respondents from the transportation agency group and highway user group, respectively. The survey participants from the agency group comprise 29 officials including executive staff, district directors, and division chiefs of a state transportation agency. The survey participants from highway user group contain 28 highway drivers randomly selected for participation. Each of the survey attendants is asked to assign the relative importance of the above performance criteria using a rating scale of 1 to 10 to indicate ascending importance levels. Two rounds of surveys are arranged using the Delphi technique. For participants from each group, the average and standard deviation ratings of the first-round surveys are provided to each survey participant, followed by the second-round surveys.

Having collected the second-round survey data from the two groups of participants, ratings of the five performance criteria assigned by each respondent are normalized and treated as BBAs follow the DS rules as Expressions (2)–(6). As shown in Table 2, BBAs of a decision maker are presented in a form of relative importance next to the performance criteria. For instance, BBAs of decision maker 1 in the agency group are recorded as $\{\{\mathrm{K_1}, 0.179\}, \{\mathrm{K_2}, 0.143\}, \{\mathrm{K_3}, 0.286\}, \{\mathrm{K_4}, 0.250\}, \{\mathrm{K_5}, 0.142\}\}$, indicating that in a normalized total scale of 1, degrees of belief in the relative importance of agency costs, user costs, mobility, safety, and environmental impacts are 0.179, 0.143, 0.286, 0.250, and 0.142, respectively.

The dataset on candidate projects proposed for U.S. state-maintained urban Interstate highway improvements in a six-year budget allocation period contains details of 233 bridge and pavement preservation projects, which mainly include project ID, project description, implementation year,

TABLE 2. Summary of basic belief assignments by survey participants.

Decision maker's ID	Basic belief assignments on propositions of 2^Θ: Agency group	Basic belief assignments on propositions of 2^Θ: User group
1	$\{\{K_1, 0.179\}, \{K_2, 0.143\}, \{K_3, 0.286\}, \{K_4, 0.250\}, \{K_5, 0.142\}\}$	$\{\{K_1, 0.143\}, \{K_2, 0.029\}, \{K_3, 0.286\}, \{K_4, 0.257\}, \{K_5, 0.286\}\}$
2	$\{\{K_1, 0.184\}, \{K_2, 0.211\}, \{K_3, 0.184\}, \{K_4, 0.263\}, \{K_5, 0.158\}\}$	$\{\{K_1, 0.182\}, \{K_2, 0.159\}, \{K_3, 0.227\}, \{K_4, 0.227\}, \{K_5, 0.205\}\}$
3	$\{\{K_1, 0.205\}, \{K_2, 0.227\}, \{K_3, 0.205\}, \{K_4, 0.227\}, \{K_5, 0.136\}\}$	$\{\{K_1, 0.143\}, \{K_2, 0.143\}, \{K_3, 0.229\}, \{K_4, 0.257\}, \{K_5, 0.229\}\}$
4	$\{\{K_1, 0.231\}, \{K_2, 0.128\}, \{K_3, 0.231\}, \{K_4, 0.231\}, \{K_5, 0.179\}\}$	$\{\{K_1, 0.159\}, \{K_2, 0.227\}, \{K_3, 0.159\}, \{K_4, 0.227\}, \{K_5, 0.227\}\}$
5	$\{\{K_1, 0.195\}, \{K_2, 0.220\}, \{K_3, 0.171\}, \{K_4, 0.220\}, \{K_5, 0.195\}\}$	$\{\{K_1, 0.200\}, \{K_2, 0.178\}, \{K_3, 0.200\}, \{K_4, 0.222\}, \{K_5, 0.200\}\}$
6	$\{\{K_1, 0.200\}, \{K_2, 0.178\}, \{K_3, 0.200\}, \{K_4, 0.222\}, \{K_5, 0.200\}\}$	$\{\{K_1, 0.116\}, \{K_2, 0.233\}, \{K_3, 0.186\}, \{K_4, 0.233\}, \{K_5, 0.233\}\}$
7	$\{\{K_1, 0.205\}, \{K_2, 0.179\}, \{K_3, 0.205\}, \{K_4, 0.231\}, \{K_5, 0.179\}\}$	$\{\{K_1, 0.132\}, \{K_2, 0.211\}, \{K_3, 0.263\}, \{K_4, 0.211\}, \{K_5, 0.184\}\}$
8	$\{\{K_1, 0.186\}, \{K_2, 0.186\}, \{K_3, 0.209\}, \{K_4, 0.233\}, \{K_5, 0.186\}\}$	$\{\{K_1, 0.150\}, \{K_2, 0.200\}, \{K_3, 0.250\}, \{K_4, 0.250\}, \{K_5, 0.150\}\}$
9	$\{\{K_1, 0.200\}, \{K_2, 0.225\}, \{K_3, 0.200\}, \{K_4, 0.225\}, \{K_5, 0.150\}\}$	$\{\{K_1, 0.167\}, \{K_2, 0.194\}, \{K_3, 0.222\}, \{K_4, 0.250\}, \{K_5, 0.167\}\}$
10	$\{\{K_1, 0.190\}, \{K_2, 0.190\}, \{K_3, 0.214\}, \{K_4, 0.238\}, \{K_5, 0.167\}\}$	$\{\{K_1, 0.161\}, \{K_2, 0.194\}, \{K_3, 0.194\}, \{K_4, 0.290\}, \{K_5, 0.161\}\}$
11	$\{\{K_1, 0.146\}, \{K_2, 0.171\}, \{K_3, 0.195\}, \{K_4, 0.244\}, \{K_5, 0.244\}\}$	$\{\{K_1, 0.182\}, \{K_2, 0.227\}, \{K_3, 0.159\}, \{K_4, 0.227\}, \{K_5, 0.205\}\}$
12	$\{\{K_1, 0.184\}, \{K_2, 0.184\}, \{K_3, 0.211\}, \{K_4, 0.237\}, \{K_5, 0.184\}\}$	$\{\{K_1, 0.208\}, \{K_2, 0.208\}, \{K_3, 0.188\}, \{K_4, 0.188\}, \{K_5, 0.208\}\}$
13	$\{\{K_1, 0.225\}, \{K_2, 0.150\}, \{K_3, 0.225\}, \{K_4, 0.250\}, \{K_5, 0.150\}\}$	$\{\{K_1, 0.125\}, \{K_2, 0.167\}, \{K_3, 0.375\}, \{K_4, 0.250\}, \{K_5, 0.083\}\}$
14	$\{\{K_1, 0.225\}, \{K_2, 0.150\}, \{K_3, 0.200\}, \{K_4, 0.250\}, \{K_5, 0.175\}\}$	$\{\{K_1, 0.241\}, \{K_2, 0.172\}, \{K_3, 0.138\}, \{K_4, 0.207\}, \{K_5, 0.241\}\}$
15	$\{\{K_1, 0.190\}, \{K_2, 0.167\}, \{K_3, 0.214\}, \{K_4, 0.238\}, \{K_5, 0.190\}\}$	$\{\{K_1, 0.125\}, \{K_2, 0.063\}, \{K_3, 0.250\}, \{K_4, 0.281\}, \{K_5, 0.281\}\}$
16	$\{\{K_1, 0.163\}, \{K_2, 0.209\}, \{K_3, 0.233\}, \{K_4, 0.209\}, \{K_5, 0.186\}\}$	$\{\{K_1, 0.174\}, \{K_2, 0.217\}, \{K_3, 0.196\}, \{K_4, 0.217\}, \{K_5, 0.196\}\}$
17	$\{\{K_1, 0.211\}, \{K_2, 0.211\}, \{K_3, 0.184\}, \{K_4, 0.211\}, \{K_5, 0.184\}\}$	$\{\{K_1, 0.190\}, \{K_2, 0.190\}, \{K_3, 0.238\}, \{K_4, 0.214\}, \{K_5, 0.167\}\}$
18	$\{\{K_1, 0.206\}, \{K_2, 0.176\}, \{K_3, 0.265\}, \{K_4, 0.294\}, \{K_5, 0.059\}\}$	$\{\{K_1, 0.211\}, \{K_2, 0.237\}, \{K_3, 0.132\}, \{K_4, 0.263\}, \{K_5, 0.158\}\}$
19	$\{\{K_1, 0.237\}, \{K_2, 0.158\}, \{K_3, 0.211\}, \{K_4, 0.237\}, \{K_5, 0.158\}\}$	$\{\{K_1, 0.150\}, \{K_2, 0.175\}, \{K_3, 0.225\}, \{K_4, 0.250\}, \{K_5, 0.200\}\}$
20	$\{\{K_1, 0.171\}, \{K_2, 0.195\}, \{K_3, 0.220\}, \{K_4, 0.244\}, \{K_5, 0.171\}\}$	$\{\{K_1, 0.172\}, \{K_2, 0.138\}, \{K_3, 0.103\}, \{K_4, 0.310\}, \{K_5, 0.276\}\}$
21	$\{\{K_1, 0.162\}, \{K_2, 0.162\}, \{K_3, 0.243\}, \{K_4, 0.216\}, \{K_5, 0.216\}\}$	$\{\{K_1, 0.125\}, \{K_2, 0.225\}, \{K_3, 0.250\}, \{K_4, 0.225\}, \{K_5, 0.175\}\}$
22	$\{\{K_1, 0.214\}, \{K_2, 0.190\}, \{K_3, 0.190\}, \{K_4, 0.214\}, \{K_5, 0.190\}\}$	$\{\{K_1, 0.119\}, \{K_2, 0.214\}, \{K_3, 0.190\}, \{K_4, 0.238\}, \{K_5, 0.238\}\}$
23	$\{\{K_1, 0.167\}, \{K_2, 0.194\}, \{K_3, 0.222\}, \{K_4, 0.222\}, \{K_5, 0.194\}\}$	$\{\{K_1, 0.237\}, \{K_2, 0.132\}, \{K_3, 0.211\}, \{K_4, 0.237\}, \{K_5, 0.184\}\}$
24	$\{\{K_1, 0.189\}, \{K_2, 0.162\}, \{K_3, 0.243\}, \{K_4, 0.243\}, \{K_5, 0.162\}\}$	$\{\{K_1, 0.179\}, \{K_2, 0.231\}, \{K_3, 0.231\}, \{K_4, 0.231\}, \{K_5, 0.128\}\}$
25	$\{\{K_1, 0.211\}, \{K_2, 0.158\}, \{K_3, 0.211\}, \{K_4, 0.237\}, \{K_5, 0.184\}\}$	$\{\{K_1, 0.216\}, \{K_2, 0.189\}, \{K_3, 0.162\}, \{K_4, 0.270\}, \{K_5, 0.162\}\}$
26	$\{\{K_1, 0.211\}, \{K_2, 0.158\}, \{K_3, 0.237\}, \{K_4, 0.237\}, \{K_5, 0.158\}\}$	$\{\{K_1, 0.071\}, \{K_2, 0.250\}, \{K_3, 0.036\}, \{K_4, 0.286\}, \{K_5, 0.357\}\}$
27	$\{\{K_1, 0.179\}, \{K_2, 0.154\}, \{K_3, 0.205\}, \{K_4, 0.256\}, \{K_5, 0.205\}\}$	$\{\{K_1, 0.196\}, \{K_2, 0.174\}, \{K_3, 0.217\}, \{K_4, 0.217\}, \{K_5, 0.196\}\}$
28	$\{\{K_1, 0.214\}, \{K_2, 0.190\}, \{K_3, 0.214\}, \{K_4, 0.214\}, \{K_5, 0.167\}\}$	$\{\{K_1, 0.225\}, \{K_2, 0.200\}, \{K_3, 0.200\}, \{K_4, 0.250\}, \{K_5, 0.125\}\}$
29	$\{\{K_1, 0.179\}, \{K_2, 0.179\}, \{K_3, 0.231\}, \{K_4, 0.256\}, \{K_5, 0.154\}\}$	

project duration, number of travel lanes, project length, daily traffic, work type, and estimated costs. In order to apply the proposed model to prioritize available budget, benefits of each candidate project under individual performance criteria need to be estimated. In this respect, additional data details of agency and user costs associated with the same highway system are collected. The specifics include unit rates of construction, maintenance, and repair treatments for pavements and bridges; unit rates concerning vehicle operations, travel time, vehicle crashes, and air emissions; annual traffic growth rates; and discount rates.

B. ESTIMATION OF PROJECT BENEFITS

1) HIGHWAY COSTS

Highway costs include agency costs and system usage costs. Agency costs are expenses of the highway agency during the entire service life of the highway facility, mainly including costs of facility construction, maintenance, and repair in the facility lifespan. Construction cost relates to right-of-way acquisition, pre-engineering, and the activities on designing and constructing the highway facility. Maintenance cost pertains to annual and periodic (with multi-year interval) maintenance activities to preserve the aging condition of the highway facility. Repair cost is related to interventions for facility condition restoration.

Highway user costs are costs of system usage largely concerned with vehicle operations, travel time, crashes, and vehicle air emissions. Each cost can be calculated as a function of factors including traffic volume, vehicle composition, engine type and age, vehicle speed and speed-change cycle, geometry of the facility, traffic control measures, pavement surface conditions, climate features, and weather conditions.

2) HIGHWAY PROJECT BENEFITS

The benefits of implementing a highway project can be drawn from reductions in agency and user cost perspectives. Agency benefits are computed as the decrease of agency costs in the facility service life cycle as a result of timely investment implementation. User benefits are estimated in aspects of reductions in vehicle operating costs, improvements of traffic mobility, enhancements of safety, and cutbacks of environmental impacts such as vehicle air emissions.

To calculate reductions in agency costs in the highway facility service life cycle, the base-case agency cost profile where all required maintenance and repair treatments are timely implemented in an ideal manner to yield the lowest life-cycle agency costs is compared with the actual life-cycle agency profile reflecting the real-world implementation of maintenance and repair interventions. The base-case and actual life cycle agency costs are directly subtracted to establish agency benefits, typically expressed in equivalent uniform annualized amounts.

Similarly, the based-case and actual user cost profiles in the highway facility service life cycle could be separately created for itemized user costs concerning vehicle operations, mobility, safety, and environmental impacts. By comparing the two sets of itemized user cost profiles and adopting the concept of changes in consumer surplus, user benefits of timely investing in a candidate project could be estimated and expressed in equivalent uniform annualized values.

TABLE 3. Costs and estimated benefits of some candidate projects.

Project No.	Let Year	Work Type	Annualized project costs ($ mil/yr)	Estimated Project Benefits: Agency benefits ($ mil/yr)	Veh. opt cost reductions ($/VMT)	Travel time savings (hr/VMT)	Veh. crash decreases (crashes/MVMT)	Veh. air emission cutbacks (kg/VMT)
1	2003	New Bridge Construction	2.025000	0.039700	0.3254632	0.0114729	4.4979955	0.9777365
15	2001	Bridge Deck Overlay	0.807000	0.050281	0.3661053	0.0141120	3.5273353	0.9776838
18	2004	Bridge Deck Reconstruction & Widening	1.510000	0.696750	0.3092063	0.0104173	4.8862595	0.9777577
40	2004	Replace Superstructure	1.340000	1.771554	0.3132705	0.0106812	4.7891935	0.9777524
41	2004	Bridge Rehabilitation/ Repair	0.605000	2.592157	0.3715242	0.0144639	3.3979140	0.9776767
50	2001	Bridge Deck Replacement & Widening	2.746000	0.062583	0.3688147	0.0142880	3.4626247	0.9776802
…	…	…	...	…	…	…	…	…
80	2001	New Bridge Construction	1.883000	1.247614	0.3579768	0.0135842	3.7214674	0.9776943
81	2001	New Bridge Construction	2.718000	0.141913	0.3633958	0.0139361	3.5920460	0.9776873
83	2005	New Bridge Construction	1.260000	0	0.3268179	0.0115609	4.4656402	0.9777348
84	2006	New Bridge Construction	0.840000	0.211368	0.3322368	0.0119128	4.3362188	0.9777277
85	2006	New Bridge Construction	1.400000	0.050281	0.3281726	0.0116489	4.4332848	0.9777330
95	2004	Bridge Replacement	2.470000	0.002958	0.3227537	0.0112970	4.5627062	0.9777401
97	2004	Bridge Replacement	7.810000	0.057190	0.3200442	0.0111211	4.6274168	0.9777436
114	2003	Bridge Deck Reconstruction	2.020000	0.192343	0.3268179	0.0115609	4.4656402	0.9777348
115	2005	Bridge Deck Replacement & Widening	1.025000	0.000425	0.3132705	0.0106812	4.7891935	0.9777524

Table 3 presents information on costs and estimated benefits of some candidate projects. Specifically, project costs, agency benefits are expressed in 2022 constant million U.S. dollars per year with a discount rate of 4% used for calculations. The remaining user benefits are first quantified as dollars of vehicle operating cost reductions, vehicle-hours of travel time savings, decreases in number of crashes, and kilograms of cutbacks in vehicle air emissions.

TABLE 4. Initial weights of performance criteria.

Performance Criteria	Initial Relative Weights: Agency group (w_k^A)	User group(w_k^U)	Combined(w_k^I)
Agency costs (K_1)	0.1953	0.1671	0.1614
Vehicle operating costs (K_2)	0.1797	0.1854	0.1650
Travel time (K_3)	0.2154	0.2034	0.2169
Vehicle crashes (K_4)	0.2360	0.2427	0.2836
Vehicle air emissions (K_5)	0.1736	0.2014	0.1731

C. METHOD APPLICATION

For establishing initial weights of the performance criteria including agency costs, user costs, mobility, safety, and environmental impacts, the DS rule of combining evidence and pignistic transformation as Equation (8), (9) and (18) are separately applied to data as in Table 2 on BBAs from the agency survey group, user survey group, and the two groups combined. Table 4 lists initial weights of performance criteria.

The multi-objective optimization model for allocating budget to 233 candidate projects proposed for urban Interstate highway improvements that could help achieve maximized overall benefits can be formulated as:

Maximize

$$F(X) = \{F_1(X), F_2(X), F_3(X), F_4(X), F_5(X)\} \tag{25}$$

Subject to

$$R_N = \begin{cases} 97,395 \le \sum_{n_1=1}^{174} c_{n_1} . x_{n_1}^B \le 78,840,500 \\ 187,298 \le \sum_{n_2=1}^{59} c_{n_2} . x_{n_2}^P \le 278,116,000 \\ x_{n_1}^B,\ x_{n_2}^P = 0/1, n_1 = 1, 2, \ldots, 174, \\ \qquad n_2 = 1, 2, \ldots, 59 \\ 0 \le \sum_{n_1=1}^{174} x_{n_1}^B + \sum_{n_2=1}^{59} x_{n_2}^P \le 233 \end{cases} \tag{26}$$

where $F(X) = \{F_k(X)\}$ is a vector of project benefits associated with multiple performance criteria and $F_k(X) = \sum b_k^{n_1} . x_{n_1}$, $b_k^{n_1}$ represents itemized benefits of the k^{th} performance criterion expected to be generated from candidate project n_1; c_{n_1} is the cost of candidate project n_1; $x_{n_1}^B, x_{n_2}^P$ represent the decision variable of candidate project n_1 and n_2 under work categories of bridge preservation and pavement preservation, respectively; $x_{n_1}^B, x_{n_2}^P = 0/1$ is a decision variable for rejection or selection of candidate project n_1 and n_2 corresponding to work categories of bridge preservation and pavement preservation; $k = 1, 2, \ldots, 5$; $n_1 = 1, 2, \ldots, 174$; $n_2 = 1, 2, \ldots, 59$. Lower and upper bounds in the first and second terms of Expression (26) refer to the lowest investment amount of a single project and the total budget for bridge and pavement preservation projects, respectively.

The decision matrix is established as illustrated in Expression (10). Based on the derived decision matrix, the procedure of applying MACONT technique as Equations (11)–(14) and entropy measures as Equation (19) is executed and context-dependent adjustments to the initial weights are calculated using Equation (20). Table 5 summarizes payoff matrix of some candidate projects, entropy measures, context-dependent adjustments, and refined weights of performance criteria.

After deriving refined weights for the performance criteria, the multi-objective optimization formulation can be readily converted to a linear programming (LP) model with a single

TABLE 5. Payoff matrix, entropy measures, and refined weights of performance criteria.

Measures	Performance Criterion				
	Agency benefits ($mil/year)	Veh. opt. cost reductions ($/VMT)	Travel time savings (Hr/VMT)	Veh. crash decreases (No. crashes/MVMT)	Veh. Air emission cutbacks (Kg/VMT)
Entropy ($e(d_k)$)	0.9848	0.9902	0.9861	0.9820	0.9998
Adjustment factor (α_k)	0.2663	0.1722	0.2441	0.1656	0.1518
Calibrated weights (w_k)	0.2007	0.1626	0.2472	0.2179	0.1716

objective of minimizing the Chebyshev distance under budget and other constraints as Expressions (25) and (26). The optimal solution shows that the available budget should be allocated to 121 out of the 233 candidate projects. Of which, 79 projects are for bridge preservation, and 42 are for pavement preservation. The annualized total benefits include $458,409,663 of agency cost decrements, $198,865,639 of vehicle operating cost (VOC) reductions, 2,844,899 vehicle-hours of travel timing savings, 656 crash decreases, and 190,976,861 kg of vehicle air emission cutbacks per year. The total costs of 121 prioritized projects are $351,741,230 with $73,984,606 allocated to bridge preservation and $277,752,624 for pavement preservation.

D. COMPARISONS OF BUDGET ALLOCATION USING DIFFERENT METHODS

To further assess the significance of the DSM-eSTEP tradeoff method for transportation budget allocation, especially in the process of determining relative weights of performance criteria, cross comparisons are made between the proposed method and the traditional compromise programming (CP) method that utilizes the same set of performance criteria for highway budget allocation. In general, the CP method uses distance measure to emulate the ideal solution as close as possible with no preferences in the relative importance among performance criteria [59], [104]. Since the proposed method and the CP method are both based on the same minimax optimization mechanism, they should derive the same optimal outcomes if the same set of relative weights is used. To facilitate the comparative analysis, the proposed method with two weighting scenarios, with and without context-dependent adjustments, is used to compare with the CP method using four budget levels that are equivalent to 25%, 50%, 75%, and 100% of the original budget amount, respectively.

With no preferences on relative weights of the performance criteria, the CP method could convert the multi-objective optimization model shown in Equations (22) and (23) to an LP model in the minimax sense as follows:

Minimize max

$$\left\{\left|\frac{20,054,165-F_1(X)}{20,054,165}\right|;\left|\frac{22,449,467-F_2(X)}{22,449,467}\right|;\left|\frac{281,593-F_3(X)}{281,593}\right|;\left|\frac{56-F_4(X)}{56}\right|;\left|\frac{30,548,073-F_5(X)}{30,548,073}\right|\right. \tag{27}$$

Subject to

$$R_N=\begin{cases} 97,395\leq\sum_{n_1=1}^{174}c_{n_1}.x_{n_1}^B\leq 78,840,500 \\ 187,298\leq\sum_{n_2=1}^{59}c_{n_2}.x_{n_2}^P\leq 278,116,000. \\ x_{n_1}^B,x_{n_2}^P=0/1, n_1=1,2,\ldots,174, \\ \quad n_2=1,2,\ldots,59 \\ 0\leq\sum_{n_1=1}^{174}x_{n_1}^B+\sum_{n_2=1}^{59}x_{n_2}^P\leq 233 \end{cases} \tag{28}$$

Table 6 summarizes comparative results of budget allocation using proposed DSM-eSTEP tradeoff method, the DSM-eSTEP method without adjustments, and the CP model. For the annual benefits achieved, both agency benefits and VOC reductions are expressed in dollar values where VOC reductions amount to 4.3–6.2% of agency benefits. Travel time savings, crash decreases, and emission cutbacks are in vehicle-hours, number of crashes, and kilograms of pollutants per year, respectively.

The proposed DSM-eSTEP method, utilizing the refined weights, demonstrates superior performance compared to the DSM-eSTEP method without context-dependent adjustments of initial weights and the CP method, across budget levels ranging from 40% to 100% of the original budget amount. This performance improvement is evident in at least three out of the five performance criteria analyzed, with a notable emphasis on the benefits achieved, particularly in terms of agency cost reductions and travel time savings. These benefits are often the most significant components driving positive outcomes in transportation budget allocation decisions. For the remaining benefits relating to decreases in vehicle crashes and cutbacks of vehicle air emissions, the budget allocation by the proposed method would result in either a lower level of decreases in vehicle crashes coupled with a higher level of cutbacks of vehicle air emissions, or vice versa. The change in the combined benefits appears to be marginal.

In comparison of the proposed DSM-eSTEP method without context-dependent adjustments of initial weights to the proposed method using the refined weights, the losses of agency benefits and travel time savings that could be achieved at 40–100% of the original budget level vary by 3.2–6.3% and 5.0–11.6%, respectively. Further comparing the CP method with the proposed method using the refined weights, the losses of agency benefits and travel time savings that could be

TABLE 6. Payoff matrix, entropy measures, and refined weights of performance criteria.

Method		Proposed DSM-eSTEP method	Proposed DSM-eSTEP method without context-dependent adjustments	CP Method
Relative weights of performance criteria		$w_1 = 0.2007$, $w_2 = 0.1626$, $w_3 = 0.2472$, $w_4 = 0.2179$, $w_5 = 0.1716$.	$w_1 = 0.1614$, $w_2 = 0.1650$, $w_3 = 0.2169$, $w_4 = 0.2836$, $w_5 = 0.1731$	$w_1 = 0.20$, $w_2 = 0.20$, $w_3 = 0.20$, $w_4 = 0.20$, $w_5 = 0.20$.
Budget level	Budget allocation outcome			
100%	Number of selected projects	121	108	125
	Annual benefits			
	- Agency benefits (million $/year)	4,584	4,389 (-4.3%)	4,459 (-2.7%)
	- VOC reductions (million $/year)	198.9	182 (-8.5%)	204 (2.6%)
	- Travel timing savings (veh-hrs/year)	2,844,899	2,702,222 (-5.0%)	2,670,514 (-6.1%)
	- Veh. crash decreases (crashes/year)	656	663 (1.1%)	635 (-3.2%)
	- Veh air emission cutbacks (kg/year)	190,976,861	185,198,663 (-3.0%)	193,963,905 (1.6%)
80%	Number of selected projects	86	93	88
	Annual benefits			
	- Agency benefits (million $/year)	3,254	3,150 (-3.2%)	3,109 (-4.5%)
	- VOC reductions (million $/year)	169	173 (2.4%)	170 (0.6%)
	- Travel timing savings (veh-hrs/year)	2,190,572	2,032,448 (-7.2%)	1,994,512 (-9.0%)
	- Veh. Crash decreases (crashes/year)	597	607 (1.7%)	567 (-5.0%)
	- Veh. air emission cutbacks (kg/year)	152,781,489	149,434,164 (-2.2%)	157,150,266 (2.9%)
60%	Number of selected projects	77	68	79
	Annual benefits			
	- Agency benefits (million $/year)	2,521	2,362 (-6.3%)	2,250 (-10.7%)
	- VOC reductions (million $/year)	125	127 (1.6%)	124 (-0.8%)
	- Travel timing savings (veh-hrs/year)	1,678,490	1,588,126 (-5.4%)	1,597,649 (-4.8%)
	- Veh. crash decreases (crashes/year)	506	532 (5.1%)	454 (-10.3%)
	- Veh. air emission cutbacks (kg/year)	126,044,728	120,099,788 (-4.7%)	134,447,710 (6.7%)
40%	Number of selected projects	42	56	48
	Annual benefits			
	- Agency benefits (million $/year)	882	851 (-3.5%)	829 (-6.0%)
	- VOC reductions (million $/year)	55	59 (7.3%)	58 (5.5%)
	- Travel timing savings (veh-hrs/year)	805,675	712,546 (-11.6%)	732,832 (-9.0%)
	- Veh. crash decreases (crashes/year)	202	210 (4.0%)	189 (-6.4%)
	- Veh. air emission cutbacks (kg/year)	70,585,048	66,308,171 (-6.1%)	70,989,689 (0.6%)

Note: Negative values in the brackets of the last two columns refer to lower levels of benefits achieved.

achieved at 40–100% of the original budget level correspond to 2.7–10.7% and 4.8–9.0%.

VI. SUMMARY AND CONCLUSION

This paper presents a new multicriteria tradeoff analysis method for efficient transportation budget allocation. The proposed method consists of several key components, including two rounds of relative weight derivation, multi-objective optimization model formulation, model conversion, and iterative model execution to generate a tradeoff solution.

To establish the initial weights for the performance criteria, the pignistic possibility-probability transformation technique, rooted in the DS evidence theory, is used. Once additional information on the relative importance of the performance criteria is made available, the initial weights are refined by context adjustments using the MACONT technique and entropy measures of the e-STEP method. With the refined weights established, the multi-objective optimization model can be converted into a linear programming model that is executed iteratively to deriving the optimal tradeoff solution. Python scripts and MS Excel solver are used to execute the computational steps.

The proposed DSM-eSTEP tradeoff method is implemented in an empirical study using a dataset on six-year budget allocation for a U.S. state-maintained urban Interstate highway network. To gain insights into the efficiency of the proposed method incorporating context-dependent adjustments to the initial weights of performance criteria, the same dataset is applied to the proposed method without context-dependent adjustments and traditional CP method for budget allocation by varying budget amounts at 40%, 60%, 80%, and 100% of the original budget level, respectively.

Compared to the proposed method that uses the refined weights for budget allocation, the proposed method relying on the initial weights and CP method appear to be less efficient in maximizing agency benefits, with up to 6.3% and 10.7% lower agency benefits, and travel time savings up to 9.0% and 11.6% lower, respectively. Meanwhile, the combined effect of changes in vehicle crashes and air emissions tends to be marginal. Since agency benefits and travel time savings constitute the predominant portion of the overall benefits, it reveals that adopting the proposed method will be beneficial to transportation agencies in developing efficient investment programs.

The proposed method offers several advantages over existing approaches to transportation budget allocation. It uses a rigorous procedure to derive and refine the relative weights of transportation performance criteria, thereby ensuring a comprehensive and robust evaluation of the investment alternatives. Additionally, it incorporates a tradeoff analysis feature that enables transportation agencies to make informed decisions about the allocation of limited budgets among competing investment alternatives. Finally, the computational study provides evidence of the efficiency of the proposed method in maximizing overall benefits, which suggests its potential as a valuable tool in support of optimal transportation investment decisions.

With the passage of time, new multicriteria decision-making methods and models are expected to be developed and used by various transportation agencies. Cross-comparisons can be carried out between the proposed method and those methods and models to identify the strengths and limitations of the current method. Meanwhile, further refinements to the proposed method could be explored by incorporating more advanced multicriteria optimization techniques or applying it to multimodal transportation budget allocation. In addition, it may be useful to investigate the potential benefits of integrating the proposed method into other decision-making frameworks to provide a more comprehensive and holistic approach to transportation budget allocation.

REFERENCES

[1] FHWA. (2018). *Highway Statistics 2018. Federal Highway Administration*. U.S. Department of Transportation, Washington, DC, USA. [Online]. Available: https://www.fhwa.dot.gov/policyinformation/statistics/2018/

[2] Z. Li, *Transportation Asset Management: Methodology and Applications*, 1st ed. Boca Raton, FL, USA: CRC Press, 2018.

[3] Z. Li and K. C. Sinha, "Methodology for multicriteria decision making in highway asset management," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1885, no. 1, pp. 79–87, Jan. 2004.

[4] K. C. Sinha and S. Labi, *Transportation Decision Making: Principles of Project Evaluation and Programming*. New York, NY, USA: Wiley, 2007.

[5] *Cross-Asset Resource Allocation and the Impact on Transportation System Performance*, NAs, The National Academies Press, Washington, DC, USA, 2016, doi: 10.17226/22177.

[6] LADOTD. (2019). *2019 Federal NHS Transportation Asset Management Plan*. Louisiana Department of Transportation and Development, Baton Rouge, LA, USA. [Online]. Available: http://wwwsp.dotd.la.gov/Inside_LaDOTD/Divisions/Multimodal/Data_Collection/Asset%20Management/LADOTD%20TAMP%202019%20Final%20Issued.pdf

[7] KSDOT. (2019). *Transportation Asset Management Plan*. Kansas Department of Transportation, Topeka, KS, USA. [Online]. Available: https://www.ksdot.org/Assets/wwwksdotorg/bureaus/burTransPlan/pubtrans/pdf/KDOT_TAMP_Final_062819.pdf

[8] MSDOT. (2019). *Transportation Asset Management Plan*. Mississippi Department of Transportation, Jackson, MS, USA. [Online]. Available: https://tamptemplate.org/wp-content/uploads/tamps/065_mississippidot.pdf

[9] CODOT. (2019). *Transportation Asset Management Plan*. Colorado Department of Transportation, Denver, CO, USA. [Online]. Available: https://www.codot.gov/programs/transitandrail/assets/plans-studies-reports/2018-TAMplan

[10] *Transportation Asset Management Plan*, Georgia Dept. Transp., Atlanta, GA, USA, 2019.

[11] *Transportation Asset Management Plan*, South Carolina Dept. Transp. (SCDOT), Columbia, SC, USA, 2019.

[12] *Transportation Asset Management Plan*, Virginia Dept. Transp., Richmond, VA, USA, 2019.

[13] *Transportation Asset Management Plan*, Arizona Dept. Transp., Phoenix, AZ, USA, 2019.

[14] *Transportation Asset Management Plan*, Ohio Dept. Transp., Columbus, OH, USA, 2019.

[15] *Transportation Asset Management Plan*, North Carolina Dept. Transp. (NCDOT), Raleigh, NC, USA, 2019.

[16] *Transportation Asset Management Plan*, Michigan Dept. Transp., Lansing, MI, USA, 2019.

[17] *Transportation Asset Management Plan*, Washington Dept. Transp. (WSDOT), Olympia, WA, USA, 2019.

[18] *Transportation Asset Management Plan*, Utah Dept. Transp., Taylorsville, UT, USA, 2019.

[19] *Transportation Asset Management Plan*, Florida Dept. Transp., Tallahassee, FL, USA, 2019.

[20] H. Zimmerman, *Fuzzy Set Theory and Applications*, 2nd ed. Boston, MA, USA: Kluwer Academic, 1991.

[21] S.-J. Chen and C.-L. Hwang, "Fuzzy multiple attribute decision making methods," in *Fuzzy Multiple Attribute Decision Making*. Berlin, Germany: Springer, 1992, pp. 289–486.

[22] M. Ehrgott, *Multicriteria Optimization*, 2nd ed. Berlin, Germany: Springer, 2005.

[23] I. Kaliszewski, *Soft Computing for Complex Multiple Criteria Decision Making*. New York, NY, USA: Springer, 2006.

[24] S. Abu Dabous and S. Alkass, "A multi-attribute ranking method for bridge management," *Eng., Construct. Architectural Manage.*, vol. 17, no. 3, pp. 282–291, May 2010.

[25] G.-H. Tzeng, C.-W. Lin, and S. Opricovic, "Multi-criteria analysis of alternative-fuel buses for public transportation," *Energy Policy*, vol. 33, no. 11, pp. 1373–1383, Jul. 2005.

[26] E. K. Zavadskas, T. Vilutienė, Z. Turskis, and J. Šaparauskas, "Multi-criteria analysis of projects' performance in construction," *Arch. Civil Mech. Eng.*, vol. 14, no. 1, pp. 114–121, Jan. 2014.

[27] H.-P. Kao, B. Wang, J. Dong, and K.-C. Ku, "An event-driven approach with makespan/cost tradeoff analysis for project portfolio scheduling," *Comput. Ind.*, vol. 57, no. 5, pp. 379–397, Jun. 2006.

[28] B. Pollack-Johnson and M. J. Liberatore, "Incorporating quality considerations into project time/cost tradeoff analysis and decision making," *IEEE Trans. Eng. Manag.*, vol. 53, no. 4, pp. 534–542, Nov. 2006.

[29] H. Xiong, Q. Shi, X. Tao, and W. Wang, "A compromise programming model for highway maintenance resources allocation problem," *Math. Problems Eng.*, vol. 2012, pp. 1–11, Mar. 2012.

[30] M. Hamurcu and T. Eren, "An application of multicriteria decision-making for the evaluation of alternative monorail routes," *Mathematics*, vol. 7, no. 1, p. 16, Dec. 2018.

[31] Q. Bai and S. Labi, "Uncertainty-based tradeoff analysis methodology for integrated transportation investment decision-making," USDOT Region V Regional Univ., Transp. Center Final Rep., Nextrans, West Lafayette, IN, USA, NEXTRANS Project no. 020PY01, 2009.

[32] Z. Li, S. Madanu, B. Zhou, Y. Wang, and M. Abbas, "A heuristic approach for selecting highway investment alternatives," *Comput.-Aided Civil Infrastruct. Eng.*, vol. 25, no. 6, pp. 427–439, Feb. 2010.

[33] M. B. Barfod and S. Leleur, *Multi-Criteria Decision Analysis for Use in Transport Decision Making* (DTU Transport Compendium Series Part 2), 2nd ed. Lyngby, Denmark: Technical Univ. of Denmark, 2014.

[34] M. Yadollahi and R. Zin, "Applied multi-criteria ideal rehabilitation model for budget allocation across road infrastructure," *Int. J. Innov. Sci.*, vol. 3, no. 4, pp. 193–202, Dec. 2011.

[35] W. Huang, J. Teng, and M. Lin, "The budget allocation model of public infrastructure projects," *J. Marine Sci. Technol.*, vol. 18, no. 5, pp. 697–708, 2010.

[36] A. M. Roshandeh, Z. Li, M. Neishapouri, H. Patel, and Y. Liu, "Trade-off analysis approach for multiobjective transportation investment decision making," *J. Transp. Eng.*, vol. 141, no. 3, Mar. 2015, Art. no. 04014085.

[37] T. Q. Truong, J. Zhang, Z. Li, and L. Wang, "Integrated Herfindahl–Hirschman index, compromise programming, and ε-constraint method for multicriteria performance-based transportation budget allocation," *Transp. Res. Record, J. Transp. Res. Board*, vol. 2675, no. 10, pp. 468–480, Oct. 2021, doi: 10.1177/03611981211011648.

[38] T. Truong, Z. Li, and K. Kepaptsoglou, "Entropy-STEP multiobjective trade-off analysis method for optimal transportation investment decisions," *J. Transp. Eng., A, Syst.*, vol. 144, no. 1, Jan. 2018, Art. no. 04017065.

[39] Z. Wen, H. Liao, and E. K. Zavadskas, "MACONT: Mixed aggregation by comprehensive normalization technique for multi-criteria analysis," *Informatica*, vol. 31, no. 4, pp. 857–880, 2020, doi: 10.15388/20-INFOR417.

[40] R. Benayoun, J. D. De Montgolfier, J. Tergny, and O. Laritchev, "Linear programming with multiple objective functions: Step method (STEM)," *Math. Program.*, vol. 1, no. 1, pp. 366–375, 1971.

[41] M. Beynon, D. Cosker, and D. Marshall, "An expert system for multi-criteria decision making using Dempster Shafer theory," *Exp. Syst. Appl.*, vol. 20, no. 4, pp. 357–367, May 2001.

[42] A. P. Dempster, "Upper and lower probabilities induced by a multivalued mapping," *Ann. Math. Statist.*, vol. 38, no. 2, pp. 325–339, Apr. 1967.

[43] G. A. Shafer, *Mathematical Theory of Evidence*. Princeton, NJ, USA: Princeton Univ. Press, 1976.

[44] A. Huang, R. Shen, Y. Li, H. Han, W. Di, and D. F. T. Hagan, "A methodology to generate integrated land cover data for land surface model by improving Dempster–Shafer theory," *Remote Sens.*, vol. 14, no. 4, p. 972, Feb. 2022, doi: 10.3390/rs14040972.

[45] L. Pan and Y. Deng, "A new complex evidence theory," *Inf. Sci.*, vol. 608, pp. 251–261, Aug. 2022, doi: 10.1016/j.ins.2022.06.063.

[46] X. Deng and W. Jiang, "A framework for the fusion of non-exclusive and incomplete information on the basis of D number theory," *Appl. Intell.*, vol. 53, pp. 11861–11884, Sep. 2022, doi: 10.1007/s10489-022-03960-z.

[47] Z. Hua and X. Jing, "An improved belief Hellinger divergence for Dempster–Shafer theory and its application in multi-source information fusion," *Int. J. Speech Technol.*, vol. 53, no. 14, pp. 17965–17984, Jul. 2023, doi: 10.1007/s10489-022-04428-w.

[48] Q. Liang, Z. Liu, and Z. Chen, "A networked method for multi-evidence-based information fusion," *Entropy*, vol. 25, no. 1, p. 69, Dec. 2023, doi: 10.3390/E25010069.

[49] Y. Tang, S. Wu, Y. Zhou, Y. Huang, and D. Zhou, "A new reliability coefficient using betting commitment evidence distance in Dempster–Shafer evidence theory for uncertain information fusion," *Entropy*, vol. 25, no. 3, p. 462, Mar. 2023, doi: 10.3390/e25030462.

[50] B. Wu, W. Qiu, W. Huang, G. Meng, J. Huang, and S. Xu, "A multi-source information fusion approach in tunnel collapse risk analysis based on improved Dempster–Shafer evidence theory," *Sci. Rep.*, vol. 12, no. 1, p. 3626, Mar. 2022, doi: 10.1038/s41598-022-07171-x.

[51] F. Xiao, "GEJS: A generalized evidential divergence measure for multi-source information fusion," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 53, no. 4, pp. 2246–2258, Apr. 2023, doi: 10.1109/TSMC.2022.3211498.

[52] F. Xiao and W. Pedrycz, "Negation of the quantum mass function for multisource quantum information fusion with its application to pattern classification," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 45, no. 2, pp. 2054–2070, Feb. 2023, doi: 10.1109/TPAMI.2022.3167045.

[53] K. Zhao, L. Li, Z. Chen, R. Sun, G. Yuan, and J. Li, "A survey: Optimization and applications of evidence fusion algorithm based on Dempster–Shafer theory," *Appl. Soft Comput.*, vol. 124, Jul. 2022, Art. no. 109075, doi: 10.1016/j.asoc.2022.109075.

[54] N. Wang and D. Wei, "An adaptive Dempster–Shafer theory of evidence based trust model in multiagent systems," *Appl. Sci.*, vol. 12, no. 15, p. 7633, Jul. 2022, doi: 10.3390/app12157633.

[55] T. Denoeux and M. H. Masson, "Dempster-Shafer reasoning in large partially ordered sets: Applications in machine learning," in *Integrated Uncertainty Management and Applications* (Advances in Intelligent and Soft Computing), vol. 68. Basel, Switzerland: Springer, 2010, pp. 39–54.

[56] M. Shoyaib, M. Abdullah-Al-Wadud, S. M. Z. Ishraque, and O. Chae, "Facial expression classification based on Dempster-Shafer Theory of evidence," in *Belief Functions: Theory and Applications* (Advances in Intelligent and Soft Computing), vol. 164. Basel, Switzerland: Springer, 2012, pp. 213–220.

[57] L. Li, C. Li, X. Lu, H. Wang, and D. Zhou, "Multi-focus image fusion with convolutional neural network based on Dempster–Shafer theory," *Optik*, vol. 272, Feb. 2023, Art. no. 170223, doi: 10.1016/j.ijleo.2022.170223.

[58] J. Ren, L. Jiang, H. Peng, Z. Liu, J. Wu, and P. S. Yu, "Evidential temporal-aware graph-based social event detection via Dempster–Shafer theory," in *Proc. IEEE Int. Conf. Web Services (ICWS)*, Jul. 2022, pp. 331–336, doi: 10.1109/ICWS55610.2022.00055.

[59] L. Ma, P. Wei, X. Qu, S. Bi, Y. Zhou, and T. Shen, "Apple grading method based on neural network with ordered partitions and evidential ensemble learning," *CAAI Trans. Intell. Technol.*, vol. 7, no. 4, pp. 561–569, Dec. 2022, doi: 10.1049/cit2.12140.

[60] Q. Chen and U. Aickelin, "Dempster–Shafer for anomaly detection," in *Proc. Int. Conf. Data Mining*, 2006, pp. 232–238.

[61] L. Pan, X. Gao, and Y. Deng, "Quantum algorithm of Dempster rule of combination," *Appl. Intell.*, vol. 53, pp. 8799–8808, Aug. 2022, doi: 10.1007/s10489-022-03877-7.

[62] F. Xiao, "Generalized quantum evidence theory," *Appl. Intell.*, vol. 53, pp. 14329–14344, Oct. 2022, doi: 10.1007/s10489-022-04181-0.

[63] S. I. Sezer, G. Elidolu, E. Akyuz, and O. Arslan, "An integrated risk assessment modelling for cargo manifold process on tanker ships under FMECA extended Dempster–Shafer theory and rule-based Bayesian network approach," *Process Saf. Environ. Protection*, vol. 174, pp. 340–352, Jun. 2023, doi: 10.1016/j.psep.2023.04.024.

[64] Y. He and M. Y. Hussaini, "Mixed aleatory and epistemic uncertainty propagation using Dempster–Shafer theory," *J. Comput. Appl. Math.*, vol. 429, Sep. 2023, Art. no. 115234, doi: 10.1016/j.cam.2023.115234.

[65] S. M. Albogami, M. K. A. B. M. Ariffin, E. E. B. Supeni, and K. A. Ahmad, "Development of a hybrid AHP and Dempster–Shafer theory of evidence for project risk assessment problem," *J. Project Manage.*, vol. 7, no. 2, pp. 77–94, 2022, doi: 10.5267/j.jpm.2021.10.003.

[66] R. Li, Z. Chen, H. Li, and Y. Tang, "A new distance-based total uncertainty measure in Dempster–Shafer evidence theory," *Int. J. Speech Technol.*, vol. 52, no. 2, pp. 1209–1237, Jan. 2022, doi: 10.1007/s10489-021-02378-3.

[67] F. Xiao, J. Wen, and W. Pedrycz, "Generalized divergence-based decision making method with an application to pattern classification," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 7, pp. 6941–6956, Jul. 2022, doi: 10.1109/TKDE.2022.3177896.

[68] Y. Tang, S. Tan, and D. Zhou, "An improved failure mode and effects analysis method using belief Jensen–Shannon divergence and entropy measure in the evidence theory," *Arabian J. Sci. Eng.*, vol. 48, no. 5, pp. 7163–7176, May 2023.

[69] N. Balakrishnan, F. Buono, and M. Longobardi, "A unified formulation of entropy and its application," *Phys. A, Stat. Mech. Appl.*, vol. 596, Jun. 2022, Art. no. 127214, doi: 10.1016/j.physa.2022.127214.

[70] P. Bhowal, S. Sen, J. H. Yoon, Z. W. Geem, and R. Sarkar, "Evaluation of fuzzy measures using Dempster–Shafer belief structure: A classifier fusion framework," *IEEE Trans. Fuzzy Syst.*, vol. 31, no. 5, pp. 1593–1603, May 2023, doi: 10.1109/TFUZZ.2022.3206504.

[71] Y. Li and Y. Shao, "Fuzzy cognitive maps based on D-number theory," *IEEE Access*, vol. 10, pp. 72702–72716, 2022, doi: 10.1109/ACCESS.2022.3187202.

[72] Y.-T. Liu, N. R. Pal, A. R. Marathe, and C.-T. Lin, "Weighted fuzzy Dempster–Shafer framework for multimodal information integration," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 1, pp. 338–352, Feb. 2018.

[73] D. Petturiti and B. Vantaggi, "Conditional decisions under objective and subjective ambiguity in Dempster–Shafer theory," *Fuzzy Sets Syst.*, vol. 447, pp. 155–181, Oct. 2022, doi: 10.1016/j.fss.2022.02.011.

[74] A. Skoruchi and E. Mohammadi, "Uncertain portfolio optimization based on Dempster–Shafer theory," *Manage. Sci. Lett.*, vol. 12, no. 3, pp. 207–214, 2022, doi: 10.5267/j.msl.2022.1.001.

[75] A. Maseleno, Fauzi, and M. Muslihudin, "Ebola virus disease detection using Dempster–Shafer evidence theory," in *Proc. IEEE Int. Conf. Prog. Informat. Comput. (PIC)*, Dec. 2015, pp. 579–582.

[76] S. Ben Atitallah, M. Driss, W. Boulila, A. Koubaa, and H. Ben Ghézala, "Fusion of convolutional neural networks based on Dempster–Shafer theory for automatic pneumonia detection from chest X-ray images," *Int. J. Imag. Syst. Technol.*, vol. 32, no. 2, pp. 658–672, Mar. 2022, doi: 10.1002/ima.22653.

[77] I. Sujadi, F. Natalia, F. V. Ferdinand, S. Sudirman, and C. S. Ko, "A mobile-based COVID-19 decision support system using Dempster–Shafer theory," *ICIC Exp. Lett., B, Appl.*, vol. 13, no. 6, pp. 615–622, 2022.

[78] G. M. Provan, "The application of Dempster Shafer theory to a logic-based visual recognition system," *Mach. Intell. Pattern Recognit.*, vol. 10, pp. 389–405, 1990.

[79] A.-T. Phan-Ho and F. Retraint, "A comparative study of Bayesian and Dempster–Shafer fusion on image forgery detection," *IEEE Access*, vol. 10, pp. 99268–99281, 2022, doi: 10.1109/ACCESS.2022.3206543.

[80] Q. Li, C. Zhang, Q. Hu, H. Fu, and P. Zhu, "Confidence-aware fusion using Dempster–Shafer theory for multispectral pedestrian detection," *IEEE Trans. Multimedia*, early access, Mar. 21, 2022, doi: 10.1109/TMM.2022.3160589.

[81] F. Golsahni, E. Cortes-Rello, and T. H. Howell, "Dynamic route planning with uncertain information," *Knowl.-Based Syst.*, vol. 9, no. 4, pp. 223–232, Jun. 1996.

[82] J. Yang and Y. Wu, "Detection for mobile robot navigation based on multisensor fusion," *Proc. SPIE*, vol. 2591, 1995, pp. 182–192.

[83] A. Kak, K. Andress, C. Lopez-Abadia, M. Carol, and R. Lewis, "Hierarchical evidence accumulation in the Pseiki system and experiments in model-driven mobile robot navigation," *Mach. Intell. Pattern Recognit.*, vol. 10, pp. 353–369, 1990, doi: 10.1016/B978-0-444-88738-2.50035-X.

[84] D. Pagac, E. M. Nebot, and H. Durrant-Whyte, "An evidential approach to probabilistic map-building," in *Proc. IEEE Int. Conf. Robot. Autom.*, 1996, pp. 745–750.

[85] M. Garshasbi and G. Kabir, "Earthquake resilience framework for a stormwater pipe infrastructure system integrating the best worst method and Dempster–Shafer theory," *Sustainability*, vol. 14, no. 5, p. 2710, Feb. 2022, doi: 10.3390/su14052710.

[86] Y. Ding, B. Yang, G. Xu, and X. Wang, "Improved Dempster–Shafer evidence theory for tunnel water inrush risk analysis based on fuzzy identification factors of multi-source geophysical data," *Remote Sens.*, vol. 14, no. 23, p. 6178, Dec. 2022, doi: 10.3390/rs14236178.

[87] L. Fei and Y. Wang, "An optimization model for rescuer assignments under an uncertain environment by using Dempster–Shafer theory," *Knowl.-Based Syst.*, vol. 255, Nov. 2022, Art. no. 109680, doi: 10.1016/j.knosys.2022.109680.

[88] L. Fei and Y. Wang, "Demand prediction of emergency materials using case-based reasoning extended by the Dempster–Shafer theory," *Socio-Econ. Planning Sci.*, vol. 84, Dec. 2022, Art. no. 101386, doi: 10.1016/j.seps.2022.101386.

[89] L. Chen and S. S. Rao, "A modified Dempster–Shafer theory for multicriteria optimization," *Eng. Optim.*, vol. 30, nos. 3–4, pp. 177–201, Mar. 1998.

[90] R. Fang, H. Liao, and A. Mardani, "How to aggregate uncertain and incomplete cognitive evaluation information in lung cancer treatment plan selection? A method based on Dempster–Shafer theory," *Inf. Sci.*, vol. 603, pp. 222–243, Jul. 2022, doi: 10.1016/j.ins.2022.04.060.

[91] R. A. Hamid, A. S. Albahri, O. S. Albahri, and A. A. Zaidan, "Dempster–Shafer theory for classification and hybridised models of multi-criteria decision analysis for prioritisation: A telemedicine framework for patients with heart diseases," *J. Ambient Intell. Humanized Comput.*, vol. 13, no. 9, pp. 4333–4367, Sep. 2022, doi: 10.1007/s12652-021-03325-3.

[92] Z. Hua, L. Fei, and H. Xue, "Consensus reaching with dynamic expert credibility under Dempster–Shafer theory," *Inf. Sci.*, vol. 610, pp. 847–867, Sep. 2022, doi: 10.1016/j.ins.2022.08.046.

[93] Q.-H. Le, T. N. Mau, R. Tansuchat, and V.-N. Huynh, "A multi-criteria collaborative filtering approach using deep learning and Dempster–Shafer theory for hotel recommendations," *IEEE Access*, vol. 10, pp. 37281–37293, 2022, doi: 10.1109/ACCESS.2022.3165310.

[94] M. Ma and J. An, "Combination of evidence with different weighting factors: A novel probabilistic-based dissimilarity measure approach," *J. Sensors*, vol. 2015, pp. 1–9, 2015.

[95] J. M. Merigó, K. J. Engemann, and D. Palacios-Marqués, "Decision making with Dempster–Shafer belief structure and the OWAWA operator," *Technol. Econ. Develop. Economy*, vol. 19, no. 1, pp. 100–118, 2013.

[96] L. Rong, "The evaluation on development quality of open education based on Dempster–Shafer with multigranularity unbalanced hesitant fuzzy linguistic information for Chinese case," *IEEE Access*, vol. 10, pp. 76185–76201, 2022, doi: 10.1109/ACCESS.2022.3190636.

[97] Y.-C. Tang, Z.-G. Pan, S.-Q. Sun, and Z.-Y. Li, "Probability measures compatible with the fuzzy Dempster–Shafer belief structure," in *Proc. Int. Conf. Mach. Learn. Cybern.*, 2003, pp. 2705–2710.

[98] J. Wang, L. Xu, J. Cai, Y. Fu, and X. Bian, "Offshore wind turbine selection with a novel multi-criteria decision-making method based on Dempster–Shafer evidence theory," *Sustain. Energy Technol. Assessments*, vol. 51, Jun. 2022, Art. no. 101951, doi: 10.1016/j.seta.2022.101951.

[99] X. Wu and H. Liao, "A Dempster–Shafer-theory-based entry screening mechanism for small and medium-sized enterprises under uncertainty," *Technol. Forecasting Social Change*, vol. 180, Jul. 2022, Art. no. 121719, doi: 10.1016/j.techfore.2022.121719.

[100] Y. Zhong, L. Cao, H. Zhang, Y. Qin, M. Huang, and X. Luo, "Hesitant fuzzy power Maclaurin symmetric mean operators in the framework of Dempster–Shafer theory for multiple criteria decision making," *J. Ambient Intell. Humanized Comput.*, vol. 13, no. 4, pp. 1777–1797, Apr. 2022, doi: 10.1007/s12652-021-02932-4.

[101] Y. Zhong, H. Zhang, L. Cao, Y. Li, Y. Qin, and X. Luo, "Power Muirhead mean operators of interval-valued intuitionistic fuzzy values in the framework of Dempster–Shafer theory for multiple criteria decision-making," *Soft Comput.*, vol. 27, no. 2, pp. 763–782, Jan. 2023, doi: 10.1007/s00500-022-07595-7.

[102] P. Smets, "Constructing the pignistic probability function in a context of uncertainty," *Mach. Intell. Pattern Recognit.*, vol. 10, pp. 29–39, 1990, doi: 10.1016/B978-0-444-88738-2.50010-5.

[103] H. Liao and X. Wu, "DNMA: A double normalization-based multiple aggregation method for multi-expert multi-criteria decision making," *Omega*, vol. 94, Jul. 2020, Art. no. 102058, doi: 10.1016/j.omega.2019.04.001.

[104] M. Zelany, "A concept of compromise solutions and the method of the displaced ideal," *Comput. Oper. Res.*, vol. 1, nos. 3–4, pp. 479–496, Dec. 1974.

[105] Z. Li and K. C. Sinha, "Methodology for the determination of relative weights of highway asset management system goals and of performance measures," *ASCE J. Infrastruct. Syst.*, vol. 15, no. 2, pp. 95–105, 2009, doi: 10.1061/(ASCE)1076-0342(2009)15:2(95).

[106] Q. Bai, S. Labi, and Z. Li, "Trade-off analysis methodology for asset management," Joint Transp. Res. Program. Purdue Univ., West Lafayette, IN, USA, Tech. Rep. FHWA/IN/JTRP-2008/20, 2008.