The Application of Data Envelopment Analysis for Transportation Planning based on the Viewpoint of Economic Efficiency

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There has been an ever increasing interest in the urban planning techniques, stimulated by the possibility that design strategies associated with the built environment be used well to control, manage, and shape individual behavior and socio-economic activity in cities. The numerous available evidence suggests that a combination of urban design strategies and Transit-Oriented Development (TOD) will help encourage our communities more livable, sustainable, and promoting the quality of our urban life. Therefore, the development of appropriate design techniques of TOD has become increasingly important as the TOD planning mode applied in the urban built environment. This study will try to integrate and classify the category of smart growth principles based on literature review. Followed by Fuzzy Delphi Technique (FDT) for obtaining expert's opinions and screen the most important criteria of guiding principles. And then the empirical study of Taipei Metro Transit System will be demonstrated to show the application of our proposed methodology as well as framework. Finally, the adoption of Fuzzy Analytic Hierarchy Process (FAHP) method and Data Envelopment Analysis (DEA) model which combined with assurance region analysis will be applied to measure and select the most suitable MRT stations of Taipei Metro Transit System.

INTRODUCTION

The research for a land use and transportation planning has always been an important study area among the urban planning field. Since the 20th century, automobiles had become the main modes as the transportation vehicle (for details, see Hargroves and Smith, 2005; Newman, Beatley, and Boyer, 2009). However, the automobile-oriented development (AOD) also caused the various urban sprawl problems during the past years (Newman and Kenworthy, 2015). In order to reduce the problems of urban sprawl, the Smart Growth concepts have been proposed and applied to transportation planning process (e.g., Miller and Hoel, 2002). Recently, with the vigorous development of urban growth management policy (Chapin, 2012; Rudolf, Kienast, and Hersperger, 2018), the transit-oriented development (TOD) model has turn into one of the novel transport planning strategies that utilized to improve the urban built environment by means of Smart Growth (SG) principles (e.g., Knaap and Talen, 2005; Downs, 2005).

Therefore, according to the motivation stated above, this paper presents a study on a decision-making problem integrating smart growth principles into the urban transportation planning strategies and utilize objectively scientific method to the empirical research. A case of Taipei Metro Transit system will be taken as an empirical example to illustrate the application of our proposed methodology and framework for assessing the comparative performance of TOD planning multi-criteria analysis (e.g., Wey, 2015). This paper also proposes a model to evaluate the candidate TOD station performance of future MRT locations. The station performance of TOD is based on perspectives that balance and link the quantitative and qualitative, tangible and intangible, and internal and external factors. This study uses some different perspectives to construct the performance measurement system, namely, the smart growth principles supposed to be followed by locating the TOD stations in Taipei Metro Transit System. Thus, the proposed model provides an integrated and scientific method for solving multi-criteria decision making issues within a transit-oriented development planning in Taipei city.

In general, the evaluators of public sector determined the performance evaluation framework for TOD planning must be rational, open to the public, and easy to understand. To meet these research requirements for application of Taipei Metro Transit System, we propose a consensus decision-making method that integrates the advantages of two well-known and often used methods, DEA and FAHP. DEA and FAHP are commonly used assessment methods, but both have limitations. The new hybrid FAHP/DEA developed here makes full use of the advantages of both assessment models, and avoids the pitfalls of each other through mutual cooperation.

The literature contains some prior limited attempts to merge traditional AHP and DEA. For example, Shang and Sueyoshi (1995) used the subjective AHP results in DEA to select a flexible manufacturing system. Yoshiharu and Kaoru (2003) developed an integrated DEA and AHP model for relocating the Diet and other Japanese government organizations outside Tokyo. Lin, Lee, and Ho (2011) aimed at integrating DEA and AHP to evaluate the economic development achieved by local governments in China. Lai et al. (2015) used the multi-criteria decision making method AHP to incorporate the weightings of input and output variables into DEA and Assurance Region DEA (DEA-AR) models, with 24 major international airports in the empirical analysis. Li et al. (2016) tried to comb the AHP with DEA to deliver a robust enhanced DEA model for transit operator efficiency assessment.

For overcoming the limitations of past research and constructing even more powerful usefulness, we also attempt to propose a newly integrated FAHP/DEA methodology, consisting of combined data envelopment and fuzzy hierarchy analysis that seems suitable for a candidate-TOD station selection problem. Similarly, the Taipei City Council is responsible for selecting one station, based on the public sector evaluators' decision, to be the future TOD station of Taipei Metro Transit System. And, the TOD station-selection process must be rational, open to the public, as well as easily understandable. To meet these requirements and illustrate the complexity of such comparisons and integration by objectively scientific assessment, we propose a consensus decision-making method based on a combination of the FAHP and the Assurance Region (AR) models of DEA.

LITERATURE REVIEW

The pioneering works on transport-related location studies include the excellent ones by Neufville and Keeney (1972), Paelinck (1977), and Neufville (1990). Specifically, Neufville and Keeney (1972) developed multi-attribute utility (MAU) functions to evaluate two alternative airport sites near Mexico City. Although they considered the location along with a host of location factors of uncertain significance, their analysis did not consider the potential economic benefits associated with each alternative. In addition, none of these studies did sensitivity analysis; moreover, they were confined to un-capacitated problems. To overcome some of those shortcomings, Min (1994) proposed an AHP model that considered cost/benefit trade-offs and conducted sensitivity analyses. Earlier studies based on either MAU or AHP measures were not designed to assess the location planner's dynamic utility functions (DeWispelare and Sage, 1981). Unlike the previous studies, our proposed model can generate a set of non-dominated solutions without *a priori* articulation of preference information. Another benefit of our proposed model is its ability to solve a location problem of doable size without serious computational difficulty.

Transportation planning and strategies affect not only the landscape style and land use of a city, but also the relationship between urban sprawl and population density (Peiser, 1989). In summary, urban sprawl is due to inappropriate urban development planning and management. Specifically, an excess of urban development projects has caused rapid urban expansion, as well as the inadequate and inefficient use of public facilities. Sustainable transportation can be regarded as an operations approach to the sustainable development of transportation systems. On the environmental dimension, transportation authorities must consider the externality of transportation behaviors in its decision-making, such as air pollution, noise, and traffic accidents. Moreover, the development of transportation infrastructure must not exceed the carrying capacity of the natural environment.

On the social dimension, promoting transportation behaviors must involve fair consideration of the benefits to all people and cater to the needs of vulnerable groups such as elderly adults, people with disabilities, and disadvantaged groups. Finally, on the economic dimension, transportation resources must be used and maintained efficiently by minimizing resource use in order to maximize efficiency (Zhao, 2010). Considerable attention has recently been focused on the efficiency of various facility locations; however, available studies have not provided a satisfactory answer to the problem of few decision-making units (DMU) and *a priori* specification of input and output weights. We used DEA and AR models to investigate the technical efficiency and pure technical efficiency of the major transportation facilities in Taiwan. The DEA technique is useful in resolving the measurement of a transportation location's efficiency because the calculations are non-parametric, can handle more than one output, and do not require an explicit *a priori* determination of relationships between outputs and inputs, as is required for conventional estimation of efficiency using production functions. The AR approach overcomes the issues caused by free running of input and output weights in basic DEA models.

Many researchers highlight the relationship between DEA and Multi-Criteria Decision Analysis (MCDA): "Indeed in common with many approaches to multiple criteria analysis, DEA incorporates a process of assigning weights to criteria" (Belton and Vickers, 1993; see also Belton, 1992; Cook et al., 1990, 1992; Doyle and Green, 1993; Stewart, 1994, 1996). Ranking is very common in MCDA literature, especially when there is a discrete list of elements or alternatives with a single criterion or multiple criteria to evaluate and compare or select. Various approaches are suggested in the literature for fully ranking elements, ranging from the utility theory approach (see Keeney and Raiffa, 1976; Keeney, 1982; Sinuany-Stern and Mehrez, 1987; Fishburn, 1988) to AHP.

AHP, a multi-criteria decision-making approach introduced by Saaty (1980), is a subjective method used to analyze qualitative criteria to generate weights of importance of the decision criteria and the relative performance measures of the alternatives in terms of each individual decision criterion. The Evaluators, using their own subjective judgments, estimate weights for each criterion. For this purpose, AHP is useful for quantifying these subjective (or qualitative) judgments. Yang et al. (2000) used AHP to evaluate multiple-objective layout design alternatives generated from systematic layout planning (SLP) procedure. AHP provides objective weights against a set of qualitative layout evaluation criteria, but it is efficient neither in evaluating a large number of alternatives nor in choosing performance frontiers. We reviewed the literature to understand the implications of sustainable transportation and TOD—a land use planning approach to achieving a sustainable transportation system. Sustainable transportation was established as the principal development goal, with economic efficiency, environmental sustainability, and social equity in connecting transportation and land use defined as subgoals (Wey, Zhang and Chang, 2016). Accordingly, we then established the criteria corresponding to the subgoals of TOD.

Further insights can be gained about DEA from the weights used. DEA assumes equally proportional improvements of all inputs or all outputs. This assumption becomes invalid when a preference structure over the improvement of inputs (or outputs) is present in evaluating inefficient DMUs. The unrestricted weight means that some of the inputs or outputs may be assigned a weight of zero, especially if the DMU is doing poorly in a particular dimension. This assumption is definitely not true in the present study, in which all the variables contribute in some way to the overall efficiency. To address this problem, in the integrated model, AHP was used to restrict the weights by using the management input. In the integrated method, AHP was used first to prioritize and derive weights for the set of predefined criteria. The derived weights were then used to establish the constraints of the DEA model.

The combined model presented a thorough decision-making process. Subjective approaches used in AHP determine weights that reflect subjective judgment, and objective approaches used in DEA determine weights by using mathematical models. By combining these two methods, most of the flaws associated with each method were eliminated, thereby yielding a more accurate and justifiable result. Charnes et al. (1979) also pointed out that the weights in a traditional DEA model might need some improvements to increase the efficiency of the model. Other researchers have proposed CCR (Charnes, Cooper, and Rhodes)/AR and BCC/AR to improve the DEA model (Thompson et al., 1986; Cooper et al., 2000; Dyson and Thanassoulis, 1988).

STRATEGIC USE OF THE METHODOLOGY

The Taipei City government in Taiwan was ultimately responsible for one transportation project and declared that the station-selection process should be rational, open to the public, and easily understandable. To meet these requirements, we propose a consensus-making method based on a combination of FAHP and the AR model of DEA. As with other typical urban problems, there are multiple criteria, both quantitative and qualitative, for comparing candidate stations. The nine main criteria derived from smart growth principles for the candidate-TOD station selection were: (C1) Mix Land Uses, (C2) Fill-in Redevelopment, (C3) Open Space, (C4) Compact Building Design, (C5) Housing Opportunities and Choices, (C6) Walkable Neighborhoods, (C7) Variety of Transportation Choices, (C8) Community Participation, and (C9) Public Policy (for details, see Knaap and Talen, 2005; Song, 2005; Downs, 2005). The evaluators individually and independently, reported their rating of each station by assigning each a cardinal number score. The higher score must be the better evaluation. The result was a score matrix with seven columns (i.e., candidate stations) and nine rows (i.e., criteria).

The problem was how to synthesize these seven evaluations in order to reach consensus. In this study, we used a methodology suitable for candidate-station selection. It consisted of a combination of DEA (Cooper et al., 1999) and Fuzzy AHP (Saaty, 1980). DEA was used to evaluate the "positives" and "negatives" of the candidate stations. Taking into account all these factors, a reasonable conclusion was sought for the group decision-making process. There are several practical issues associated with using the proposed methods for candidate-TOD station selection. These include a multi-stage procedure for applying an FAHP-like method to analyze the weights each evaluator allocated to the criteria, and the combined use of strength and weakness scores using the DEA method to characterize the candidate stations. These issues are addressed below.

At the first stage, the evaluators assigned their weights to criteria using either FAHP or their own subjective judgments. In the former case, incomplete paired comparisons were allowed so that members could skip the comparison if they had little or no confidence in comparing the criteria. At the end of the first stage, seven sets of weights on nine criteria were gathered. At the second stage, the distribution of weighted scores was shown to the evaluators. Each member thus knew where they were in the distribution and had the chance to alter their decisions. Note that this is a form of Delphi. This process continued until convergence was obtained. We then consider the sensitivity analysis required to generate a final decision. First, the sensitivities of selected criteria scores are analyzed.

Some criteria, e.g., the ease of transferring to other forms of local transportation, will have a degree of uncertainty in their scores, even if evaluators rate them. Thus, the sensitivity of results *vis-à-vis* these scores should be examined, and the robustness of any solutions verified. Secondly, the sensitivity of the criteria weights should be analyzed later. The AR model used to evaluate the efficiency measures is sensitive to the values of the lower and upper bounds, L_{ij} and U_{ij}, which restrict the ratio of weights u_i and u_j as follows: $L_{ij} \leq u_i/u_j \leq U_{ij}$. These values are derived from the minimum and maximum ratios estimated by the six evaluators. If someone's estimate of the ratio differs substantially from that of the others, thus yielding "too small an L_{ij}" or "too large a U_{ij}", we might neglect such extreme lower or upper bounds.

This reduces the interval that the ratio can accept as allowable. Note that this rule is similar to one used for scoring a gymnast in the Olympic Games in order to avoid a "home-town decision" (Wey, 2015).

Moreover, we also tried to define the "tightening the lower/upper bounds" in our research. In our station-selection problem, there are 7 targets (candidate stations), seven outputs, and nine criteria. We assume that the number of inputs is one. These numbers suggest that we lack the degrees of freedom for discriminating efficiency among the seven candidate stations. A rule of thumb demands: $n \geq \max\{m \times s, 3(m + s)\}$ where n = number of targets, m = number of inputs, and s = number of outputs (see p. 252 of Cooper et al., 1999). A straightforward application of this formula indicates that we are severely disadvantaged with regard to discrimination. Thompson et al. (1986) introduced their AR model for obtaining sharper discrimination in the station-selection process for the Super Collider project. Although the assurance region constraints contribute to narrowing the production possibility set and strengthening the discrimination power of this problem, there may still remain cases where we cannot discern significant differences in efficiency. For such cases, we are obliged to tighten the upper and lower bounds of the assurance region.

We hope the selection of one station to be the future TOD station will be based on the evaluators' rational, open to the public, and easily understandable decision. Then the proposed consensus-making method based on a combination of AHP and the AR model of DEA will be provided in this project practice. DEA is a method for estimating the efficiency of units, normally called DMUs, where it is difficult to identify absolute measures of efficiency (Charnes et al., 1978). The method is used to deal with systems with multiple inputs and multiple outputs, although these are very difficult to visualize. The main advantage of DEA is that, by comparing each unit to all other similar units, the need to unify inputs and outputs to a single scale, or to weight the relative importance of inputs and outputs, is avoided.

Ganley and Cubbin (1992) develop common weights for all the units by maximizing their sum of efficiency ratios. Sinuany-Stern et al. (1994) use linear discriminant analysis to rank units based on their pre-given DEA dichotomic classification. Friedman and Sinuany-Stern (1997) use canonical correlation analysis (CCA/DEA) to fully rank the units based on common weights. Sinuany-Stern and Friedman (1998a, 1998b) develop the discriminant analysis of ratios (DR/DEA) rather than traditional linear discriminant analysis. Oral et al. (1991) use a cross-efficiency matrix to select R&D projects. Sinuany-Stern and Friedman (1998a, 1998b) use cross-efficiency matrix to rank units. A typical application might be comparing different distribution centers in a wholesale network in which the mixture of products distributed by different DMUs varies widely. If we consider a case with only one input but two heterogeneous outputs, the method can be relatively easily visualized. If we calculate the output for each unit of input, the outputs for each DMU can then be plotted on a two-dimensional graph. The envelope enclosing the data points represents something like an optimum mix of outputs, which is achieved by using the most efficient DMUs in the system.

The DEA is a nonparametric approach that does not require any assumptions about the functional form of the production function. In the simplest case, where a unit has a single input (X) and output (Y), efficiency is defined as the output-to-input ratio: Y/X. DEA usually deals with a unit k that has multiple inputs (X_{ik} where $i = 1,...,m$) and multiple outputs (Y_{rk}, where $r = 1,..., s$), which can be incorporated into an efficiency measure: the weighted sum of the outputs divided by the weighted sum of the inputs $h_k = \sum u_r Y_{rk} / \sum v_i X_{ik}$. This definition requires a set of factor weights u_r and v_i.

Each method has its limitations (Friedman and Sinuany-Stern, 1998). Some are based on subjective data and others are limited to part of the units; none provides an ultimately good model for fully ranking units in the DEA context. The present study is another attempt to fully rank scale units in the DEA context, using one of the more popular MCDM methods, the AHP (see Saaty, 1980). AHP makes pairwise comparisons between criteria and between units, assessed subjectively by the decision maker, to rank the units overall. The eigenvector of the maximal eigenvalue of each pairwise comparison matrix is used for ranking.

Based on the hierarchy structure we describe, the experts made judgments about the elements in the hierarchy on a pairwise basis with respect to their parent element. Because the model consists of more than one level, hierarchical composition was used to weight the eigenvectors based on the weights of the criteria. The sum was taken from all weighted eigenvector entries corresponding to those in the lower level, and so on, which resulted in a global priority vector for the lowest level of the hierarchy. The global priorities are essentially the result of distributing the weights of the hierarchy from one level to the level immediately below (Wey, 2015).

EMPIRICAL STUDY

In this section, the suggested method is applied to select the candidate TOD station. The candidate stations, criteria, and evaluators are explained in detail. To simplify matters, let the seven (TOD) candidate stations be #01, #02, #03, #04, #05, #06, and #07. We also choose the nine criteria, C1, C2, C3, C4, C5, C6, C7, C8, and C9 for the sake of comparison. Suppose, further, that each candidate station is to be evaluated using nine criteria, and the scores, in cardinal numbers, recorded as in Table 1. In this problem, the highest mark for each criterion is 10, and the lowest is 0.

The evaluators estimate weights for each criterion using their own subjective judgments. Saaty's AHP (Saaty, 1980; Golden et al., 1989; Tone, 1989) is useful for quantifying these subjective (or qualitative) judgments combined with the fuzzy theory. The estimated weights of the six evaluators for each criterion are given. For example, Evaluator 1 pair-wised the comparison and obtained the weights of the nine criteria. The matrix is denoted by (W_{ki}), where k is the index for the evaluator and i for the criterion. The problem is how to reach consensus with each evaluator having different weights for each of the nine criteria. One possibility is to use the average of the weights given by the evaluators. Applying this average weight to the score matrix $S = (S_{ij})$ leads to a comparison of the seven candidate stations: #06 (9.68) and #05 (9.29) are the leading TOD station candidates (see Table 1).

TABLE 1
TOD STATION SOCRES OBTAINED FROM AVERAGE WEIGHTS

Station	#01	#02	#03	#04	#05	#06	#07
Score	7.86	8.34	9.19	8.07	9.29	9.68	7.79

It is assumed that the weights, u_i (Eq 1), which denotes a nonnegative weight set, can vary from station to station in accordance with the principle we choose for characterizing the stations (Wey, 2015). Both represent the same meanings of the weighting scales. However, the W_{ki} obtained from the evaluators are the index for each of the evaluators. Furthermore, using the average suggests that only one "virtual" evaluator was "representative" of all the evaluators' judgments.

Another way of looking at the above approach is to assume that the weights are common to all stations. We may call this a "fixed-weight" approach, as contrasted with the "variable-weight" structure. Each evaluator made the pairwise comparison and allocated weights to the nine criteria according to their individual judgments. Observe that, on average, criterion C1 (Mix Land Uses) and criterion C4 (Compact Building Design) have high scores. The u_i's, however, are chosen to maximize θ_{j_0} under the conditions that the same weights are applied when evaluating all other TOD stations and that the objective station is compared to these. This principle is in accord with DEA.

In this study, we propose a linear programming (LP) method that integrates the DEA variable-weight concept with AHP to generate the most favorable weights for criteria or alternatives based on a matrix of pairwise comparisons. The variable weights imply preference structures derived from different decision makers, which allows the interpersonal comparison of utilities to be addressed as follows. In DEA, the weights vary among the units: this variability is the essence of DEA. The values of the weights differ from unit to unit, and it is this flexibility in the choice of weights that characterizes the DEA model. It is assumed that the weights can vary from station to station in accordance with the principle we choose for characterizing the stations. This variability of weights is the strength of DEA, because DEA is directed to frontiers rather than central tendencies. Instead of trying to fit a regression plane through the center of the data, DEA floats a piecewise linear surface, the efficient frontier, to rest on top of the observations. In other words, DEA chooses the set of weights that assigns the highest possible efficiency score for each unit being evaluated (Sinuany-Stern et al., 2000).

To evaluate the positives of station j_0, the weights (u_i) in Equation 1 are chosen so that they maximize under the conditions that the same weights are applied in evaluating all other stations and that the objective station is compared relative to these, a principle in accord with DEA (Charnes et al., 1978; Cooper et al., 1999). The above statements also explain how AHP is incorporated into the DEA/AR model. A recent paper by Wang, Parkan, and Luo (2008) shows and proposes an LP method for generating the most Favorable Weights from pairwise-comparison matrices; the method incorporates the variable weight concept of DEA into the AHP priority scheme to generate the most favorable weights for the underlying criteria and alternatives based on a crisp pairwise-comparison matrix. The LP-GFW method differs from the LP-based approach presented by Chandran et al. (2005): the former uses variable weights for each criterion or alternative and consists of n LP models, while the latter uses fixed weights and is comprised of a two-stage-goal programming model.

Given the score matrix $S = (S_{ij})$ with a non-negative weight set (u_i), we evaluate the total score of station $j = j_0$ using a weighted sum of S_{ij_0} as:

$$\theta_{j_0} = \sum_i u_i S_{ij_0} \tag{1}$$

To evaluate the positives of station j_0, the weights (u_i) in Equation 1 are chosen so that they maximize θ_{j_0} under the conditions that the same weights are applied when evaluating all other stations and that the objective station is compared relative to these. This principle can be formulated as follows:

$$Max \quad \theta_{j_0} = \sum_i u_i S_{ij_0}, \tag{2}$$

$$s.t. \sum_i u_i S_{ij_0} \le 1 \ (\forall j), \tag{3}$$

$$u_i \ge 0, \ (\forall j). \tag{4}$$

It should be noted that the DEA is here directed towards "effectiveness" rather than "efficiency" since it is not a matter of resource utilization, as required for evaluating efficiency. Achieving the already stated (or prescribed) goals is the aim. The initial goals, stated broadly, are made sufficiently precise with accompanying criteria for evaluation so that (a) proposed actions can be evaluated more accurately and that (b), once the proposals are implemented, any accomplishments can be subsequently identified and evaluated (see Cooper et al., 1999, p. 66, for additional discussion). Furthermore, the weights given each criterion should reflect the preferences of all evaluators. This can be represented by a version of the AR model. For every pair of criteria i_1, i_2, the ratio u_{i_1}/u_{i_2} must be bounded by $L_{i_1 i_2}$ and $U_{i_1 i_2}$ as:

$$L_{i1i2} \le \frac{u_{i1}}{u_{i1}} \le U_{i1i2} \tag{5}$$

where, the bounds are calculated by using the evaluator's weights (W_{ki}) as:

$$L_{i_1 i_2} = \min_k \frac{W_{ki_1}}{W_{ki_2}}, \ U_{i_1 i_2} = \max_k \frac{W_{ki_1}}{W_{ki_2}}. \tag{6}$$

Thus, Equation 2 is maximized subject to the constraints expressed by Equations 3-5. The most preferable weight set, therefore, is assigned to the target station within allowable ranges so that the "positives" of the station are evaluated. However, the same weight is used to evaluate all other stations, and the target station is compared to them. If the optimal objective value $\theta_{j_0}^*$ satisfies $\theta_{j_0}^* = 1$, then the station j_0 can be judged to be the best. If, on the other hand, $\theta_{j_0}^* < 1$, the station is inferior to others with respect to some (or all) criteria. We have the lower/upper bounds of ratios for every pair of criteria. Using these bounds as the assurance region constraints, the variable weight problem was solved. The resulting optimal scores, rankings, and weights for all stations are obtained. We verify that the optimal weights for all other stations also satisfied these weight constraints. The scores indicate the relative distances from the efficient frontier. The lower score must be the weaker the "positives" of the stations.

Using both of the above traditional weighting method and the AR/DEA method, each TOD station was first evaluated numerically with respect to the set of chosen criteria. These evaluations may be made objectively (quantitatively) or subjectively (using expert knowledge). Second, each evaluator used their own judgment on the relative importance of the criteria. For this purpose, either FAHP or direct subjective judgments may be used. When these conditions are satisfied, the proposed methods rank the candidate stations to bring consensus within the evaluator group.

Results obtained using the AR model have, in particular, several merits for both candidates and evaluators. For candidate stations, the results are acceptable in the sense that the most preferable weights for the station are assigned within the allowable bounds of the evaluators. The optimal weights vary from station to station in that the best set of weights is assigned to the station. In a similar way, the relative weaknesses of each station can also be evaluated. These two measures are then used to characterize the candidate stations. For evaluators, each can be assured that their judgments on the criteria are taken into account and that the ratios of every pair of weights fall within the allowable range. Despite the exclusion of several evaluators' ratios for discrimination purposes, this approach is more reasonable and acceptable than using the average weights of all evaluators, especially when there is a relatively high degree of scatter to consider (Wey, 2015).

CONCLUSION

City assessment tools can be used as decision support framework (process) for policy making in urban development or urban growth management (e.g., Chapin, 2012), and guide us toward well development targets (e.g., Ahvenniemi et al., 2017; Bibri and Krogstie, 2017). In this paper, we have presented a method-oriented study on the assessment process for locating a TOD planning in Taipei Metro Transit System, Taiwan. We believe that the proposed method and framework can also apply to the critical portion of other cities or its development projects. And, the key characteristics of the proposed method and framework can be summarized as follows: (1) each station has been numerically evaluated with respect to the set of chosen criteria; (2) these evaluations can be made objectively (quantitatively) or subjectively (using expert knowledge); (3) in other words, each evaluator of public sector can make their own judgments about the relative importance of the criteria by using FAHP.

A wide array of methods and approaches to uncertainty, optimization, and interaction that between human being and biophysical domains in decision-making have been developed (Hill et al., 2005). There has, however, been a frustrating deficiency in the implementation of these methods and approaches within practical frameworks for decision-making and in forms that make them accessible to the lay policy analyst or regional planner. Because the AHP/MCDA approach has many advantages, including simplicity and flexibility, it has been highly successful (Ramanathan, 2001). However, MCDA would be greatly improved by having a suite of different methods and approaches that allow the user to explicitly propagate uncertainty and to apply various fuzzy and probabilistic approaches as shown in this study.

Many problems contain uncertain data because of imprecision, ongoing variation, data missing, an inability to foresee events in the future, or some combination of these. Several approaches have been developed to deal with this uncertainty in very distinct contexts. Kouvelis and Yu (1997) represent the uncertainty using scenarios, each of which is a specification of all data. Their justification for these measures is that under uncertainty it is necessary to consider all possible consequences, including the worst ones, because we do not know which may one day be a reality. Wang and Elhag (2006) also state that the normalization of interval and fuzzy weights is often necessary in MCDA under uncertainty, especially in AHP with interval or fuzzy judgments. Therefore, corrective methods such as normalization and scenarios may be a good future research direction.

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