Project outcome classification with imprecise criteria information

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Abstract: A case in which managers have to make project outcome classification decisions with uncertainty in independently related criteria values is considered in this paper. A multi-criteria decision model is developed in this paper by selecting methods which delved into data analysis to help managers make informed classification decisions. Uncertainty in the criteria values is resolved using linear programming which enables managers to know the profit outcome of their projects for efficient resource allocation. The classification scheme from the linear programming process is used as predefined classification inputs for use in the UTilités Additives DIScriminantes (UTADIS) method, which further produces a classification model. The analysis presented a no misclassification error in the predefined classifications from the linear programming and the classifications in the UTADIS method thus further boosting the confidence managers can entrust in the resulting classification model.

Keywords: multi-criteria; classification; project outcomes; imprecision: linear programming.

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1 Introduction

Investors may want to know the futures of their investments. Forecasting project outcomes provides avenues for effective control mechanisms for all procedures in any phase of the project. The outcomes of investments are based on inputs such as the type of resources that are pumped into the investment project. Investment profits is a function of an interplay of various criteria and resources that are allocated to a project and the projects can be classified based on the eventual profit outcome. Various authors have proposed multi-criteria decision methods for classification problems (Jacquet-Lagreze, 1999). Notably amongst them are the analytical hierarchical process (AHP), UTilités Additives DIScriminantes (UTADIS) and the ELECTRE TRI (Jacquet-Lagreze and Siskos, 2001; Zopounidis and Doumpos, 2002a). Amongst the most efficient methods are ELECTRE TRI and UTADIS (Wang, 2006). The intrigues of project outcome classification consists of multi-criteria classification problems which requires the analysis of all criteria facets, taking into consideration the conflicting situation between the criteria, the complex, subjective and ill-structured nature of the evaluation process and the introduction of the decision makers in the evaluation process (Cummings et al., 2012). In such real life decisions, it is hardly possible to get exhaustive and accurate information, thus in such situations, the consequences of not factoring uncertainty in the decision making process can be very damaging to the outcome of the decision making process. Classification is a very important aspect in decision making process (Ustinovichius and Simanaviciene, 2008).

Amongst the tasks setting base for outcome classification is setting of numerous criteria which are able to describe any object. Scale of all criterion is formed by setting finite set of possible values (Ustinovichius and Simanaviciene, 2008). If in the required task, there exists infinite values for the criteria, modifications can be made by adjusting it to a finite set of values. Then on expert knowledge, the classifications can be made based on the definite intervals and its criteria and of course there should be existing formulation rules on which an alternative can be assigned to a predefined class. In the UTADIS method (Jacquet-Lagreze and Siskos, 1982; Zopounidis and Doumpos, 2001) an additive utility model is developed for the ranking or classification of the alternatives with minimum ranking or classification error and the criterion weights are derived absolutely through reference set and the utility of alternatives is the sum of all criteria. In the ELECTRE TRI (Mousseau and Slowinski, 1998; Mousseau et al., 2001), criterion weights or other thresholds are obtained by solving linear programming, either weight or pseudo-criterion's parameter is confirmed, and other variables are derived through reference set in these methods. However, in reality these methods may be found wanting as they deal with finite criteria values. In real decision making processes, the situation may demand imprecise criteria values. This process would require transforming the imprecise values into finite criteria values for processing by the defined methods. Linear programming is beneficial in this process and can be used in deriving the finite criteria values and the profit outcomes of the investments for predefined classification for the UTADIS method. There is some researcher on the multi-criteria classification decision making problems with incomplete certain information on weights (Guo et al., 2009). This paper would focus on imprecision in criteria values for use in the UTADIS method since that is a short fall that requires attention, moreover, the UTADIS method already calculates the weights for use in the additive utility function. The UTADIS method would thus be used in building a classification model for project outcomes based on the profit margin of the projects.

1.1 Research motivation and related work

The managers for an e-infrastructure project, have received assessments and forecasts of project criteria from several different units of the project as separate entities that are not integrated. This has become a big task for the managers to even build a basis for decision making in classifying the projects on the basis of the profit outcome. The managers are therefore in desperate need of a classification scheme that would incorporate the present and future uncertainties in all economic variables so as to build an appropriate platform for corporate decision making. This calls for methods that would solve the problem of uncertainty in the economic variables associated with the project and also to give the decision makers an outlook of what the profits of each project would be .

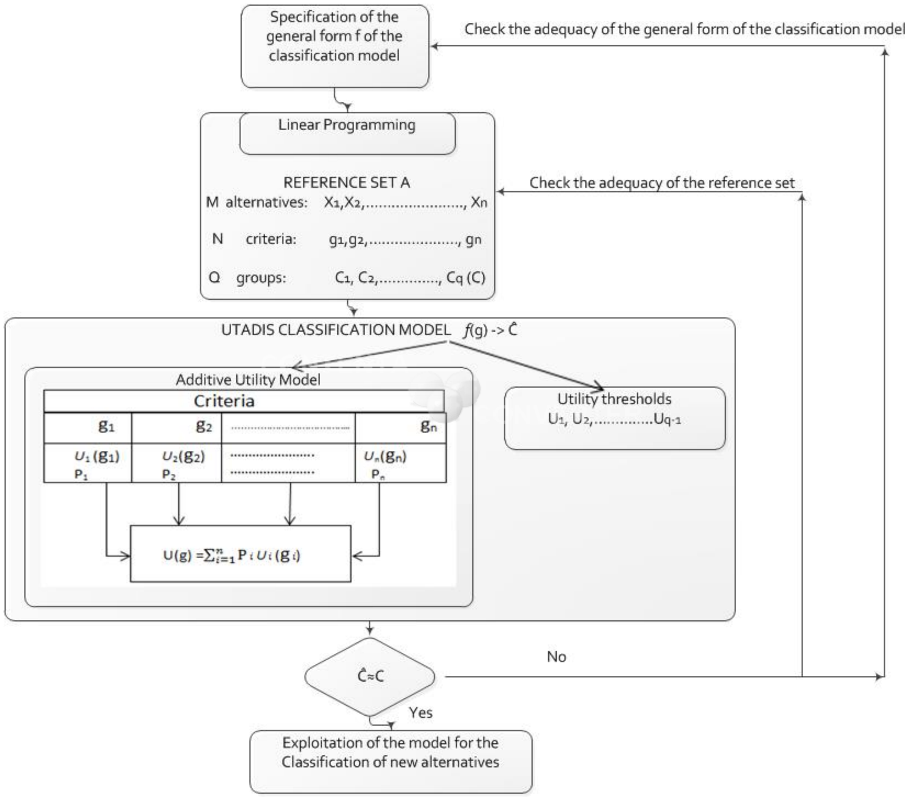
Researchers in the paradigm of multi-criteria decision analysis have attempted to solve the problem of imprecision in decision making for classification problems, however the focus has been imprecision on the weights of the criteria (Wang, 2006; Guo et al., 2009). Amongst the methods used for classification problems, the ELECTRE TRI and UTADIS are the useful and efficient ones among them (Wang, 2006). The decision maker's dilemma in the e-infrastructure project is a classification problem which requires methods which would solve the problem of imprecision in the criteria values, classify the projects based on the profit outcomes and build a classification model for classifying current and future projects which falls in this category. This calls for methods which would provide the managers with an idea of what the profits of the projects are before the classification process is carried out. Notable amongst previous research that has delved into classifying problems for decision makers is the work of Davalos et al. (2009) in the bankruptcy classification of firms investigated by the US Securities and Exchange Commission in which the authors used an evolutionary computing method and genetic algorithm, to generate an optimal set of if-then rules for bankruptcy classification of accounting and auditing enforcement release firms, the prediction of business failure using the UTADIS method (Zopounidis and Doumpos, 1999b) in which the authors classify Greek sample firms and build a classification model with the UTADIS method in comparison with other methods. Other work by the these authors and others using the UTADIS method on practical applications follow the same routine (Zopounidis and Doumpos, 2002b, 1999a; Zopounidis, 1999; Jacquet-Lagreze, 1999; Jacquet-Lagreze and Siskos, 1982) to cite a few of their work. Authors that have applied the ELECTRE TRI method on practical situations have focused their work on the variation of weights of the criteria (Mousseau and Slowinski, 1998; Mousseau et al., 2001; Ngo The and Mousseau, 2002).

The loophole in the use of the UTADIS, ELECTRE TRI, evolutionary computing and the genetic algorithm method by other authors as against what this paper is required to do is that the decision makers in predefining the classification for use in the UTADIS method for example, make the predefined classification decisions on some reference set according to their own subjective preference. This paper would adopt objective means to help the managers predefine their classifications before the UTADIS method is applied so as to minimise the misclassification errors between the predefined classifications and the UTADIS method's classification. This would further enhance the effectiveness of the classification model developed by the UTADIS method. Moreover, the decision makers in this project would want to solve the problem of imprecision in criteria values for predefined classification and thus requires a supplementary method before the UTADIS method is applied. Furthermore, after solving the problem of imprecision in criteria values, the managers would want to have an idea of what the profit margins of their projects are and base their classification schemes on that.

The work in this paper would thus modify the use of the UTADIS method in helping the managers with their classification decisions. The UTADIS method is preferred as against the other methods mentioned above because it has been proven to present lower error rates (Zopounidis and Doumpos, 1998) and a multi-criteria decision model would be developed to help the managers in their classification decisions. An improvement would however be made in the application of the UTADIS method by introducing a supplementary method-linear programming for the predefined classification problem to make the predefined classification process empirical enough to reduce the misclassification errors when the UTADIS method is applied. Linear programming method is important in this decision making process and has been chosen over other known classification methods such as the AHP (Ahmad, 2006), logit and probit analysis (Peel and Peel, 1988), discriminant analysis (Casey et al., 1986) because uncertainty exists in the criteria values in the form of constraints and the managers would want to incorporate all the uncertainties in the decision making process. This uncertain situation in the criteria values would have to be considered in the predefined classification objectively before the UTADIS method is applied because the UTADIS method has limitations in this direction. Finally, linear programming is required because the managers want to have an idea of the profit margins of the projects and base their predefined classifications on the profit margins, this would further enhance the robustness of a classification model to be developed with the UTADIS method. Modelling the objective function of the projects in a linear programme would achieve this target of calculating for the profits of the projects with knowledge of the financial relationship that exists between the projects and the criteria. The linear programming mechanism that goes into calculating the objective function selects the appropriate precise criteria value to resolve the imprecision problem, this process is further explained in the next section. The need of the ELECTRE TRI method in resolving the variation in weights is not required in this paper because as explained above, the dilemma of the managers has to do with imprecision in the criteria values and moreover, the UTADIS classification model presents the appropriate weights for the criteria of the projects.

Figure 1 was originally modelled by Zouponidis and Doumpos (2002) in their book *Multicriteria Decision Aid Classification Methods* (Chp. 1, p.18) to outline the development procedure in the UTADIS method. The procedure in the reference set A was originally a predefined classification process based on the subjective preferences of the decision maker. This paper has improved on this model by introducing the linear programming method for the predefined classification process because as mentioned above, the managers of the practical project for this paper aim at first of all solving an imprecision problem in the criteria values, secondly it is required to empirically minimise the misclassification errors between the predefinded classifications and the classification of the UTADIS method and further enhance the effectiveness of the classification model indicated by the UTADIS classification model in Figure 1 and finally, the linearly programming is required to solve for the project profits which is the objective of the classification problem.

Figure 1 Distinction between method for predefined classification and the UTADIS method



2 Imprecise criteria information

Assume there is n number of independent criteria in a decision making process $C_1, C_2, \ldots C_n$ and m alternatives $A = a_1, a_2, \ldots, a_m$. The value of alternative a_i under criterion C_j is imprecisely defined as $L_i \le a_{ij} \le U_i$ then to maximise the objective function:

$$maximise \sum_{i=1}^{m} \sum_{j=1}^{n} k_i a_{ij}$$

s.t.

$$\begin{aligned} & l_i \le a_{ij} \le u_i \\ & \begin{cases} k_i u_i \text{ if } k_i \ge 0 \\ k_i l_i \text{ if } k_i \le 0 \end{cases} \end{aligned} \tag{1}$$

The case in equation (1) is that if the weight of the criteria in the objective function is greater than zero, then since the objective function is being maximised, the upper boundary of $l_i \le a_{ij} \le u_i$, that is u_i would be used in the calculation of the profit in the objective function. The implication is that the imprecise alternative a_i under criterion C_j value in $l_i \leq a_{ij} \leq u_i$ would be converted to a precise value u_i. If the weight of the criteria in the objective function is however less than zero, then the first condition fails, the second condition is thus executed. Since the objective function is being maximised, the lower boundry of $l_i \leq a_{ij} \leq u_i$, that is l_i would be used in the calculation of the profit in the objective function instead. The situation follows that the imprecise alternative a_i under criterion C_j value in $l_i \leq a_{ij} \leq u_i$ would be converted to a precise value l_i. This linear programming is possible if the criteria are independently related.

The case in which this method is being applied requires predefined classification based on profit outcomes. The input data obtention requires field studies on criteria indicator relations and the use of metrics on indicator categories by experts to quantify the criteria's data. Sample data obtained from this approach by the managers would be used in building the multi-criteria decision model. This model would be robust enough to cater for future expansion in data size. Thus, this approach is convenient for use in taking care of uncertainty in criteria values by managers in projecting profit outcomes and project classifications

The reverse linear programming procedure holds true if the objective function is to be minimised.

$$minimise \sum_{i=1}^{m} \sum_{j=1}^{n} k_i a_{ij}$$

s.t.

$$\begin{aligned} & l_i \leq a_{ij} \leq u_i \\ & \begin{cases} k_i l_i \text{ if } k_i \geq 0 \\ k_i u_i \text{ if } k_i \leq 0 \end{cases} \end{aligned} \tag{2}$$

In equation (2) if the weight of the criteria in the objective function is greater than zero, then since the objective function is being minimised, the lower boundary of $l_i \leq a_{ij} \leq u_i$, that is l_i would be used in the calculation of the profit in the objective function. The implication is that the imprecise alternative a_i under criterion C_j value in $l_i \leq a_{ij} \leq u_i$ would be converted to a precise value li. If the weight of the criteria in the objective function is however less than zero, then the first condition fails, the second condition is thus executed. Since the objective function is being minimised, the upper boundary of $l_i \leq a_{ij} \leq u_i$, that is u_i would be used in the calculation of the profit in the objective function instead. The situation follows that the imprecise alternative a_i under criterion C_j value in $l_i \leq a_{ij} \leq u_i$ would be converted to a precise value u_i.

The UTADIS method requires predefined classification. The profit outcomes of the alternative projects calculated in the linear programming would be aid the managers in this predefined project classification for processing in the UTADIS method to build multicriteria decision model for classifying project outcomes. The precise values obtained from alternative a_i under criterion C_j in the above linear programming would be used as values in alternative a_i under criterion C_j in the UTADIS method.

2.1 Classification model MCDA method – UTADIS

Given a predefined classification of the alternatives (projects) in classes from the above linear programming, the UTADIS method estimates an additive utility function and the utility thresholds that classify the alternatives in their original classes with the minimum misclassification error (Jacquet-Lagreze, 1999).

The global utility $U(a)$ of an alternative $a \in A$ is of an additive form:

$$U(a) = \sum_{i=1}^{M} U_i\left[g_i(a)\right]$$

where $U_i\ [g_i(a)]$ is the marginal utility of the alternative a for the criteria g_i. The marginal utilities represent the relative importance of the evaluation criteria in the classification model. The marginal utilities have piece-wise linear form. For each evaluation criterion i the interval $G_i = [g_{i*}, g_i^*]$, where g_{i*} and g_i^* are the less and most preferred values respectively of the criterion i for $a \in A$. The interval G_i is divided into $a_i - 1$ equal intervals, $[g_i^j, g_i^{j+1}]$, $j = 1, 2,\ldots,a_i - 1$ where ai is defined by the decision maker as the number of estimated points for every marginal utility u_i. Each point g_i^j can be calculated using linear interpolation (Zopounidis and Doumpos, 1999a).

$$g_i^j = g_{i*} + \frac{j-1}{a_i - 1}\left(g_i^* - g_{i*}\right)$$

The aim is to estimate the marginal utilities in each of these points. Suppose that the evaluation of an alternative a on criterion i is $g_i(a) \in [g_i^j, g_i^{j+1}]$. The marginal utility of an alternative a, $U_i\ [g_i(a)]$ can be approximated through linear interpolation, in the following way:

$$U_i\left[g_i(a)\right] = U_i\left(g_i^j\right) + \frac{g_i(a) - g_i^j}{g_i^{j+1} - g_i^j}\left[U_i\left(g_i^{j+1}\right) - U_i\left(g_i^j\right)\right] \tag{3}$$

Supposing that the preferences of the decision maker on each one of the evaluation criteria are monotone, the following constraint must be satisfied (Zopounidis and Doumpos, 2002b):

$$U_i\left(g_i^{j+1}\right) - U_i\left(g_i^j\right) \geq 0.\forall i$$

The monoticity constraints can be converted into non-negativity constraints through the following transformations (Zopounidis and Doumpos, 1998):

$$m_{ij} = U_i\left(g_i^{j+1} - U_i\left(g_i^j\right) \geq 0, \quad \forall i, j\right.$$

$$U_i\left(g_{i*}\right) = 0$$

$$U_i\left(g_i^*\right) = \sum_{k=1}^{a_i - 1} W_{ik}$$

$$U_i\left(g_i^j\right) = \sum_{k=1}^{j-1} W_{ik}$$

where $\sum_{k=1}^{j-1} W_{ik}$ is the summation of the marginal utilities on $U_i(g_i^j)$.

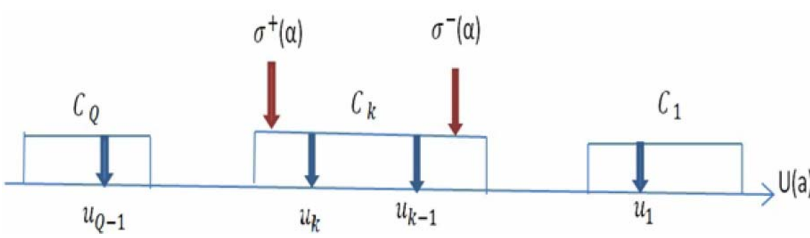
Equation (1) can therefore be re-written as follows:

$$U_i\left[g_i(a)\right] = \sum_{k=1}^{j-1} W_{ik} + \frac{g_i(a) - g_i^j}{g_i^{j+1} - g_i^j}\left[\sum_{k=1}^{j} W_{ik} - \sum_{k=1}^{j-1} W_{ik}\right]$$

2.2 The misclassification errors

The misclassification errors are accessed based on the global utility $U(a)$ and the utility thresholds:

Figure 2 Distribution of the classes on the assessed utility (see online version for colours)



Overestimation error $\sigma^+(a)$: it is where an alternative according to its utility is classified to lower class than the class that it belongs to as shown in Figure 2. Underestimation error $\sigma^-(a)$: it is where an alternative according to its utility is classified to a higher class than the class that it belongs to as shown in Figure 2. The classification of the alternatives is achieved through the comparison of their global utilities with the corresponding utility thresholds (Zopounidis et al., 1995)

$$U(a) \geq U_1 \rightarrow a \in C_1$$
$$U_k \leq U(a) < U_{k-1} \rightarrow a \in C_k$$
$$U(a) < U_{Q-1} \rightarrow a \in C_Q$$

The assessment of both the marginal utilities U_i $[g_i(a)]$ and the utility thresholds U_k, is achieved by linear programming (Zopounidis and Doumpos, 1998)

$$\textit{Minimise } F = \sum_{a \in C_1} \sigma^+(a) + \ldots + \sum_{a \in C_k}\left[\sigma^+(a) + \sigma^-(a)\right] + \ldots + \sum_{a \in C_Q \sigma^-(a)}$$

s.t.

$$\sum_{i=1}^{M} U_i\left[g_i(a)\right]-U_1+\sigma^+(a)\geq 0 \quad \forall a\in C_1$$

$$\left.\begin{aligned}
&\sum_{i=1}^{m} U_i\left[g_i(a)\right]-U_{k-1}-\sigma^-(a)\leq -\delta \quad \forall a\in C_k\\
&\sum_{i=1}^{m} U_i\left[g_i(a)\right]-U_k+\sigma^+(a)\geq 0\\
&\sum_{i=1}^{m} U_i\left[g_i(a)\right]-U_{q-1}-\sigma^-(a)\leq -\delta
\end{aligned}\right\}\forall a\in C_k$$

$$\sum_{i=1}^{m}\sum_{j=1}^{a_i-1} W_{ij}=1$$

$$U_{k-1}-U_k\geq s \quad k=2,3,\ldots,Q-1$$

$$W_{ij}\geq 0, \sigma^+(a)\geq 0, \sigma^-(a)\geq 0$$

where δ is a small positive real number used to ensure the strict inequality of $U(a)$ to U_{k-1} ($\forall a \in C_k$, $K > 1$) and $U_{Q-1}(\forall a \in C_Q)$. The threshold s is used to denote the preference between the utility thresholds that distinguish the classes ($s > \delta > 0$).

2.3 Sensitivity analysis

The optimal solution F^* achieved by solving the linear programme:

$$Minimise\ F=\sum_{a\in C_1}\sigma^+(a)+\ldots+\sum_{a\in C_k}\left[\sigma^+(a)+\sigma^-(a)\right]+\ldots+\sum_{a\in C_Q\sigma^-(a)}$$

is examined by through a post-optimality analysis. The aim is to find, if possible, multiple or generally near optimal solutions corresponding to error values lower than $F^* + k(F^*)$ where $k(F^*)$ is a small portion of F^*. Therefore, the error object is transformed into a new constraint of the type (Doumpos and Zopounidis, 2002):

$$\sum_{a\in C_1}\sigma^+(a)+\ldots+\sum_{a\in C_k}\left[\sigma^+(a)+\sigma^-(a)\right]+\ldots+\sum_{a\in C_Q\sigma^-(a)}\leq F^*+k\left(F^*\right)$$

The new objective is thus to maximise and minimise the marginal utilities of each criterion and the utility thresholds U_k (Devaud et al., 1980). In this way, the sensitivity analysis of the marginal utilities of the criteria is achieved, and at the same time on can have an idea of the sensitivity of the utility thresholds:

$$Max\left[\sum_{j=1}^{a_i-1}W_{ij}+\sum_{k=1}^{Q-1}U_k\right]\text{ and } Min\left[\sum_{j=1}^{a_i-1}W_{ij}+\sum_{k=1}^{Q-1}U_k\right]\forall i$$

The first two of the sums in the post-optimality analysis represents the marginal utilities of each criterion. Therefore, it is used to examine the sensitivity of the criteria's marginal utilities. On the other hand, the second sum is used to examine the sensitivity of the utility thresholds. Thus by maximising and minimising both the marginal utilities of each criterion and the utility thresholds, a range is defined within which there is an optimal or near optimal solution (Zopounidis et al., 1995).

3 Data

The data used in this report is obtained from a database of e-infrastructure projects. It is important that the criteria selected are independently related for the predefined classification linear programming method to be effective. The managers of the project identified six criteria required for the project. Each criteria has a set of indicators that provide specific measurements. In consultation with stakeholders in the field, 89 indicators for the criteria were outlined. The number of indicators identified for a criteria is based on experience from previous work that the managers and stakeholders had conducted and also new information received from the field of work by the stakeholders. Metrics are then used to measure the indicators and develop data for a criteria in an interval form with a fuzzy approach. Five projects were identified for the alternatives and the criteria are as follows:

- C_1 – research
- C_2 – education
- C_3 – skilled labour
- C_4 – productivity
- C_5 – technology
- C_6 – transport.

Alternative, criteria values are obtained in imprecise form as shown in Table 1:

Table 1 Imprecise alternative-criteria values

Project	*Research*	*Education*	*Skilled labour*	*Productivity*	*Technology*	*Transport*
1	0.4–0.9	0.1–2	0.5–4	2–5	1–2	2.1–4.2
2	0.2–0.8	0.3–0.5	1–3	1.2–3	1.2–2	0.4–0.8
3	2–4	0.1–0.3	0.4–1	2–4	0.2–3	2–3.1
4	1.1–2	2–4	1.3–2	0.3–0.5	1.5–2	1–2
5	4–5	0.3–1	3–4	0.1–3	1.1–2.3	2–4

3.1 Imprecision to precision and profitability

The objective is to be able to preclassify the projects based on the profit outcome of the projects. The objective function is obtained by modelling the decision problem and obtaining the financial relationship between the projects and the criteria. So the objective function is maximised and solved with the constraints as follows:

For project 1:

$$\textit{maximise}\ 5C_1 + C_6 + 2C_3 + 3C_4 - (2C_5 + C_2)$$

s.t.

$0.4 \le C_1 \le 0.9$
$0.1 \le C_2 \le 2$
$0.5 \le C_3 \le 4$
$2 \le C_4 \le 5$
$1 \le C_5 \le 2$
$2.1 \le C_6 \le 4.2.$

Solving the above by linear programming the objective function for project 1,project 2, project 3, project 4 and project 5 produces the profits of 29.6, 4.8, 2.8, 27.1 and 36.3 respectively. The objective functions and equations for projects 2,3,4 and 5 are attached in Appendix. The predefined classifications in terms of project outcome profitability is as shown in Table 2:

Table 2 Predefined classification of project alternatives for use in the UTADIS method

Project	*Classification category*
Project 5	1
Project 1	2
Project 4	2
Project 2	3
Project 3	3

Table 3 shows the precise values obtained as a result of solving for the projects Profitability objective function as described in equation (1) and equation (2) above.

Table 3 Precise alternative-criteria values for use in the UTADIS method

Project	*Research*	*Education*	*Skilled labour*	*Productivity*	*Technology*	*Transport*
1	0.9	0.1	4	5	1	4.2
2	0.8	0.5	1	3	1.2	0.4
3	4	0.3	1	2	0.2	2
4	1.1	4	2	0.5	1.5	2
5	4	0.3	4	3	2.3	4

4 The multi-criteria decision model using the UTADIS method

As defined above given a predefined classification of the alternatives (projects) in classes from the above linear programming, the UTADIS method estimates an additive utility function and the utility thresholds that classify the alternatives in their original classes with the minimum misclassification error (Jacquet-Lagreze, 1999). Table 4 shows the inputs with respect to the precise values and predefined classifications for processing using the UTADIS method.

Table 4 Precise alternative-criteria values and predefined projects for use in the UTADIS method

Project	*Research*	*Education*	*Skilled labour*	*Productivity*	*Technology*	*Transport*	*Preclass*
1	0.9	0.1	4	5	1	4.2	2
2	0.8	0.5	1	3	1.2	0.4	3
3	4	0.3	1	2	0.2	2	3
4	1.1	4	2	0.5	1.5	2	2
5	4	0.3	4	3	2.3	4	1

The scores produced by the UTADIS method is demonstrated in Table 5:

Table 5 Project scores defined by the UTADIS method

Project	*UTADIS scores*
Project 1	0.6359
Project 2	0.1483
Project 3	0.2016
Project 4	0.4708
Project 5	0.8563

With utility thresholds of 0.3583 and 0.8322 and comparing the scores values of the projects it is realised that:

$$\textit{project } 5 \textit{ score } 0.8563 \; > \; 0.8322$$
$$\textit{project } 1 \textit{ score } 0.3583 < 0.6359 < 0.8322$$
$$\textit{project } 4 \textit{ score } 0.3583 < 0.4708 < 0.8322$$
$$\textit{project } 3 \textit{ score } 0.2016 < 0.3583$$
$$\textit{project } 2 \textit{ score } 0.1483 < 0.3583.$$

thus the projects outcome can be classified as shown in Table 6:

Table 6 Projects outcome classification defined by the UTADIS method

Project	*Classification category*
Project 5	1
Project 1	2
Project 4	2
Project 3	3
Project 2	3

It is realised that the classification in Table 6 matches that of the classification in Table 2 which was classified based on the profits outcome of the projects. There is therefore no Misclassification error. The additive utility model for our classification problem is:

$$0.0978u_1(g_1) + 0.0910u_2(g_2) + 0.2560u_3(g_3)$$
$$+0.1044u_4(g_4) + 0.2627u_5(g_5) + 0.1882u_6(g_6)$$

The coefficients represent the weights of the criteria. The criteria weights provides information to managers as to the contribution of each criteria to the classification process. Managers and decision makers can thus make informed decisions on when allocation criteria resources. The technology criteria for example according to the classification model has the highest contributory factor of 0.2627 and therefore contributes more to the profit outcome of the projects than the education criteria with weight of 0.0910. Managers in evaluating the projects would therefore allocate more resources into the technology criteria for the projects to produce the profits as indicated in the linear programming method. This additive utility model can be used in classifying project alternatives based on profit outcomes of the projects. Future projects data gathered can be used in testing the validity of this model for classification problems.

5 Conclusions

This paper solved the classification decision making problem for managers in a case of uncertainty in criteria values, by developing methods and analysing the decision problem to help the managers in their decision making process. The objective is to classify projects based on the projects profit outcome. Profits of the projects were calculated for predefined classifications and the problem of imprecision in criteria values was solved using linear programming. The classification model is implemented using the UTADIS method with no misclassification errors. Five projects and six criteria with imprecise values were considered.

The results reveals the importance of objectivity in all stages of classification decisions for the managers of the case under consideration. Subjective preferences in the classification of projects can be misleading and costly to managers as it may lead to the misallocation of resources. To mitigate such costly risks, the methods derived in this paper provides the managers with a clear idea of the profit of the projects for the managers to objectively classify their projects and further implement a classification model. Knowing the profitability of projects before implementation is obviously a good approach, since managers would for example focus more attention on project 5 which produces a profit of 36.3 million dollars as compared to project 3 which secures 2.8 million dollars profit. Managers, in their classification decision making process would want a robust model for the classification of their projects, thus adopting efficient methods to minimise misclassification errors as achieved in this paper would further enhance the effectiveness of the classification model for classifying current projects and future projects. It is proven in this paper, that managers in the case considered can make effective classification decisions with uncertainty in their input data as prevails in real life situations.

5.1 Future research

This paper focused on appropriate methods to develop a multi-criteria decision model to aid managers in classifying their projects based on profit outcomes with uncertainty in criteria values. The use of the model is another area that the researchers are actively exploring. Since the objective is to aid managers in their decision making process, the convenience in use and dependability of the model to the managers is of paramount interest to the researchers. For future research considerations, it would be interesting to develop user interfaces to aid managers in the use and testing the robustness of the multi-criteria decision model in predicting their project profit outcomes and classifying their projects. Issues of criteria relations and expanding the base of the criteria would also require attention in future research work.

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Appendix

For project 2:

$$\textit{maximise } C_1 + 8C_2 + C_4 - (C_3 + 2C_5 + C_6)$$

s.t.

$$0.2 \le C_1 \le 0.8$$
$$0.3 \le C_2 \le 0.5$$
$$1 \le C_3 \le 3$$
$$1.2 \le C_4 \le 3$$
$$3 \le C_5 \le 4$$
$$0.4 \le C_6 \le 0.8$$

For project 3:

$$\textit{maximise } C_1 + 4C_2 + 2C_3 - (C_4 + 2C_5 + C_6)$$

s.t.

$$2 \le C_1 \le 4$$
$$0.1 \le C_2 \le 0.3$$
$$0.4 \le C_3 \le 1$$
$$2 \le C_4 \le 4$$
$$0.2 \le C_5 \le 3$$
$$2 \le C_6 \le 3.1$$

For project 4:

$$\textit{maximise } 2C_1 + 8C_3 + C_4 + 5C_6 - (4C_1 + 2C_5)$$

s.t.

$$1.1 \le C_1 \le 2$$
$$2 \le C_2 \le 4$$
$$1.3 \le C_3 \le 2$$
$$0.3 \le C_4 \le 0.5$$
$$1.5 \le C_5 \le 2$$
$$1 \le C_6 \le 2.$$

For project 5:

$$\textit{maximise } C_3 + 8C_4 + 2C_5 + 3C_6 - (C_1 + 4C_2)$$

s.t.

$$4 \le C_1 \le 5$$
$$0.3 \le C_2 \le 1$$
$$3 \le C_3 \le 4$$
$$0.1 \le C_4 \le 3$$
$$1.1 \le C_5 \le 2.3$$
$$2 \le C_6 \le 4.$$