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Research Article

Material Handling Equipment Selection Using Weighted Utility Additive Theory

Prasad Karande[1] and Shankar Chakraborty[2]

[1] *Mechanical Engineering Department, Government Polytechnic Mumbai, Maharashtra 400 051, India*
[2] *Department of Production Engineering, Jadavpur University, Kolkata, West Bengal 700 032, India*

Correspondence should be addressed to Shankar Chakraborty; s_chakraborty00@yahoo.co.in

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Better utilization of manpower, providing product flexibility, increasing productivity, decreasing lead time, reduction in handling cost, increased efficiency of material flow, and enhancement of production process are some of the most important issues influencing material handling (MH) equipment selection decision. As a wide variety of MH equipment is available today, selection of the proper equipment for a designed manufacturing system is a complicated task. Selection of suitable MH equipment for a typical handling environment is found to be a multicriteria decision-making (MCDM) problem. As the selection process is found to be unstructured, characterized by domain dependent knowledge, there is a need to apply an efficient MCDM tool to select the most suitable MH equipment for the given application. This paper applies weighted utility additive (WUTA) method to solve an MH equipment selection problem. The ranking obtained using the WUTA method is compared with that derived by the past researchers which proves its potentiality, applicability, and accuracy to solve complex decision-making problems.

1. Introduction

Material handling (MH) is an activity that uses the right method to provide the right amount of the right material at the right place, at the right time, in the right sequence, in the right position, and at the right cost [1]. An MH system is responsible for transporting materials between workstations with minimum obstruction and joins all the workstations and workshops in a manufacturing system by acting as a basic integrator. The MH task accounts for 30–75% of the total cost of a product, and efficient MH can be responsible for reducing the manufacturing system operations cost by 15–30% [2]. These figures justify the importance of MH cost as an element in improving the cost structure of a manufacturing organization. An efficient MH system greatly improves the competitiveness of a product through the reduction of handling cost, enhances the production process, increases production and system flexibility, increases efficiency of material flow, improves facility utilization, provides effective utilization of manpower, and decreases lead time [3].

The functions performed by MH equipment can be classified into four broad categories, that is, (a) transport, (b) positioning, (c) unit formation, and (d) storage. Usually, all the MH functions are composed of one or more combinations of these four primary functions. Equipment in transport category simply moves materials from one point to another, which includes conveyors, industrial trucks, cranes, and so forth. Unlike transport equipment, positioning equipment is usually employed at workstations to aid machining operations. Robots, index tables, rotary tables, and so forth are the examples of this type of equipment. Unit formation equipment is used for holding or carrying materials in standardized unit load forms for transport and storage and generally includes bins, pallets, skids, and containers. Storage equipment is used for holding or buffering materials over a period of time. Typical examples that perform this function are AS/RS, pallet racks, and shelves.

The MH equipment selection is an important function in the design of an MH system and, thus, a crucial step for facility planning. The determination of an MH system involves both the selection of suitable MH equipment and the assignment of MH operations to each individual piece of equipment. As a wide variety of equipment is available today, each having distinct characteristics and cost that distinguish from others, selection of the proper equipment for a designed manufacturing system is a very complicated task and is often influenced by the ongoing development of new technology, practices, and equipment. While choosing the best MH equipment, the successful solution would likely involve matching the best solution with the existing or contemplated physical facilities and environment. The major factors contributing to the complexity of MH selection process are constraints imposed by the facility and materials, multiple conflicting design criteria, uncertainty in the operational environment, and the wide variety of equipment types and models available.

When implementing a new MH equipment, the decision makers are faced with the following issues, that is, (a) selection of an MH equipment that would give the desired benefits to the manufacturing organization with due consideration to its objectives and operating characteristics, (b) financial justification of the investment, and (c) development of a plan to ensure that the set objectives are met when the selected MH equipment is implemented and evaluated. For these reasons, the decision makers have to consider various quantitative (load capacity, energy consumption, reliability, cost, etc.) and qualitative (flexibility, performance, environmental hazard, safety, load shape, load type, etc.) criteria. On the other hand, some of the selection criteria are beneficial (higher values are preferred) and some are nonbeneficial (lower values are desired). Therefore, MH equipment selection can be viewed as a multicriteria decision-making (MCDM) problem in the presence of many conflicting criteria.

As the MH equipment selection is a difficult and knowledge intensive process, various mathematical tools can be effectively applied to solve this problem. However, it is always observed that the evaluation criteria involved in MH equipment selection problems have contradictory effects on the performance of the alternatives, are versatile in nature, and often expressed in different units with varying ranges. Therefore, a strong and unprejudiced mathematical model is essential for selection of the most appropriate MH equipment for a given industrial application. The weighted utility additive (WUTA) method having a sound mathematical background, ability to incorporate preferences for the selection criteria, and competency to handle mixed (cardinal and ordinal) data is a perfect choice to rank and select the best suited MH equipment. In this method, the reference ranking of the alternatives is formulated, and the indifference as well as preference relations between the alternatives are utilized for ranking purpose, deriving almost accurate results. It enhances the strengths of the conventional utility additive (UTA) method by incorporating criteria weights, which are usually observed as essential for solving the decision-making problems. Thus, the aim of this paper is set to show the viability of the WUTA method to solve decision-making problems with any number of selection criteria and candidate alternatives, with special emphasis on MH equipment selection. It is a variant of UTA family of models. The effectiveness and solution accuracy of any MCDM method can only be validated by comparing the derived rankings with those obtained by the earlier researchers. Here, the rank orderings of the alternatives derived by the past researchers act like some benchmarks. The cited example, already solved using different MCDM methods for ranking of MH equipment alternatives, thus provides sufficient ground for comparison of the performance of the proposed WUTA method.

2. Literature Review

Since 1990s, research concentrating on the selection and assignment of MH equipment has been carried out, and significant achievements have been attained. Chakraborty and Banik [4] applied analytic hierarchy process (AHP) for selecting the best MH equipment under a specific handling environment. The relative importance of each criteria and subcriteria was measured using pair-wise comparison matrices, and the overall rankings of all the alternative equipment were then determined. To identify the most critical and robust criteria in the MH equipment selection process, sensitivity analysis was also performed. Sujono and Lashkari [5] proposed a method for simultaneously determining the operation allocation and MH system selection in a flexible manufacturing environment with multiple performance objectives. A 0-1 integer programming model was developed to select machines, assign operations of part types to the selected machines, allocate MH equipment to transport the parts from machine to machine, and as to handle the part at a given machine. Onut et al. [6] proposed an integrated fuzzy analytic network process (F-ANP) and fuzzy technique for order performance by similarity to ideal solution (F-TOPSIS) methodology for evaluating and selecting the most suitable MH equipment types for a manufacturing organization. Komljenovic and Kecojevic [7] applied coefficient of technical level and AHP methods for selection of rail-mounted boom type bucket wheel reclaimers and stacker-reclaimers as used for material handling at the stockyards. Tuzkaya et al. [8] suggested an integrated F-ANP and fuzzy preference ranking organization method for enrichment evaluation (F-PROMETHEE) approach for solving the MH equipment selection problems. Sawant et al. [9] applied preference selection index (PSI) method to choose automated guided vehicle (AGV) in a given manufacturing environment. An AGV selection index was proposed to evaluate and rank the considered alternatives. Maniya and Bhatt [10] used AHP to assign the relative importance between different AGV selection criteria and then applied modified grey relational analysis (M-GRA) method to determine the corresponding index values for AGV selection.

On the other hand, some researchers have attempted to develop knowledge-based systems for proper selection of equipment used for varying handling tasks. Welgama and Gibson [11] proposed a methodology for automating the selection of an MH system while combining the knowledge-base and optimization approaches. Chu et al. [12] developed a microcomputer-based system called "ADVISOR" to help user to design, select, and evaluate the proper MH equipment for a production shop. Chan et al. [13] proposed an intelligent MH equipment selection advisor (MHESA), composed of a database to store equipment types with their specifications, knowledge-based expert system for assisting MH equipment selection, and an AHP model to choose the most appropriate MH equipment. Yaman [14] described a knowledge-based approach for MH equipment selection and re-design of equipment in a given facility layout. Fonseca et al. [15] developed a prototype expert system for industrial conveyor selection which would provide the user with a list of conveyor solutions for their MH needs along with a list of suppliers for the suggested conveyors. Conveyor types were selected on the basis of a suitability score, which was a measure of the fulfillment of MH requirements by the characteristics of the conveyor. Kulak [2] developed a fuzzy multiattribute MH equipment selection system consisting of a database, a rule-based system, and multiattribute decision-making modules. A fuzzy information axiom approach was also introduced and used in the selection of MH equipment in a real case. Cho and Edbelu [16] developed a web-based system, called as "DESIGNER" for the design of integrated MH systems in a manufacturing environment, which could model and automate the MH system design process, including the selection of MH equipment. Mirhosseyni and Webb [17] presented a hybrid method for selection and assignment of the most appropriate MH equipment. At first, the system would select the most appropriate MH equipment type for every MH operation in a given application using a fuzzy knowledge-based expert system, and in the second phase, a genetic algorithm would search throughout the feasible solution space, constituting of all possible combinations of the feasible equipment specified in the previous phase, in order to discover the optimal solution. The main disadvantage of the knowledge-based expert systems is that, in these approaches, as the set rules are static in nature and domain-specific, it is very difficult for the decision makers to know how the decision for the best MH equipment has been arrived.

3. The WUTA Method

The WUTA method which is an extension of the UTA approach, proposed by Jacquet-Lagreze and Siskos [18], aims at inferring one or more additive value functions from a given ranking on reference set, A_R. In MCDM problems, the decision makers usually consider a set of alternatives, called A, which is valued by a family of criteria, $g = (g_1, g_2, \ldots, g_n)$. A classical operational attitude of assessing a model of overall preference of the decision makers leads to the aggregation of all the criteria into a unique criterion, called a utility function ($U(g)$).

$$U(g) = U(g_1, g_2, \ldots, g_n). \tag{1}$$

Let P be the strict preference relation, and let I be the indifference relation, and if $g(a) = [g_1(a), g_2(a), \ldots, g_n(a)]$ and $g(b) = [g_1(b), g_2(b), \ldots, g_n(b)]$ are the multicriteria evaluations of the alternatives "a" and "b", respectively, then the following properties generally hold for the utility function ($U(g)$).

$$\begin{aligned} U[g(a)] > U[g(b)] &\Longleftrightarrow aPb, \\ U[g(a)] = U[g(b)] &\Longleftrightarrow aIb. \end{aligned} \tag{2}$$

The relation $R = P \cup I$ is a weak order.

The utility function is additive if it is of the following form.

$$X(g) = \sum_{i=1}^{n} x_i(g_i), \tag{3}$$

where $x_i(g_i)$ is the marginal utility of the attribute, g_i for the given alternative. When different weight values (relative importance) are assigned to the attributes, the weighted utility function can be expressed as follows:

$$U(g) = \sum_{i=1}^{n} u_i(g_i), \tag{4}$$

where $u_i(g_i) = w_i x_i(g_i)$, and w_i is the weight for ith attribute.

Again, for alternative "a," (4) can be written as

$$U[g(a)] = \sum_{i=1}^{n} u_i[g_i(a)]. \tag{5}$$

Now, g_i^+ and g_i^-, respectively, denote the most and the least preferred value of ith attribute. The most common normalization constraints using the additive form of (4) are as follows:

$$\begin{gathered} \sum_{i=1}^{n} u_i(g_i^+) = 1, \\ u_i(g_i^-) = 0 \quad \forall i. \end{gathered} \tag{6}$$

On the basis of the additive model, as shown in (5) and taking into account the preference conditions, the value of each alternative, $a \in A_R$ can be written as follows:

$$U'[g(a)] = \sum_{i=1}^{n} u_i[g_i(a)] + \sigma(a) \quad \forall a \in A_R, \tag{7}$$

where $\sigma(a) \geq 0$ is a potential error relative to the utility.

To estimate the marginal value functions in a piecewise linear approach, a linear interpolation method is proposed [18–20]. For each attribute, the interval $[g_i^-, g_i^+]$ is divided into $(\alpha_i - 1)$ equal segments. The end points, (g_i^j) are given as follows:

$$g_i^j = g_i^- + \frac{j-1}{\alpha_i - 1}(g_i^+ - g_i^-) \quad \forall j = 1, 2, \ldots, \alpha_i. \tag{8}$$

Now, the variable to estimate is $u_i(g_i^j)$. The marginal utility of an alternative is approximated by a linear interpolation method, and thus, for $g_i(a) \in [g_i^j, g_i^{j+1}]$,

$$\begin{aligned} u_i[g_i(a)] = {} & u_i\left(g_i^j\right) \\ & + \frac{g_i(a) - g_i^j}{g_i^{j+1} - g_i^j}\left[u_i\left(g_i^{j+1}\right) - u_i\left(g_i^j\right)\right]. \end{aligned} \tag{9}$$

The set of preference alternatives, $A_R = \{a_1, a_2, \ldots, a_m\}$, is also rearranged in such a way that a_1 is the head of the ranking (best) and a_m is its tail (worst). Since, the ranking has the form of a weak order, R for each pair of alternatives (a_k, a_{k+1}), it holds either $a_k \succ a_{k+1}$ or $a_k \approx a_{k+1}$. Thus if

$$\Delta(a_k, a_{k+1}) = U'[g(a_k)] - U'[g(a_{k+1})] \qquad (10)$$

then one of the following relationships holds:

$$\begin{aligned} &\Delta(a_k, a_{k+1}) \geq \delta \quad \text{if } a_k \succ a_{k+1} \ \text{(preference)}, \\ &\Delta(a_k, a_{k+1}) = 0 \quad \text{if } a_k \approx a_{k+1} \ \text{(indifference)}, \end{aligned} \qquad (11)$$

where δ is a small positive number to discriminate significantly two successive equivalence classes of R.

The marginal value functions are finally estimated using the following linear program (LP), in which the objective function depends on $\sigma(a)$, indicating the amount of total deviation.

$$[\min] \quad F = \sum_{a \in A_R} \sigma(a)$$

subject to

$$\begin{aligned} &\Delta(a_k, a_{k+1}) \geq \delta \quad \text{if } a_k \succ a_{k+1} \ \forall k, \\ &\Delta(a_k, a_{k+1}) = 0 \quad \text{if } a_k \approx a_{k+1} \ \forall k, \\ &u_i\left(g_i^{j+1}\right) - u_i\left(g_i^j\right) \geq 0 \quad \text{for } i = 1, 2, \ldots, n, \ j = 1, 2, \ldots, \alpha_i, \\ &\sum_{i=1}^{n} u_i\left(g_i^+\right) = 1, \\ &u_i\left(g_i^-\right) = 0; \quad u_i\left(g_i^j\right) \geq 0; \quad \sigma(a) \geq 0; \quad \forall a \in A_R; \ \forall i, j. \end{aligned} \qquad (12)$$

This LP model is solved to obtain the marginal utility values. Then, the utility value ($U[g(a)]$) for each alternative is calculated. The higher the $U[g(a)]$ value, the better the alternative.

It is observed that the WUTA method generally copes well with noisy or inconsistent data [21], it is least sensitive to changes in preferences for the considered criteria, and it is not as time consuming, redundant, and boring as the other MCDM methods where the decision makers have to define certain preference functions to evaluate the superiority of one alternative over the other. This method is based on two fundamental concessions; that is, (a) it does not allow any situation of incomparability between two alternatives, and (b) it addresses the evaluation (assessment) problem in a synthesizing, exhaustive, and definite way. It has also several interesting features, like it makes possible estimation of a nonlinear additive function which is obtained by the use of a linear program that provides convenient piecewise linear approximation of the function, and the only information required from the decision makers is the global stated preferences between different alternatives of the reference set. It also perfectly fits in those situations where there are difficulties in directly obtaining from the users the values of the preference model.

Generally, the data available for various criteria in a decision-making problem are expressed in different dimensional units with varying ranges. In order to eradicate these effects, it is required to normalize the criteria values within a range of 0 to 1. On the contrary, if criteria values are not normalized, those criteria with higher weights will be more prone to affect the final ranking of the alternatives. In case of nonnormalized data, the change in unit for a particular criterion will directly affect the values of the weighted decision matrix, which will ultimately have an effect on the ranking of the alternatives. In order to consider the effects of higher and lower preferences of beneficial and non-beneficial criteria in a decision-making problem, they have to be treated separately, which is taken into care in the normalization procedure. In the WUTA method, if the criteria values are not normalized, all the criteria will be treated as beneficial because in this method, the final ranking of the alternatives is based on the reference ranking, which is obtained by adding the weighted normalized criteria values.

4. Illustrative Example

In order to illustrate and validate the applicability of the WUTA method for solving MH equipment selection problems, a real time example considering the selection of a conveyor [2] is cited here. The final ranking of the alternative MH equipment as obtained using the WUTA method is also compared with that derived by the past researchers.

This MH equipment selection problem is aimed to determine the most appropriate conveyor among the alternatives of the same type. The related objective and subjective data of the attributes are given in Table 1 [2]. The attributes considered are fixed cost per hour (FC), variable cost per hour (VC), speed of conveyor (SC), item width (IW), item weight (W), and flexibility (F). Among those six attributes, flexibility was defined subjectively. Rao [22] converted the linguistic terms for flexibility criterion into corresponding fuzzy scores, and appropriate objective values were subsequently assigned. The conveyor should have low fixed and variable costs, higher speed, ability to handle large item widths and weights, and have higher flexibility. FC and VC are nonbeneficial attributes (where lower values are desired), and the remaining four attributes are considered as beneficial (where higher values are preferred).

Rao [22] considered equal weights for all the six criteria and obtained the best and the worst choices as conveyor 3 and conveyor 1, respectively, while solving this problem using simple additive weighting (SAW), weighted product method (WPM), AHP, graph theory and matrix approach (GTMA), TOPSIS and modified TOPSIS methods. Giving equal weights to the considered criteria may sometimes lead to wrong and biased decisions. Hence, the criteria weights are recalculated here using AHP method, as shown in Table 2, and are used for subsequent WUTA method-based analysis.

Table 1: Quantitative data for the conveyor selection problem [2].

Conveyor	Fixed cost per hour (FC)	Variable cost per hour (VC)	Speed of conveyor (m/min) (SC)	Item width (cm) (IW)	Item weight (kg) (W)	Flexibility (F)
A_1	2	0.45	12	15	10	Very good (0.745)
A_2	2.3	0.44	13	20	10	Excellent (0.955)
A_3	2.25	0.45	11	30	20	Excellent (0.955)
A_4	2.4	0.46	10	25	15	Very good (0.745)

Table 2: Criteria weights for conveyor selection problem.

Attributes	FC	VC	SC	IW	W	F
Weights	0.1049	0.1260	0.1260	0.2402	0.2245	0.1782

Table 3: Normalized decision matrix for conveyor selection problem.

Conveyor	FC	VC	SC	IW	W	F
A_1	1.0000	0.9778	0.9231	0.5000	0.5000	0.7801
A_2	0.8696	1.0000	1.0000	0.6667	0.5000	1.0000
A_3	0.8889	0.9778	0.8462	1.0000	1.0000	1.0000
A_4	0.8333	0.9565	0.7692	0.8333	0.7500	0.7801

For solving this problem using the WUTA method, the criteria values of Table 1 are first normalized using the following equations.

For beneficial attribute:

$$y_{ij} = \frac{x_{ij}}{\max\left(x_{ij}\right)} \quad \text{for } i = 1,2,\ldots,m;\ j = 1,2,\ldots,n. \tag{13}$$

For nonbeneficial attribute:

$$y_{ij} = \frac{\min\left(x_{ij}\right)}{x_{ij}}, \tag{14}$$

where x_{ij} is the performance of ith alternative with respect to jth criterion, and y_{ij} is the normalized value of x_{ij}.

Then, the weighted normalized criteria values (r_{ij}) are obtained using the following expression:

$$r_{ij} = w_i y_{ij}. \tag{15}$$

The normalized and weighted normalized decision matrices are given in Tables 3 and 4, respectively.

From the $\sum r_{ij}$ values, the reference sequence (A_R) for the alternative conveyors is observed as $A_3 - A_2 - A_1 - A_4$. Now, the range $[g_i^-, g_i^+]$ for each conveyor selection criterion is divided into equal intervals. The number of intervals and the interval difference for each criterion, as calculated using (8), with their corresponding g_i^- and g_i^+ values are given in Table 5. The number of intervals (α_i) is selected in such a way that the interval for each criterion is almost equal. However, a large number of intervals may cause an increase in the computational complexity as well as time. In order to minimize the computation time, a minimum possible number of intervals is selected here, so that the final results are not affected. For example, in case of "VC" criterion, the value for the number of intervals is chosen as 2 because it has the lowest range between $[g_i^-, g_i^+]$. As the criteria "FC", "SC", and "F" have ranges close to that for "VC" criterion, the same number of intervals is also selected for those criteria. On the other hand, for "IW" and "W" criteria, the number of intervals is selected as 3 for their wider ranges.

Now, we have the following set of equations.

For attribute FC:

$$\begin{gathered} u_1(0.0874) = u_{11} = 0, \\ u_1(0.0874 + 0.0087) = u_1(0.0962) = u_{12}, \\ u_1(0.0962 + 0.0087) = u_1(0.1049) = u_{13}. \end{gathered} \tag{16}$$

For attribute VC:

$$\begin{gathered} u_2(0.1205) = u_{21} = 0, \\ u_2(0.1205 + 0.0027) = u_2(0.1233) = u_{22}, \\ u_2(0.\ 1233 + 0.0027) = u_2(0.1260) = u_{23}. \end{gathered} \tag{17}$$

For attribute SC:

$$\begin{gathered} u_3(0.0969) = u_{31} = 0, \\ u_3(0.0969 + 0.0145) = u_3(0.1115) = u_{32}, \\ u_3(0.1115 + 0.0145) = u_3(0.1260) = u_{33}. \end{gathered} \tag{18}$$

For attribute IW:

$$\begin{gathered} u_4(0.1201) = u_{41} = 0, \\ u_4(0.1201 + 0.0400) = u_4(0.1602) = u_{42}, \\ u_4(0.1602 + 0.0400) = u_4(0.2002) = u_{43}, \\ u_4(0.2002 + 0.0400) = u_4(0.2402) = u_{44}. \end{gathered} \tag{19}$$

For attribute W:

$$\begin{gathered} u_5(0.1123) = u_{51} = 0, \\ u_5(0.1123 + 0.0374) = u_5(0.1497) = u_{52}, \\ u_5(0.1497 + 0.0374) = u_5(0.1871) = u_{53}, \\ u_5(0.1871 + 0.0374) = u_5(0.2245) = u_{54}. \end{gathered} \tag{20}$$

For attribute F:

$$\begin{gathered} u_6(0.1390) = u_{61} = 0, \\ u_6(0.1390 + 0.0196) = u_6(0.1586) = u_{62}, \\ u_6(0.1586 + 0.0196) = u_6(0.1782) = u_{63}. \end{gathered} \tag{21}$$

Table 4: Weighted normalized decision matrix.

Conveyor	FC	VC	SC	IW	W	F	$\sum r_{ij}$	Rank
A_1	0.1049	0.1232	0.1163	0.1201	0.1123	0.1390	0.7159	3
A_2	0.0912	0.1260	0.1260	0.1602	0.1123	0.1782	0.7940	2
A_3	0.0933	0.1232	0.1066	0.2402	0.2245	0.1782	0.9662	1
A_4	0.0874	0.1205	0.0969	0.2002	0.1684	0.1390	0.6735	4

Table 5: Most and least preferred values with interval difference for each criterion.

Attribute	FC	VC	SC	IW	W	F
g_i^+	0.1049	0.1260	0.1260	0.2402	0.2245	0.1782
g_i^-	0.0874	0.1205	0.0969	0.1201	0.1123	0.1390
$(g_i^+ - g_i^-)$	0.0175	0.0055	0.0291	0.1201	0.1123	0.0392
Intervals (α_i)	2	2	2	3	3	2
$[(g_i^+ - g_i^-)/\alpha_i]$	0.0087	0.0027	0.0145	0.0400	0.0374	0.0196

The utility values for the alternative conveyors are now calculated as below:

$$\begin{aligned} U[g(A_1)] &= u_1(0.1049) + u_2(0.1232) + u_3(0.1163) \\ &\quad + u_4(0.1201) + u_5(0.1123) + u_6(0.1390), \\ U[g(A_2)] &= u_1(0.0912) + u_2(0.1260) + u_3(0.1260) \\ &\quad + u_4(0.1602) + u_5(0.1123) + u_6(0.1782), \\ U[g(A_3)] &= u_1(0.0933) + u_2(0.1232) + u_3(0.1066) \\ &\quad + u_4(0.2402) + u_5(0.2245) + u_6(0.1782), \\ U[g(A_4)] &= u_1(0.0874) + u_2(0.1205) + u_3(0.0969) \\ &\quad + u_4(0.2002) + u_5(0.1684) + u_6(0.1390). \end{aligned} \tag{22}$$

Now, after solving the above set of equations using (9), the following results are derived.

For alternative A_1:

$$\begin{aligned} &u_1(0.1049) = u_{13}, \qquad u_2(0.1232) = u_{22}, \\ &u_3(0.1163) = u_{32} + \left(\frac{0.1163 - 0.1115}{0.0145}\right)(u_{33} - u_{32}), \\ &u_4(0.1201) = u_{41} = 0, \qquad u_5(0.1123) = u_{51} = 0, \\ &u_6(0.1390) = u_{61} = 0. \end{aligned} \tag{23}$$

For alternative A_2:

$$\begin{aligned} &u_1(0.0912) = u_{11} + \left(\frac{0.0912 - 0.0874}{0.0087}\right)(u_{12} - u_{11}), \\ &u_2(0.1260) = u_{23}, \qquad u_3(0.1260) = u_{33}, \\ &u_4(0.1602) = u_{42}, \\ &u_5(0.1123) = u_{51} = 0, \\ &u_6(0.1782) = u_{63}. \end{aligned} \tag{24}$$

For alternative A_3:

$$\begin{aligned} &u_1(0.0933) = u_{11} + \left(\frac{0.0933 - 0.0874}{0.0087}\right)(u_{12} - u_{11}), \\ &u_2(0.1232) = u_{22}, \\ &u_3(0.1066) = u_{31} + \left(\frac{0.1066 - 0.0969}{0.0145}\right)(u_{32} - u_{31}), \\ &u_4(0.2402) = u_{44}, \quad u_5(0.2245) = u_{54}, \quad u_6(0.1782) = u_{63}. \end{aligned} \tag{25}$$

For alternative A_4:

$$\begin{aligned} &u_1(0.0874) = u_{11} = 0, \quad u_2(0.1205) = u_{21} = 0, \\ &u_3(0.0969) = u_{31} = 0, \quad u_4(0.2002) = u_{43}, \\ &u_5(0.1684) = u_{52} + \left(\frac{0.1684 - 0.1497}{0.0374}\right)(u_{53} - u_{52}), \\ &u_6(0.1390) = u_{61} = 0. \end{aligned} \tag{26}$$

Now, the utility values for all the four alternatives are calculated using (7) and are shown below:

$$\begin{aligned} U'[g(A_1)] &= u_{13} + u_{22} + 0.6687u_{32} + 0.3313u_{33} + \sigma_1, \\ U'[g(A_2)] &= 0.4291u_{12} + u_{23} + u_{33} + u_{42} + u_{63} + \sigma_2, \\ U'[g(A_3)] &= 0.6692u_{12} + u_{22} + 0.6643u_{32} + u_{44} + u_{54} + u_{63} + \sigma_3, \\ U'[g(A_4)] &= u_{43} + 0.5003u_{52} + 0.4997u_{53} + \sigma_4. \end{aligned} \tag{27}$$

The mathematical model for the problem is formulated as below:

$$\begin{aligned} \text{Min} \quad & (F) = \sigma_1 + \sigma_2 + \sigma_3 + \sigma_4 \\ \text{subject to} \quad & \Delta(3,2) \geq \delta, \ \Delta(2,1) \geq \delta, \ \Delta(1,4) \geq \delta, \\ & u_{13} - u_{12} \geq 0, \quad u_{23} - u_{22} \geq 0, \\ & u_{33} - u_{32} \geq 0, \quad u_{44} - u_{43} \geq 0, \\ & u_{43} - u_{42} \geq 0, \quad u_{54} - u_{53} \geq 0, \\ & u_{53} - u_{52} \geq 0, \quad u_{63} - u_{62} \geq 0, \\ & u_{13} + u_{23} + u_{33} + u_{44} + u_{54} + u_{63} = 1, \\ & u_{12}, u_{13}, u_{22}, u_{23}, u_{32}, u_{33}, u_{42}, u_{43}, \\ & u_{44}, u_{52}, u_{53}, u_{54}, u_{62}, u_{63}, \sigma_1, \sigma_2, \sigma_3, \sigma_4 \geq 0. \end{aligned} \tag{28}$$

Table 6: Sensitivity analysis for conveyor selection problem.

Conveyor	Decreased weights of IW and W by 25%	Decreased weights of IW and W by 10%	Basic solution	Increased weights of IW and W by 10%	Increased weights of IW and W by 25%
A_1	3	3	3	3	4
A_2	2	2	2	2	2
A_3	1	1	1	1	1
A_4	4	4	4	4	3

Table 7: Rankings of conveyor alternatives using different MCDM methods.

Conveyor	FUMAHES	GTMA	VIKOR	PROMETHEE	ELECTRE	WUTA
A_1	2	4	4	2	4	3
A_2	1	2	2	3	3	2
A_3	3	1	1	1	1	1
A_4	4	3	3	4	2	4

Now considering the value of $\delta = 0.0001$, the final mathematical formulation for the given conveyor selection problem is written as follows:

$$\begin{aligned}
&\text{Minimize} \quad (F) = \sigma_1 + \sigma_2 + \sigma_3 + \sigma_4 \\
&\text{subject to} \\
&0.2401u_{12} + u_{22} - u_{23} + 0.6643u_{32} - u_{33} \\
&\quad - u_{42} + u_{44} + u_{54} + \sigma_3 - \sigma_2 \geq 0.0001, \\
&0.4291u_{12} - u_{13} - u_{22} + u_{23} - 0.6687u_{32} \\
&\quad + 0.6687u_{33} + u_{42} + u_{63} + \sigma_2 - \sigma_1 \geq 0.0001, \\
&u_{13} + u_{22} + 0.6687u_{32} + 0.3313u_{33} - u_{43} - 0.5003u_{52} \\
&\quad - 0.4997u_{53} + \sigma_1 - \sigma_4 \geq 0.0001, \\
&u_{13} - u_{12} \geq 0, \quad u_{23} - u_{22} \geq 0, \quad u_{33} - u_{32} \geq 0, \\
&u_{44} - u_{43} \geq 0, \quad u_{43} - u_{42} \geq 0, \\
&u_{54} - u_{53} \geq 0, \quad u_{53} - u_{52} \geq 0, \quad u_{63} - u_{62} \geq 0, \\
&u_{13} + u_{23} + u_{33} + u_{44} + u_{54} + u_{63} = 1, \\
&u_{12}, u_{13}, u_{22}, u_{23}, u_{32}, u_{33}, u_{42}, u_{43}, u_{44}, u_{52}, \\
&\quad u_{53}, u_{54}, u_{62}, u_{63}, \sigma_1, \sigma_2, \sigma_3, \sigma_4 \geq 0.
\end{aligned} \tag{29}$$

This LP problem is solved using LINDO software which gives the results as $F = 0, u_{12} = 0, u_{13} = 0, u_{22} = 0, u_{23} = 0, u_{32} = 0, u_{33} = 0.0003, u_{42} = 0, u_{43} = 0, u_{44} = 0.9997, u_{52} = 0, u_{53} = 0, u_{54} = 0, u_{62} = 0$, and $u_{63} = 0$.

Now, applying (4), the utility values of the alternative conveyors are calculated as follows:

$$\begin{aligned}
U[g(A_1)] &= 0.0001, \quad U[g(A_2)] = 0.0003, \\
U[g(A_3)] &= 0.9997, \quad U[g(A_4)] = 0.0000.
\end{aligned} \tag{30}$$

As the optimal solution of the objective function in the LP problem results in a zero value, the utility functions are perfectly compatible with the reference sequence. After arranging these utility values in descending order, the final ranking of the four conveyors is $A_3 - A_2 - A_1 - A_4$, suggesting that A_3 is the best conveyor among the considered alternatives, followed by A_2. A_4 is the worst choice. Rao [22] also obtained A_3 as the best choice and a total ranking for the conveyors as $A_3 - A_2 - A_4 - A_1$. The Spearman's rank correlation coefficient (r_s) between these two rank orderings is calculated as 0.8, which represents the capability of the WUTA method for solving this conveyor selection problem.

Often the criteria weights in MCDM problems are challenged because of assortment and uncertainty involved in their calculations. Therefore, in order to deal with this issue, a sensitivity analysis is performed to study the impact of different criteria weights on the final ranking of the alternative conveyors. In this example, the weights for "IW" and "W" criteria are maximum, and hence, they are selected for increasing and decreasing their values in steps on either side. The weights of these two criteria are subsequently changed by −25%, −10%, +10%, and +25% in steps, and the weights of the remaining criteria are equally adjusted, so that the sum of all the criteria weights must add up to one. The results of this sensitivity analysis are exhibited in Table 6. It is observed from this table that changes in weights of the two most important criteria by +10%, +25%, and −10% do not show any variation in the final rankings of the alternative conveyors, but when the weights of the two selected criteria are changed by −25%, the positions of the last two alternative conveyors are just reversed. In all the cases, the best chosen conveyor remains unaffected. This result proves the robustness of the WUTA method for solving such types of MCDM problems.

Table 7 compares the rankings of the alternative conveyors as obtained by WUTA and other popular MCDM methods, like VIKOR (VIse Kriterijumska Optimizacija kompromisno Resenje), PROMETHEE, and ELECTRE (ELimination and Et Choice Translating Reality). These derived rankings are also compared with those obtained by Kulak [2] and Rao [22]. Kulak [2] developed a decision support system (FUMAHES: fuzzy multiattribute material handling equipment selection), and Rao [22] mainly applied GTMA method for solving this problem. It is observed that in most of the MCDM methods, the best and the least preferred alternative conveyors remain unchanged. Even though, the results obtained using different MCDM methods are quite similar, the WUTA method requires less computational time, as the LP-based mathematical formulations can be quickly solved employing LINDO software tool. A sound, systematic and logical base for this method provides almost robust rankings for the candidate alternatives as compared to other MCDM methods, which can be judged through the results of sensitivity analysis. In this method, the decision makers need not to perform tedious and repetitive pair-wise comparisons between the performance of different alternatives with respect to each criterion, thus saving computational time. In addition, the results obtained from this method are completely free from inconsistent and biased judgments of the decision makers. Thus, it may always be expected that this robust method would provide accurate ranking preorders for the alternatives, having minimally affected by the change in criteria weights and decision makers' perceptions.

5. Conclusions

The problem of selecting the most appropriate MH equipment for a specific task is a strategic issue, greatly influencing the performance and profitability of the manufacturing organizations. This paper presents the use of WUTA method for solving an MH equipment selection problem. It is observed that the WUTA method is a viable tool in solving the MH equipment selection problems. It allows the decision makers to rank the candidate alternatives more efficiently and accurately. As this method has a strong and sound mathematical foundation, it is capable of deriving more accurate ranking of the considered alternatives. It can not only help in just selecting the best MH equipment, but it can also be applied for any decision-making problem with any number of selection criteria and feasible alternatives while offering a more objective and straightforward approach. It is also observed that this method is quite robust against changes in the criteria weights.

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