International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:5, No:11, 2011

Material Handling Equipment Selection using Hybrid Monte Carlo Simulation and Analytic Hierarchy Process

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***Abstract*—**The many feasible alternatives and conflicting objectives make equipment selection in materials handling a complicated task. This paper presents utilizing Monte Carlo (MC) simulation combined with the Analytic Hierarchy Process (AHP) to evaluate and select the most appropriate Material Handling Equipment (MHE). The proposed hybrid model was built on the base of material handling equation to identify main and sub criteria critical to MHE selection. The criteria illustrate the properties of the material to be moved, characteristics of the move, and the means by which the materials will be moved. The use of MC simulation beside the AHP is very powerful where it allows the decision maker to represent his/her possible preference judgments as random variables. This will reduce the uncertainty of single point judgment at conventional AHP, and provide more confidence in the decision problem results. A small business pharmaceutical company is used as an example to illustrate the development and application of the proposed model.

***Keywords*—**Analytic Hierarchy Process (AHP), Material handling equipment selection, Monte Carlo simulation, Multi-criteria decision making

I. INTRODUCTION

IN any organization, be it big or small, involving manufacturing or construction type work, materials have to be handled as raw materials, work-in-process, or finished goods from the point of receipt and storage, through production processes and up to finished goods warehouse and dispatch points [1]. Examples of common used material handling equipments (MHE) include containers, carts, forklifts, automated-guided vehicles (AGV), conveyors, cranes, storage and retrieval equipments, etc. Details about MHE types and applications can be found in [1] and [2]. In a typical manufacturing plant material handling accounts for 25% of all employees, 55% of all company space, 87% of the production time, and 15-75% of the total cost of a product [2]. Therefore, material handling is certainly on of the first places to look for effective utilization of workforce and facility space, reducing production lead times, improving efficiency of material flow, increasing productivity, and reducing the total cost.

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Selecting the proper MHE is a very important task due to the considerable capital investment involved. At the same time, an efficient material handling system can reduce the operating cost and increase profit. Inaccurate selection of the MHE can interfere with the overall performance of the system and lead to unacceptable long lead times, and hence lead to substantial losses in productivity and competitiveness [3]. In recent days, a wide variety of MHE is available, each having distinct characteristics and cost that distinguish from others, making the selection of the proper equipment a very complicated process [4]-[8]. The constraints imposed by the facility layout and materials to be moved, multiple conflicting design criteria, and uncertainty in the operational environment, make the decision task more complicated. The decision maker has to consider various quantitative (i.e. load weight, moving distance, cost, etc.) and qualitative (i.e. load shape, load type, equipment maintainability, safety, etc.) criteria. Therefore, MHE selection problem can be considered as multiple criteria decision making (MCDM) problem in the existence of these quantitative and qualitative attributes to consider. Nowadays, there are many MCDM methods in use aimed of supporting decision makers in making numerous and sometimes conflicting evaluations. In these methods, a finite number of alternatives have to be evaluated and ranked based on different and sometimes conflicting attributes. Some of the most popular MCDM methods are Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), utility models, Goal Programming, Data Envelopment Analysis (DEA), Simple Multi-Attribute Ranking (SMART), outranking methods, TOPSIS, and disaggregate-aggregate approaches. A detailed description of MCDM methods and applications can be found in [9] and [10].

Various researchers have studied different methods to deal with the problem of MHE selection process such as MCDM methods and expert systems [3]-[8] & [11]-[14]. The application of different integrated AHP approaches is found to be the most popular ones. Even though, the use of conventional AHP in MHE selection has some shortcomings [8], mainly a difficulty in capturing the uncertainty in the operational environment. Besides, it is very difficult for the decision maker to precisely describe preferences of one alternative over another, and to provide exact numerical values for the criteria assessments. The current research proposed a hybrid AHP and Monte Carlo (MC) simulation model to solve the MHE selection problem with higher confidence. The role of MC simulation is to reduce uncertainties of the decision where each pair wise comparison in conventional AHP is treated as a random variable with a specific distribution [15]. The paper is organized as follows. The next section presents a brief theoretical background on AHP and MC simulation. Section 3 presents the development of the hybrid AHP and MC simulation model. In section 4 a real-world case study is given to demonstrate the application of the model, and the computational results. Finally, some conclusions are summarized in section 5.

II. AHP and MC Simulation

The Analytic Hierarchy Process (AHP) developed by T. L. Saaty in 1980 is a useful decision making tool for managing and solving multiple criteria decision problems. The method has been widely applied to decision problems in different fields such as social, education, manufacturing, healthcare, political, government, industry, sports, economics, personal, and many others [16] & [17]. AHP involves the comparison of several candidate alternatives based on several different criteria. A ratio-scaled importance of these alternatives is calculated through pair wise comparisons of evaluation criteria and alternatives. In this method, a numeric scale for measurement of quantitative and qualitative performance is provided. The main steps of AHP are summarized below [9] & [18]:

1. Construct the decision hierarchy by breaking down the decision into a hierarchy of criteria and alternatives. The goal appears at the higher level, and then the criteria and sub-criteria appear in the followed levels. The alternatives appear on the hierarchy at the lowest level.
2. Perform pair wise comparisons of criteria and alternatives. This is used to determine the relative importance of criteria, and also compare how well the alternatives perform on different criteria.
3. Transform the comparisons into weights and check the consistency of the decision makers' comparisons. Saaty recommends a mathematical approach based on eigen-values.
4. Use the weights to obtain scores for the alternatives and make a provisional decision.

For more details about AHP and calculation steps, see [18].

Although AHP is one of the most widely used multiple criteria decision making tools, it forces the decision makers to express their judgments as single numeric preferences while performing the pair wise comparisons of all decision criteria and alternatives [19]. This means, traditional AHP does not take into account uncertainty in the human judgments. This limitation greatly reduces the applicability of the AHP, and also reduces the confidence of the decision maker on the final results of the AHP methodology [20]. To overcome this limitation, several researchers have suggested the use of either fuzzy theory [4], [5], [8], [21] & [22] in which judgments are represented as fuzzy variables, or probabilistic approaches [15], [19] & [20] in which judgments are represented as random variables. In probabilistic approaches, operations on random variables are based on unique definitions, while in the fuzzy theory different definitions of the fuzzy operations lead to different methods and different results which are difficult to compare [20]. References [15], [19] & [23] have suggested the use of Monte Carlo (MC) simulation in probabilistic approach to calculate and estimate the probability information for the pair wise comparisons in conventional AHP. The role of MC simulation is to generate random sample data based on some known distributions for numerical experiments. Reference [15] has recommended that the pair wise comparisons be viewed as random variables a_{ij} with the provision that the distribution is bounded between 1/9 and 9, and $a_{ij} = 1/a_{ji}$, and $a_{ii}=1$. The random variable a_{ji} will be dependent on a_{ij}. Therefore, it is reasonable to assume that $\{a_{ij}/i>j\}$ are independent, and the final scores $s_1, s_2, \ldots, s_n$ of the probabilistic AHP will also be random variables. In state of multiple decision makers, it is assumed that each decision maker has an equal probability of being correct in his or her judgment of each pair wise comparison, a_{ij}. As a result, each a_{ij} will be a discrete random variable. In the state of single decision maker, his or her judgment is modeled as continuous random variable and then can be converted to discrete random variable as suggested by the extended Pearson-Tukey method [15]. When using MC simulation to calculate the principle Eigen vector, each replication would be a realization of all the pair wise comparisons (a_{ij}) in the decision hierarchy followed by the conventional AHP methodology. These replications will ultimately provide estimates of the probabilities associated with the final scores.

In this paper, a hybrid Monte Carlo (MC) simulation and AHP model is proposed to solve the problem of MHE selection taking into account the uncertainty in human preferences. This model will provide more confidence in the decision problem results, and enable decision makers to express their preferences in more flexible manner than conventional AHP. The triangular distribution has been used for its efficiency when the distribution is unknown but three points, minimum, maximum, and most likely can be estimated.

III. Hybrid MC Simulation and AHP Model for MHE Selection

The proposed hybrid MC simulation and AHP model for MHE selection follows the main steps of traditional AHP combined with Monte Carlo simulation. As shown in Figure 1, the model is divided into three main steps. The initial step is defining the MHE selection problem and constructing the decision hierarchy by breaking down the problem into a hierarchy of criteria and alternatives. Then the pair wise comparisons of decision elements are collected as random variables. The pair wise comparisons in traditional AHP are deterministic, while in this model the pair wise comparisons are probabilistic. Monte Carlo simulation is then used to generate 'n' replications for each pair wise comparison. The resulted values from simulation are entered to the AHP commutations to evaluate the weight for each alternative, and estimate their probabilistic superiority. The next sections describe the proposed model in more details.

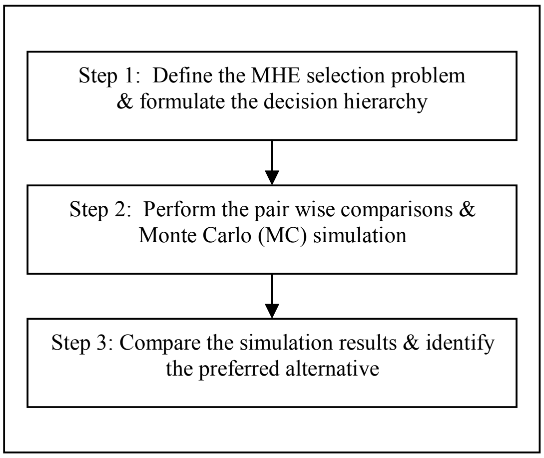

Fig. 1 Steps of Hybrid MC simulation and AHP model for MHE selection

A. Define the MHE Selection Problem and Formulate the Decision Hierarchy

In this step, an initial identification of the problem at hand is made. This involves definition of the scope of the study, the problem statement, the criteria that are relevant to the MHE selection, the feasible alternatives, and the subject-matter decision maker. After that, the decision hierarchy is constructed by breaking down the decision problem into a hierarchy of criteria and alternatives. It is important to ensure that the constructed hierarchy realistically represents the decision problem under study. At the top of the hierarchy is a statement of the general objective of the decision, in our case, 'choose the best MHE'. The general criteria associated with the decision problem are then set out below the general objective. These criteria can be broken down into more detail at the next level. Finally, the alternatives are added to the hierarchy below each of the lower level criteria.

Table I shows the list of criteria and sub-criteria that will be used as a basis for comparison between the alternative MHEs. These criteria and Sub-criteria are adopted from [4] & [6] with some modifications. Depending on the attributes considered in the material handling equation (materials plus moves equals methods), there are three main criteria: material criteria, moving criteria, and method criteria. Material criteria refer to material type, volume, shape, and weight. Moving criteria refer to distance from source to destination, path, level, speed, frequency of move, and moving type such as stacking, transferring, or positioning. Method criteria refer to control methods, fixed and variable costs, safety issues, equipment maintainability, and facility restrictions such as facility area and lifting height. Figure 2 shows the hierarchy structure for the MHE selection problem.

TABLE I
CRITERIA AND SUB-CRITERIA USED AS BASIS FOR COMPARISON BETWEEN ALTERNATIVE MHE.

criteria	**Sub-criteria**	**Sub-sub-criteria**
Material attributes	Material Type	Unit load
		Bulk material
		Fluid and gas
	Material Characteristics	Material volume
		Material shape
		Weight of the loads
Moving attributes	Source & destination	Distance from source and destination
		Path
		Level
	Move Characteristics	Speed
		frequency of move
	Move type	Stacking
		Transferring
		Positioning
Method attributes	Facility restriction	Area
		Lifting height
	Control method	
	Safety	
	Fixed cost	
	Variable cost	
	Maintainability	
	Variability	

B. Perform the Pair Wise Comparisons and MC Simulation

At this step, pair wise comparisons of criteria and alternatives are performed. This is done to determine the relative importance of criteria, and also to identify how well the alternatives perform on the different criteria. The importance of each criterion at the first level in the decision hierarchy is firstly compared. Then the sub-criteria immediately below each criterion are compared. Finally, the alternatives are compared based on each lower level sub-criterion. All of these pair wise comparisons are probabilistic. The triangular distribution is found to be suitable to represent these probabilistic judgments when the distribution is unknown but three points minimum, maximum, and most likely can be estimated. The importance of the ith alternative/criterion compared with jth alternative/criterion can be expressed by three parameters; minimum value, most likely value, and maximum value. These parameters follow Saaty's scale of preferences as shown in table II [18]. To calculate the composite priority vector from the probabilistic judgments, 'n' replications of Monte Carlo simulation and standard AHP calculations of eigenvectors for each replication are used. The resulted composite priority vector will be stochastic as well. For more detailed steps of Monte Carlo method see [15].

C. Compare the Simulation Results and Identify the Preferred Alternative

In this step, the probability distributions associated with the composite priority vector are inspected to estimate the probabilistic superiority of the alternatives. This includes plotting the probability distribution graphs, and comparing the mean and the standard deviation. Details and applications of statistical tools and techniques to understand and select the most appropriate alternative such as mean-standard deviation method, hypothesis testing, confidence interval analysis, rank reversal analysis, stochastic dominance, and mean square deviation can be found in [9] & [19].

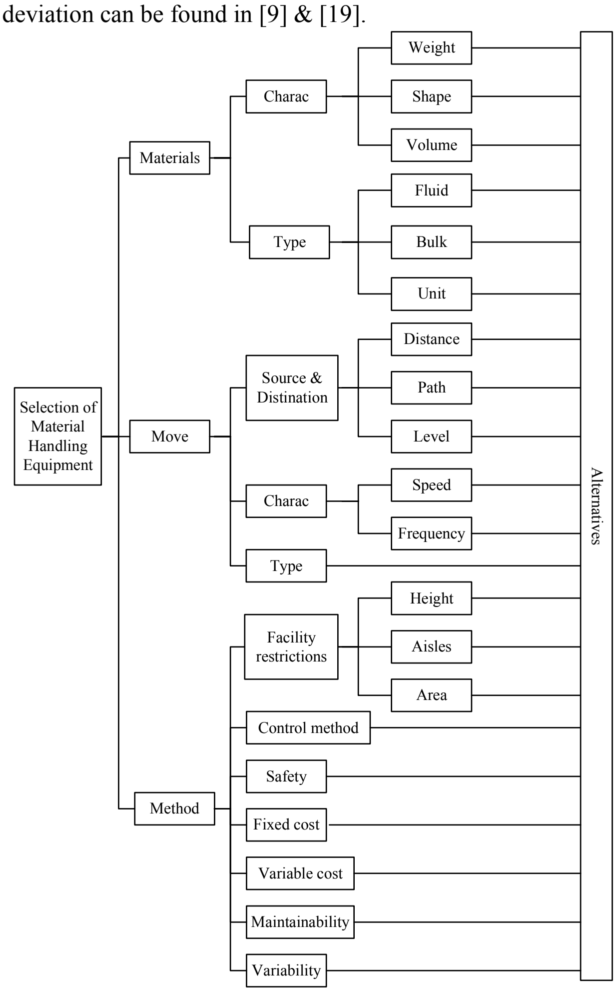

Fig. 2 Hierarchical structure for the MHE selection problem

TABLE II
SAATY'S SCALE OF PREFERNCE

Definition	Scale of Preference
Equally important	1
Weakley more important	3
Strongly more important	5
Very Strongly more important	7
Extremely more important	9

IV. CASE STUDY

The proposed model is implemented in a pharmaceutical production plant, which contains three production departments; tablets and capsules, syrup, and ointments department. Pharmaceutical products from all departments are packed in cubic cartoons and sometimes palletized depend on the customer requirements, and then transferred to main storage. The goal is to choose the best MHE to carry the material from packaging department to the main storage. The plant manger has been identified as the only decision maker. A preliminary filed study and interviews are conducted to identify the material and facility characteristics and to figure out all potential quantitative and qualitative criteria that may affect the goal. As mentioned before, the criteria and sub-criteria in this case are adopted from [4] & [6] with some modifications. After that, the decision hierarchy from the top through the intermediate levels to the lowest level of the hierarchy is developed (see figure 2).

After determining all selection criteria and sub-criteria, the potential Material Handling Equipments are analyzed. Four alternatives are then chosen. These alternatives are as follows:

Alternative 1: Lift set down truck
Alternative 2: Pallet standup truck
Alternative 3: Pallet jack
Alternative 4: Conveyer

The pair wise comparisons of criteria and alternatives are done by the decision maker with the help of the authors. Triangular distribution is used to represent the decision maker's preferences by specifying three parameters; minimum, most likely, and maximum in the range of (1/9-9). Selected pair wise comparisons are shown in table 3.

After that, Microsoft Excel is used to perform 1000 replications of Monte Carlo simulations. The resulted values from simulation are then entered to the AHP commutations to evaluate the weight for each alternative and construct the composite priority vector. Microsoft Excel is also used to perform this step. Figure 3 is a plot of the resulted probabilistic composite priority vector. Table 4 reports the parameters of the composite priority vector such as the distribution mean, standard deviation, maximum value, minimum value, and standard error and ranking of each alternative.

TABLE III
VALUES OF PAIR WISE COMPARISON WITH TRIANGULAR DISTRIBUTION FOR SELECTED CRITERIA AND ALTERNATIVE

	Material	Method	Move	
Material	[1,1,1]	[5,7,9]	[3,5,7]	
Method	[1/5,1/7,1/9]	[1, 1, 1]	[1/3, 1/2, 1]	
Move	[1/7,1/5,1/3]	[3, 2, 1]	[1, 1, 1]	
	Shape	Weight	Volume	
Shape	[1, 1, 1]	[1/9, 1/7, 1/5]	[1/7, 1/5, 1/3]	
Weight	[5, 7, 9]	[1, 1, 1]	[2, 3, 5]	
Volume	[3, 5, 7]	[1/5, 1/3, 1/2]	[1, 1, 1]	
	Type	Material char		
Type	[1, 1, 1]	[1/7, 1/5, 1/3]		
Material char	[3, 5, 7]	[1, 1, 1]		
	Source & destination	Move char		
Source & destination	[1, 1, 1]	[1/5, 1/3, 1/2]		
Move char	[2, 3, 5]	[1, 1, 1]		
	Distance	Path		
Distance	[1,1, 1]	[1/5, 1/3, 1/2]		
Path	[2, 3, 5]	[1, 1, 1]		
The alternatives relative to material type				
	Alternative 1	Alternative 2	Alternative 3	Alternative 4
Alter 1	[1, 1, 1]	[2,2, 3]	[2, 2, 3]	[2, 3, 5]
Alter 2	[1/3, 1/2, 1/2]	[1, 1, 1]	[1/4, 1/2, 1]	[2, 3, 5]
Alter 3	[1/3, 1/2, 1/2]	[1, 2, 4]	[1, 1, 1]	[5, 5, 7]
Alter 4	[1/5, 1/3, 1/2]	[1/5, 1/3, 1/2]	[1/7, 1/5, 1/5]	[1, 1, 1]
The alternatives relative to shape characteristics				
	Alternative 1	Alternative 2	Alternative 3	Alternative 4
Alter 1	[1, 1, 1]	[1, 2, 4]	[2, 3, 5]	[2, 3, 5]
Alter 2	[1/4, 1/2, 1]	[1, 1, 1]	[2, 2, 3]	[2, 3, 5]
Alter 3	[1/5, 1/3, 1/2]	[1/3, 1/2, 1/2]	[1, 1, 1]	[3, 5, 7]
Alter 4	[1/5, 1/3, 1/2]	[1/5, 1/3, 1/2]	[1/7, 1/5, 1/3]	[1, 1, 1]

As shown, Alternative 1, namely lift set down truck, is the preferred material handling equipment in order to meet the company's requirements. Note that the maximum and minimum of all weights for all alternatives do not overlap, so the probability of ranking is 100% with less than 1% error, and 95% confidence level. These results do not contradict with the decision maker's intuitive as stated by the plant manager.

TABLE IV
PARAMETERS OF THE RESULTED COMPOSITE PRIOITY VECTOR

	Distribution mean	Max	Min	SD	Standard error	Rank
Alter1	0.4449	0.4852	0.4056	0.0122	0.0004	1
Alter2	0.277	0.3060	0.2485	0.0092	0.0094	2
Alter3	0.1920	0.2126	0.1711	0.0073	0.0073	3
Alter 4	0.0855	0.0958	0.0772	0.0033	0.0001	4

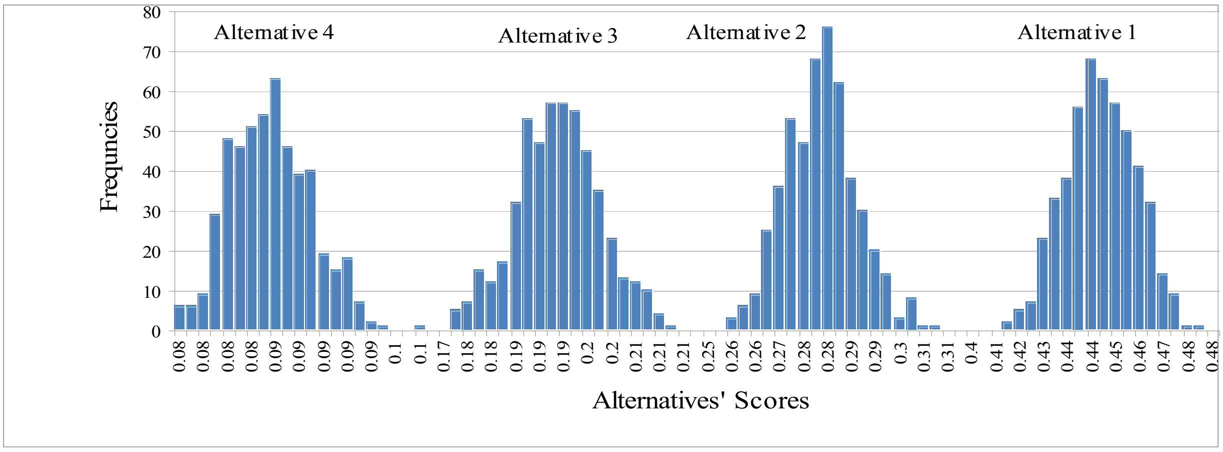

Fig. 3 The probabilistic composite priority vector

V. CONCLUSIONS

In this paper a hybrid MC simulation and AHP model for MHE selection is presented. The role of MC simulation is to reduce uncertainties of the decision by representing the preference judgments of criteria and alternatives as random variables. Triangular distribution is used to represent these probabilistic judgments by identifying three parameters; minimum value, most likely value, and maximum value. The Monte Carlo simulation examines all values between the three points. From this prospective, the risk and uncertainty of single judgment point made in traditional AHP are reduced, and more confidence in the decision problem results can be gained. The proposed model is demonstrated through an application of example of real world.

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