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Non-traditional machining processes selection using data envelopment analysis (DEA)

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ABSTRACT

The generic term 'non-traditional machining' (NTM) refers to a variety of thermal, chemical, electrical and mechanical material removal processes which have been developed due to lack of efficiency of the traditional machining processes to generate complex and intricate shapes in materials with 'high strength-to-weight' ratio. For effective utilization of the capabilities of different NTM processes, utmost care is needed for the selection of the most suitable process for a given machining application. Due to the lack of experienced experts in the domain of NTM processes, there is a need for a simple scientific/mathematical tool for selecting the most suitable NTM process when a particular shape feature is to be generated on a given work material. This paper focuses on the development of a two-phase decision model in this aspect. In the first phase, the most efficient NTM processes are selected for a given shape feature and work material combination having the best combination of performance parameters with the help of input-minimized-based Charnes, Cooper and Rhodes (CCR) model of data envelopment analysis (DEA). In the second phase, those efficient NTM processes are ranked in descending order of priority using the weighted-overall efficiency ranking method of multi-attribute decision-making (MADM) theory. Two real time machining applications are cited which prove the applicability, versatility and adaptability of this two-phase NTM process selection decision-making model as the results are quite consistent with those as derived by the past researches.

1. Introduction

Scientific and engineering advances in recent years have placed an unusual demand on the metal-working industries to develop materials with 'high strength-to-weight ratio' to serve the specific purposes of aerospace, nuclear reactor, missile, turbine and automobile industries. The impetus for the development of new methods of metal cutting and forming has come as a result of search for better and faster manufacturing processes to reduce cost, demand for new standards of product performance and durability, complex and intricate shapes of products engineered for specific purposes, and considerations of tool wear and economic return. The difficulty in machining posted by the advanced engineering materials, such as titanium, stainless steel, high-strength temperature-resistant alloys, ceramics, refractories, fibre-reinforced composites and other difficult-to-machine alloys having higher strength, hardness, toughness, low machinability and other diverse mechanical properties has placed a demand for the non-traditional machining (NTM) processes due to lack of availability of sufficiently hard and strong cutting tool materials for the generation of complex and accurate shapes on those new work materials. Conventional edged cutting tool machining processes often face difficulties in such applications due to the following reasons:

(a) Low machinability of the newly developed engineering materials.
(b) Requirements for higher dimensional accuracy.
(c) Higher production rate and economy.

To obtain the desired shape and size, materials are removed from the workpiece surface in the form of chips in the traditional machining processes, so high degree of precision and accuracy cannot be achieved. Whereas, the non-traditional machining (NTM) processes use energy in its direct form (mechanical, thermoelectric, electrochemical, chemical, sound, etc.) to remove materials in the form of atoms or molecules to obtain the required accuracy and burr-free machined surface. Low applied forces can prevent damage to the workpiece surface that may occur during traditional machining. It has been observed that in NTM processes, performance is independent of the strength barriers. Because the NTM processes can provide new ways of satisfying the demands of nascent technological advances in many areas, like automated data transmission and miniaturization, the design engineers need not only limit their ideas to the traditional machining processes, but

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also venture for the application of different NTM processes to fulfill the machining and surface quality requirements. A new horizon of choices from a pool of NTM processes has been opened up for the design and machining of products (Ghosh & Mallik, 1985; Jain, 2005; Pandey & Shan, 1981; Weller & Haavisto, 1984). Thus, for effective utilization of the capabilities of different NTM processes, an in-depth knowledge about various machining characteristics of those processes is of utmost importance.

As the selection of NTM processes for different engineering applications involves complex process characteristics, cost considerations and in-depth technological knowledge regarding the applicability of those NTM processes, there is a shortage of experienced experts in the field of NTM processes. To guide the design engineers to select the most suitable NTM process for machining a specific shape feature on a given work material, there is a need for development of a simple scientific/mathematical tool to fulfill this real time machining requirement. Cogun (1993, 1994) used an interactively generated 16-digit classification code to choose and rank the non-traditional machining processes for a given part. Yurdakul and Cogun (2003) combined two multi-attribute decision-making (MADM) tools, e.g. analytic hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS) to narrow down the list of NTM processes to a shortlist containing only the feasible processes and then ranked those feasible NTM processes according to their suitability for a specific machining application. Chakroborty and Dey (2006) applied analytic hierarchy process to develop an expert system to simplify the NTM process selection procedure that relies on the priority values for different criteria and sub-criteria, as related to a specific NTM process selection problem. In this expert system, the feasible NTM processes lie in the acceptability zone and the process having the highest acceptability index value is the best choice. Chakroborty and Dey (2007) developed a quality function deployment (QFD)-based expert system for NTM process selection where various relevant product and process characteristics, and the related weights for the process characteristics are used to calculate an overall score for each of the NTM processes to select the most suitable one. Chakrabarti, Mitra, and Bhattacharyya (2007) took in account the typical problems of parameter selection and optimization in non-traditional machining processes to bring out the related design ideas that form the foundation of an *n*-tier management information system (MIS). All the parametric data for some of the complex NTM processes, like abrasive water jet machining (AWJM), wire electric discharge machining (WEDM) and electric discharge machining (EDM) are accumulated to facilitate extraction of the relevant information using a distinct architecture of MIS, having three scalable layers. Das Chakladar and Chakraborty (2008) employed a combination of the TOPSIS and AHP methods, and Das Chakladar, Das, and Chakraborty (2009) applied a digraph method to select the best suited NTM process for a given machining application. Edison Chandrasselan, Jehadeesan, and Raajenthiren (2008) designed a web-based knowledge base system for identifying the most appropriate non-traditional machining process to suit specific circumstances based on some input parameter requirements, such as material type, shape applications, process economy and process capabilities. Designers and engineers who are geographically apart but well connected by the Internet can use this web-based system. It is observed that the system which employs a three-tier web architecture for implementing user module to do the selection and expert module to update the knowledge base, can reduce the product cost, enhance the product quality and decrease the product lead-time. From the above works carried out by the past researchers, it is observed that the mathematical tools employed by them are too complex and sometimes, extensive computer skill is required for the development of those expert systems or knowledge-base systems.

In this paper, a two-phase decision model is proposed for NTM process selection where ten alternative NTM processes and ten performance criteria affecting the NTM process selection decision are considered. In the first phase, data envelopment analysis (DEA) is used for identifying the most efficient NTM processes with the best combination of the performance parameters. In the second phase, the multi-attribute decision-making (MADM) approach is employed to rank those efficient NTM processes, as identified in the first phase, in descending order of priority. The proposed NTM process selection approach is computationally simple, and requires only the basic knowledge of computer language and linear programming (LP) models.

2. Modeling for DEA

Data envelopment analysis (DEA) was initiated in 1978 when Charnes, Cooper and Rhodes (CCR) demonstrated how to change a fractional linear measure of efficiency into a linear programming (LP) format (Charnes, Cooper, & Rhodes, 1978). As a result, the decision-making units (DMUs) can be assessed on the basis of multiple inputs (non-beneficial attributes) and outputs (beneficial attributes), even if the production function is unknown. DEA is a technique for measuring the relative efficiencies using multiple inputs and outputs with no *a priori* information regarding which inputs and outputs are the most important in determining an efficiency score. This non-parametric approach solves an LP formulation per DMU and the weights assigned to each linear aggregation are the results of the corresponding LP. The weights are chosen so as to show the specific DMU in as positive a light as possible, under the restriction that no other DMU, given the same weights, is more than 100% efficient. Consequently, a Pareto frontier is attained, marked by specific DMUs on the boundary envelope of the input–output variable space. This frontier is considered as a sign of relative efficiency, which has been achieved by at least one DMU. An efficient alternative possesses a relative efficiency score of 1 that indicates none of its outputs can be increased without either increasing one or more of its inputs or decreasing some of its other outputs.

Charnes, Cooper, and Lewin (1994) described DEA as 'a mathematical programming model applied to observational data (which) provides a new way of obtaining empirical estimates of external relations, such as the production functions and/or efficient production possibility surfaces that are a cornerstone of modern economics'. DEA has become one of the fastest growing areas of operations research and management science in the past decade (Adler, Friedman, & Sinuany-Stern, 2002; Cook & Seiford, 2009).

2.1. The CCR model

In the 'ratio-form' of DEA, the so-called CCR model as originally introduced by Charnes, Cooper and Rhodes (Khouja, 1995), the ratio of total weighted output to total weighted input is used to measure the relative efficiency of a particular DMU. The CCR model is related to the reduction of the multiple-output/multiple-input situation (for each DMU) to that of a single 'virtual' output and 'virtual' input model. For a particular DMU, the ratio of this single virtual output to single virtual input provides a measure of efficiency which is a function of the corresponding multipliers. By comparing n units with s outputs denoted by y_{rk} (for $r = 1,\ldots,s$) and m inputs denoted by x_{ik} (for $i = 1,\ldots,m$), the efficiency measure for DMU k can be given by the following equation:

$$h_k = \underset{u_r, v_i}{\text{Max}} \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}}, \tag{1}$$

where u_r and v_i are non-negative weights, u_r is the weight associated with rth output (beneficial attribute) and v_i is the weight asso-