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Data Envelopment Analysis and Machinability Evaluation

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Abstract – In the present paper a Data Envelopment Analysis approach for determining ranking indices among the work material available for the machining is presented. Due to immense number of different available materials dealing with such enormous information made possible to generate quick and accurate decision or action. The classical DEA-CCR model is an extreme point method and compares each decision making unit with only the best decision making unit. The typical parameters considered are cutting speed, cutting force and power requirements.

Keywords*: Data Envelopment analysis, CCR model, Machinability evaluation, concordance, disconcordance, credibility indexing*

1. INTRODUCTION

The field of manufacturing with solid – state processes are distinguished into two classes, wise deformation processes**,** where the required shape is produced with the necessary mechanical properties by plastic deformation in which the material is removed and its volume is conserved. Machining processes produce the required shape by removal of selected areas of the workpiece through a machining process. Most machining can be accomplished because of workpiece fracture by the relative motion of the tool and the workpiece. Mechanical energy is the usual input to most machining processes. Machining usually is employed to produce shapes with high dimensional tolerance, good surface finish and often with complex geometry.

The machinability of engineering materials, owing to the marked influence on the production cost, needs to be taken into account in the product design, although it will not always be a criterion considered top priority in the process of material selection. If there are finite number of work materials form among which the best material is to be chosen, and if each work material satisfies the required design and functionality of the product, then the main criterion to choose the work material is its operational performance during machining, i.e., machinability.

In the past decades, industries developed the statistical records document and progress. There have been many studies utilising input-output analysis which can be attempted to measure the change of parameters concerned. As pointed out by [1,2,3] collection of the necessary data and the process of estimation and modification of technical coefficients required by the input-output analysis models are generally difficult to implement on a timely basis. They employed Data Envelopment Analysis (DEA), an alternative approach for measuring the relative efficiency of decision making units (DMUs) with multiple outputs and multiple inputs, to evaluate and monitor the industrial performance.

Various approaches including knowledge based and intelligent database had been developed in the past to help address the issue of machinability evaluation of work materials used in varieties of machining operations.

DEA-CCR is a method for assessing the efficiency index of DMUs which are homogeneous in the sense that they use the same types of resources (inputs) to produce the same kinds of goods or services (outputs) [4]. DEA-CCR requires the data sets to be non-negative for the outputs and strictly positive for the inputs, it is also assumes that input values are improving as they get smaller and output values are improving as they get larger [5].

The proposed approach gives the selection of an appropriate work material for the given job and cutting conditions.

The paper is organized as follows. A literature review o n methods and tools in support of machinability evaluation of the work materials are given in section 2. Section 3 describes the problem and solution procedure for the evaluation and selection of the work material under the given condition. In section 4, the mathematical steps and assumptions are given for the work material evaluations. Section 5 describes the evaluations of work materials with all the necessary mathematical formulations and the realists obtained at the end of this section give the raking of those materials. Finally, concluding remarks are given in section 6.

2. LITERATURE REVIEW ON MACHINABILITY EVALUATIONOF WORK MATERIALS

In general, a manufacturing process for a product consists of several phases such as product design, process planning, machining operations, and quality control. The machinability aspect is related to all phases of manufacturing, especially to process planning and machining operations. Machinability is a measure of ease with which a work material can satisfactorily be machined. The machinability aspect is of considerable importance for production engineers to know in advance the machinability of work materials so that the processing can be planned in an efficient manner.

The machining process is influenced by a number of variables. The basis of machinability evaluation depends on the manufacturer's interest, and many other aspects. For instance, some manufacturers consider tool life as the most important criterion to evaluate machinability, while others consider quality of surface cut the dominant factor. A machining attributes is defined as a machining process variable.

Reference [6] presented the result of an experimental investigation on the machinability of silicon carbide particulate aluminium metal matrix composite during turning using fixed rhombic tools. The influence of machining parameters, e.g. cutting speed, feed and depth of cut on the cutting force and surface finish criteria were investigated during the experimentation. The combined effect of cutting speed and feed on the flank wear was investigated during experimentation. The influence of cutting speed, feed rate and depth of cut on the tools wear and built-up edges (BUEs) were analysed. The BUE and chip formation at different sets of experiments were examined through SEM micrographs. Test results show that no BUE is formed during machining of Al/SiC-MMC at high speed and low depth of cut. From the test results and different SEM graphs suitable range of cutting speed, feed and low depth of cut can be selected for proper machining of Al/SiC-MMC.

An economical analysis of the plastic injection market highlights the necessity to increase productivity in [7]. Mold steel influences the total cost of an injected part more through its capability to be worked than through its own price. Among the mold manufacturing operations, rough and finish machining are two of the most expensive, depending strongly upon the mold steel machinability. A new method had been developed to compare the machinability of three 300 HB mold steels during rough milling. Based on a half-fractional design of experiments, a new model was proposed which takes into account material variation, as well as cutting parameter interactions. The application of this approach had shown the interest of a new redesigned grade presenting high surface properties, which could be as machinable as a high sulfur content grade which presents limited surface finishing capabilities.

Reference [8] presented a logical procedure to evaluate the machinability of work materials for a given machining operation. The procedure was based on a combined TOPSIS and AHP method. The proposed global machinability index helps to evaluate and rank the work materials for a given machining operation. He validated the approach using various examples and illustrated the applicability of the methodology used in his work.

Reference [9] investigated the machinability of ECAE-processed pure copper using both tungsten carbide (WC) and polycrystalline diamond (PCD) cutting tools in order to facilitate broad applications of ECAE-processed UFG coppers. It is found that despite its higher cost, PCD is favoured to machine UFG copper based on this study since it has better wear resistance, gives lower cutting forces, yields a better workpiece surface finish, and results in no smearing on the workpiece. In machining UFG copper, depth of cut notching was observed as the wear pattern and abrasion as the wear mechanism for the WC tool, while flank wear was observed as the wear pattern and diffusion as the wear mechanism for the PCD too.

Reference [10] presented the machinability study of standard GGG40 nodular cast iron by WEDM using different parameters (machining voltage, current, wire speed, and pulse duration). From the results, the increase in surface roughness and cutting rate clearly follows the trend indicated with increasing discharge energy as a result of an increase of current and pulse on time, because the increased discharge energy will produce larger and deeper discharge craters. Three zones were identified in rough regimes of machining for all samples: decarburized layer, heat affected layer, and bulk metal. High machining efficiency can be obtained when the proper electrical parameters are selected, but whether high energy or the low energy is used, a coarse surface is always obtained. The variation of surface roughness and cutting rate with machining parameters is mathematically modeled by using the regression analysis method.

The production of sintered structural components by powder metallurgy (PM) route is basically done by uniaxial cold pressing of metal powders in closed dies followed by sintering at temperatures in the range of 1120–1300 °C in H/N atmospheres (solid phase sintering). The machinability of PM steels was tested by different methods for the various cutting processes were analyzed in [11]. Compared to wrought steels, PM steels shown an almost unlimited variety of microstructures. This fact complicates creation of a uniform solution for testing and characterizing the problems in machinability of PM steels. The short time face turning method using common small ring-shaped specimens as test pieces was presented in this case as a new method for testing the machinability of PM steels. The method was tested on Fe–C and Distally type materials. The critical number of cutting passes up to a tool flank wear of VB = 0.3 mm, critical time, critical volume of removed material, surface finish and morphology of the chips were the criteria for checking the technical affectivity of the method applied. The results attained proved that the face turning test method used here was simple and easy and can fulfill many requirements for assessing the machinability of PM steels in turning.

Reference [12] presented the results of machining tests carried out to determine the effect of microstructure and mechanical properties of austempered ductile irons (ADIs) on cutting forces and surface roughness. Specimens were prepared under different austempering times with the addition of Cu and Ni at various contents. Six different specimen groups were austenised at 900 °C for 90 min and then austempered in molten salt at 370 °C for 60, 90, 180 and 200 min. The results were evaluated after machining tests which were carried out in accordance with ISO 3685. Austempering heat treatment resulted in considerable improvement on the surface quality when compared to as-cast specimens while the changes in cutting forces remained at about 20% level for different specimens. In terms of both criterions, the best result was obtained from 60 min austempered and 0.7% Ni and 0.7% Cu added specimens.

In general, for the machinability assessment of different work materials include tool life, tool wear/tool wear rate, cutting forces/specific cutting forces, power consumption/specific energy consumption, processed surface finish, dimensional accuracy of the processed surface etc. So far, research has been based mainly on experimental work to characterize the machinability of different work materials considering any one of the above criteria only [13]. It is clear that there is a need to develop some mathematical tool for machinability evaluation that is capable of considering the requirements of a given machining operation.

3. MULTICRITERIA EVALUATION PROBLEM AND PROCEDURES

Reference [14] listed and discussed the general machining characteristics of aluminum pressure die-cast and die-cast alloys under various machining conditions for turning face milling, and drilling operations. The authors used the results of turning data [15] of non-ferrous and ferrous alloys machined with high-speed machining tools. The results are given in Table 1.

Table 1 Quantitative data of the machinability evaluation problem

Work Material	VC (m/min)	CF (N/m^2)	PI (Kw)
W1	710	400	28
W2	900	415	38
W3	1630	440	59
W4	1720	235	43
W5	120	1150	08
W6	160	1750	19

One-hour cutting speeds determined from machining tests on six different work tool combination. The attributes are one-hour cutting speed (VC), Specific cutting Force (CF) and Cutting power input (CI). The cutting conditions are: dry, tool material-K10, feed-0.175 mm/rev, and depth of cut-2 mm.

Where,
W1: GK-AlSi10Mg (aluminium-silicon die cast alloy);
W2: GK-alSi6/cu4 (aluminium-silicon die-cast alloy);
W3: GK-AlMg5 (aluminium-magnesium die-cast alloy);
W4: GK-MgAl9Zn (magnesium-alumium die-cast alloy);
W5: GG26 (Gray cast iron with lamellar graphite);
W6: C35 (low-carbon steel)

To be able to use the data for DEA evaluation model, detailed in the next sections, inputs and outputs must be identified as shown in figure 1.The inputs are specific cutting force and cutting power and output is the resulting cutting speed in hour basis under this particular example. There are six work materials that are to be evaluated in this model.

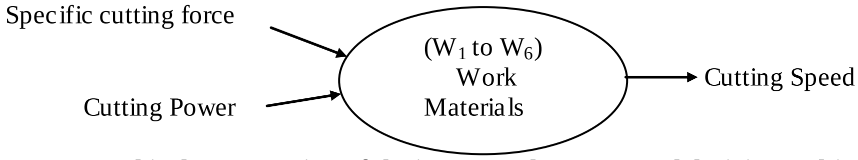

Figure 1 Graphical presentation of the inputs and outputs and decision making units for the DEA model

4. DEA METHOD AND RANKING OF THE WORK MATERIALS

The analysis of work material suitability for the machining ease will consists of a new mathematical model for efficiency analysis, which is extended to combine DEA methodology with an old idea- Ratio Analysis. In DEA, the alternatives un9der considerations are called a decision making units. Generally a DMU is regarded as the entity responsible for converting inputs into outputs and whose performances are to be evaluated. Some common input and output items for each decision making units are selected as follows:

(i) Numerical data are to be used for each input and output, with the data assumed to be positive for the outputs and strictly positive for the inputs.

(ii) The items (inputs, outputs and choice of decision making units) should clearly represent the analyst's interest in the components that will enter into the relative efficiency evaluations of the DMUs.

(iii) As mentioned above smaller input amounts are preferable and larger output amounts are preferable so the efficiency scores should reflect the reality within the data set available.

(iv) The measurement units of the different inputs and outputs need to be congruent.

The initial efficiency and ranking score then be compared to the results obtained by those non-DEA methods and incorporates value judgement through other MADM methods like AHP, TOPSIS, GTMA etc. For the batter comparison purpose the weights attached to the measuring parameters are adopted as employed by the non-DEA methods.

5. CLASSICAL DEA MODEL AND ITS MATHEMATICAL FORMULATION

In this section, we provide a basic of DEA model and extension to the DEA model. Productivity models have traditionally been used to measure efficiency of systems. Typically, DEA productivity models for a given "decision making unit" use ratios based on the amount of output per given input. The general efficiency measure that is used by DEA can best be summarized as follows:

There are s decision making units (DMUs) and that each DMU_p (p = 1, 2, ., s) utilizes m inputs and generates n outputs. The values of inputs and outputs of a DMU_p are represented by the input data matrix X and output data matrix Y respectively. Input matrix X is defined as the (m × s) matrix with columns X_p, while output matrix Y is the (n × s) matrix with columns Y_p using i(i = 1, 2, …, m) and j(j = 1, 2, …, n) to index inputs and outputs. *Then* x_{ip} is a single entry from the matrix X and it represents the value of input i of the DMU_p, while y_{jp} is a single entry of the matrix Y and it represents the value of output j of the DMU_p. Classical DEA model assume that all the inputs are relevant to all the outputs.

Let the input and output data for DMU_k be (x_{1k}, x_{2k} ,..., x_{mk}) and (y_{1k}, y_{2k} ,..., y_{sk}) respectively and can be arranged as follows:

$$X = \begin{vmatrix} x_{11} & x_{12} \cdots & x_{1s} \\ x_{21} & x_{22} \cdots & x_{2s} \\ . & . & . \\ . & . & . \\ x_{m1} & x_{m2} \cdots & x_{ms} \end{vmatrix} \qquad (1)$$

$$Y = \begin{vmatrix} y_{11} & y_{12} \cdots & y_{1s} \\ y_{21} & y_{22} \cdots & y_{2s} \\ . & . & . \\ . & . & . \\ y_{n1} & y_{n2} \cdots & y_{ns} \end{vmatrix} \qquad (2)$$

With the above notation, and according to [1], DEA-CCR input ratio form for calculating efficiency θ_k for some DMU_k is defined as:

$$\theta_k = \max_{a_i, b_j \geq 0} \left\{ \frac{\sum_{j=1}^{n} b_j y_{jk}}{\sum_{i=1}^{m} a_i x_{ik}} \middle| \frac{\sum_{j=1}^{n} b_j y_{jp}}{\sum_{i=1}^{m} a_i x_{ip}} \leq 1, \forall p (p = 1,2,...,s) \right\} \qquad (3)$$

Where,

y_{jk} – Value for output j for DMU k (Where k is the test DMU)

x_{ik} – Value for input i for DMU k

b_j – Weight of output j ≥ 0

a_i – Weight of input i ≥ 0

5.1 EVALUATION BASED ON DEA METHODOLOGY

To illustrate the use of classical DEA-CCR model in applications, we will take an example problem to evaluate the work material keeping in mind the overall performance of any alternate material. It was recommended by [8] to short-list various work materials on the basis of satisfying the required design and functionality of the product. Machining process input variables such as work material variables play an important role in short-listing. After short-listing the materials, the main criterion to choose the work material is its operational performance while being machined, i.e., the resulting machining process output variables.

Step-1 Table 1 shows the quantitative data set for the analysis. These data are normalized according to the method adopted in AHP technique and given in Table 2. The weights assigned are taken same as that of the non-DEA method for the better comparison purpose.

Weights for the input variables are:

$W_{CF} = a_1 = 0.1429$; $W_{PI} = a_2 = 0.1429$; Weight for the output variable is: $W_{VC} = b_1 = 0.7142$;

Table 2 DEA scores for the alternative work materials

Decision Units (Work Materials)	Scores
W_1: GK-AlSi10Mg (aluminium-silicon die cast alloy	0.9208
W_2: GK-alSi6/cu4 (aluminium-silicon die-cast alloy)	0.9805
W_3: GK-AlMg5 (aluminium-magnesium die-cast alloy)	0.9999
W_4: GK-MgAl9Zn (magnesium-alumium die-cast alloy)	1.0000
W_5: GG26 (Gray cast iron with lamellar graphite)	0.4056
W_6: C35 (low-carbon steel)	0.2523

Step-2 *Formulation of the input and output matrices* X and Y respectively.

$$X_{ip} = \begin{vmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} & x_{16} & x_{1p} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} & x_{26} & x_{2p} \end{vmatrix}$$

$$Y_{jp} = \begin{vmatrix} y_{11} & y_{12} & y_{13} & y_{14} & y_{15} & y_{16} & y_{1p} \end{vmatrix} \quad (4)$$

Now, the characteristics input matrix and output matrix can be represented as follow:

$$X = \begin{vmatrix} 400 & 415 & 440 & 235 & 1150 & 1750 \\ 28 & 38 & 59 & 43 & 8 & 19 \end{vmatrix}$$

$$Y = \begin{vmatrix} 710 & 900 & 1630 & 1720 & 120 & 160 \end{vmatrix} \quad (5)$$

$\langle w_1 \rangle$ max $\theta = b$

Subject to $400a_1 + 28a_2 = 710$

$710 \le 400a_1 + 28a_2$ (1) $900 \le 415a_1 + 38a_2$ (2)

$1630 \le 440a_1 + 59a_2$ (3) $1720 \le 235a_1 + 43a_2$ (4)

$120 \le 1150a_1 + 8a_2$ (5) $160 \le 1750a_1 + 19a_2$ (6)

Here, all the variables are constrained to be nonnegative. From the objective function inserting the value, $a_2 = \dfrac{710 - 400a_1}{28}$ in all the constraints from (1) to (6), and observing the relationship between a_1 and a_2. The result found optimal solution with the (2) and gives the unique optimal solution is: a_1 =0.4972, a_2 = 16.2463 and b =0.9208

Hence, $\theta = b$ =0.9208

$\langle w_2 \rangle$ max $\theta = b$

Subject to $415a_1 + 38a_2 = 900$

$710 \le 400a_1 + 28a_2$ (1) $900 \le 415a_1 + 38a_2$ (2)

$1630 \le 440a_1 + 59a_2$ (3) $1720 \le 235a_1 + 43a_2$ (4)

$120 \le 1150a_1 + 8a_2$ (5) $160a \le 1750a_1 + 19a_2$ (6)

The unique optimal solution is: a_1 = 0.0654, a_2 =22.9610

Hence, $\theta = b$ =0.9805

$\langle w_3 \rangle$ max $\theta = b$

Subject to $440a_1 + 59a_2 = 1630$

$710 \le 400a_1 + 28a_2$ (1) $900 \le 415a_1 + 38a_2$ (2)

$1630 \le 440a_1 + 59a_2$ (3) $1720 \le 235a_1 + 43a_2$ (4)

$120 \le 1150a_1 + 8a_2$ (5) $160a \le 1750a_1 + 19a_2$ (6)

The unique optimal solution is a_1 = 0.3324, a_2 = 22.5081

Hence, $\theta = b$ =0.9999

$\langle w_4 \rangle$ max $\theta = b$

Subject to $235a_1 + 43a_2 = 1720$

$710 \le 400a_1 + 28a_2$ (1) $900 \le 415a_1 + 38a_2$ (2)

$1630 \le 440a_1 + 59a_2$ (3) $1720 \le 235a_1 + 43a_2$ (4)

$120 \le 1150a_1 + 8a_2$ (5) $160 \le 1750a_1 + 19a_2$ (6)

The unique optimal solution is: a_1 = 0.3324, a_1 = 25.1482

Hence, $\theta = b$ = 0.9999

$\langle w_5 \rangle$ max $\theta = b$

Subject to $1150a_1 + 8a_2 = 120$

$710 \le 400a_1 + 28a_2$ (1) $900 \le 415a_1 + 38a_2$ (2)

$1630 \le 440a_1 + 59a_2$ (3) $1720 \le 235a_1 + 43a_2$ (4)

$120 \le 1150a_1 + 8a_2$ (5) $160a \le 1750a_1 + 19a_2$ (6)

The unique optimal solution is a_1 = 0.1808, a_2 = 10.9900

Hence, $\theta = b$ = 0.4056

$\langle w_6 \rangle$ max $\theta = b$

Subject to $1750a_1 + 19a_2 = 160$

$710 \le 400a_1 + 28a_2$ (1) $900 \le 415a_1 + 38a_2$ (2)

$1630 \le 440a_1 + 59a_2$ (3) $1720 \le 235a_1 + 43a_2$ (4)

$120 \le 1150a_1 + 8a_2$ (5) $160a \le 1750a_1 + 19a_2$ (6)

The unique optimal solution is a_1 = 0.2269, a_2 =12.4776

Hence, $\theta = b$ = 0.2523

Step-3 The indices for the overall performance of the alternative work materials are given in table 2. The DEA results obtained show that DMU_4 is the best choice from all six work material. From table 2 it is very clear that the 4th Decision making unit (W_4- GK-MgAl9Zn) is the best with maximum DEA score of 1.000 and the 6th Decision making unit (W_6-C35) is the worst with minimum DEA score of 0.2523. Rest of the decision making units are marked with their relative scores with reference to the best and worst decision making units for this particular application.

6. CONCLUSION

Various inputs and outputs are selected for the purpose of measuring efficiency from different perspectives of the various work materials. The evaluation of the overall performance shows that the 4th work material is the most significant for the suggested turning operation with high-speed machining tools. In contratory to that the 6th work material is the worst choice for the same machining operation. The other materials are suitable for the operation with their relative scores. The final ranking of the work materials can be given as given in Table 3.

Table 3 Ranking of the alternative work Materials

Decision Units (Work Materials)	Rank
W4: GK-MgAl9Zn (magnesium-alumium die-cast alloy)	1
W3: GK-AlMg5 (aluminium-magnesium die-cast alloy)	2
W2: GK-alSi6/cu4 (aluminium-silicon die-cast alloy)	3
W1: GK-AlSi10Mg (aluminium-silicon die cast alloy)	4
W5: GG26 (Gray cast iron with lamellar graphite)	5
W6: C35 (Low-carbon steel)	6

This is a very specific case of ranking with two input variables and a single output variable. If the number of attributes are found more than the problem can be solved using linear programming method to rank the alternatives.

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