Title	Decision Engineering Methodology
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Citation	
Issue Date	2005-11
Type	Conference Paper
Text version	publisher
URL	http://hdl.handle.net/10119/3936
Rights	ⓒ2005 JAIST Press
Description	The original publication is available at JAIST Press http://www.jaist.ac.jp/library/jaist-press/index.html, IFSR 2005 : Proceedings of the First World Congress of the International Federation for Systems Research : The New Roles of Systems Sciences For a Knowledge-based Society : Nov. 14-17, 2146, Kobe, Japan, Symposium 1, Session 7 : Technology Creation Based on Knowledge Science Modeling and Systems(1)

Decision Engineering Methodology

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ABSTRACT

In industry, decision makers are often confronted with multiobjective decision problems that are not easy to resolve. In this paper we suggest a comprehensive methodology which allows us to determine an adequate model predicting the performance criteria, to discretize the Pareto domain defined in terms of input parameters and to classify of large number of possible solutions from the Pareto domain with decision rules which are based on decision maker preferences. These rules are then applied to determine the preferred zone of operation. The whole approach we call the decision engineering methodology.

Keywords: neural network, genetic algorithm, Pareto domain, Rough Set Method, multi-criteria analysis, preferences, robustness analysis.

1. INTRODUCTION

During the operation of an industrial process, the operator should ideally select values of input parameters/variables from a performance criteria point of view. The main problem facing the decision maker is that the range of parameter/variable values is usually very large and the number of their combinations is even larger such that a decision aid methodology is required to assist the decision maker in the judicious selection of all values of the process parameter/variables. This is at the core of the new decision engineering methodology, which mainly consists of four steps:

- Process modelling,
- Determination of Pareto domain defined in terms of input parameters,
- Pareto Set ranking by the Rough Set Method,
- Result analysis (Robustness analysis).

2. PROCESS MODELLING

This methodology will be illustrated using two industrially-relevant examples: an extrusion process and a pulping process. The first one deals with the food granulation for cattle. In this process, a pulverulent product is converted into granules due to the conjugated effects of heat, moisture and pressure. The objective is to determine the best working conditions of the industrial process that will optimize simultaneously some relevant performance criteria. These performance criteria must be modeled in terms of input parameters/variables. For the granulation process, the aim is to minimize the friability index of the granules (Y_1), the moisture (Y_2) and the energy consumption (Y_3). Two input variables are taken into account in this study: the flour temperature (X_1) and the drawplate profile diameter (X_2). All three performance criteria are expressed by the quadratic functions of two input variables. These functions are given by Courcoux et al. [1].The second application deals with a high yield pulping process using Jack pine as the source of fibers. To determine an adequate model predicting the performance criteria as a function of the input process variables, a series of experiments were performed. These experiments were conducted by Lanouette et al. [5] in a pilot-scale pulp processing located in the Pulp and Paper Research Centre at Université du Québec à Trois-Rivières. Among the numerous performance criteria, four criteria were retained as they are considered the most important ones for this process (see Thibault et al. [9]).The aim is to maximize both the ISO brightness (Y_1) and the rupture length (Y_4), while reducing the specific refining energy (Y_2) and the extractive contents (Y_3). To evaluate the performance criteria, a D-Optimal design has been chosen. It consists of a group of design points chosen to maximize the determinant of the Fisher information matrix (X'X). To model each performance criterion of the process a neural network was used. Each neural network used the seven input process variables as input to the neural network models.

3. DETERMINATION OF PARE TO DOMAIN

The next step of the methodology consists of determining the region circumscribing all feasible solutions of the input variables represented by a large number of data points. An extension of the traditional genetic algorithm is suggested to deal with discretized data by introducing the dominance concept (see [4], [8] and [9]).The procedure to obtain a good approximation of the Pareto domain is relatively simple. The n points randomly chosen initialize the search algorithm. For each point, the performance criteria are evaluated. Then a dominance function, consisting of counting the number of times a given point is dominated by the other points, is calculated. A fraction of the dominated points corresponding to those most dominated is discarded. The non-dominated and the least dominated points are retained and recombined to replace the dominated ones. The recombination procedure is applied until all points are non-dominated. In the case of the granulation process, the Pareto domain defined in terms of input variables/parameters is represented by 5000 points whereas 6000 were used for the pulping process. This number of points is too numerous to allow the decision-maker to select the zone of optimal conditions. For this reason it is necessary to use a ranking algorithm to establish the optimal region of operation. The next step of this overall methodology deals with this problem. The particular method used in this investigation is the Rough Set method.

4. ANKING THE ENTIREPARETO SET USING THEROUGH SET METHOD

The Rough Set method is used to rank a large number of non-dominated points from the Pareto domain. The procedure of this method can be summarized as follows. Firstly, an expert provides the desired outcome of each individual criterion. (minimize, maximize or attain an actual target value). Then, a small sample of significant points from the Pareto domain (between 5 and 10) is presented to the expert who must classify these points from best to worst. The next step is to establish a set of rules that are based on the expert's classification. To do this we use the Rough Set theory suggested by Pawlak [6] [7], and developed by himself and others [2] [3] [10]. The last step of the Rough Set method is to apply the rules to rank the all n points from the Pareto domain. To do this, all points of the Pareto domain are ranked using the procedure Net-Flow score (NFS). The best point is established by ranking the n Pareto-optimal points in decreasing order of the NFS values. The rough set approach provides a clear recommendation as to the optimal zone of operation. For instance, for the food granulation problem, the best combination of the two process controlling parameters is a temperature of 74.85^{o}C and a drawplate profile diameter of 2.80 cm. In the case of the pulping process application, the Rough Set Method has suggested eight decisions rules, four preferences and four non preferences rules, which are applied to rank the whole set of 6000 point from the Pareto domain and thereby providing values of the seven process input variables that lead to the best compromise of the four objective criteria.

5. RESULT ANALYSIS (ROBUSTNESS ANALYSIS)

The last step of the proposed methodology is to perform an analysis of the results and in particular how robust is the final solution that was obtained. For the case of the food granulation process, the point chosen as the best is on the border of the Pareto domain. This solution could be considered as robust when no variation of the working conditions of the process is observed. In practice, this condition is rarely verified in an industrial process. It is therefore necessary to define another criterion to insure that the optimal solution will always lie inside the Pareto domain despite inherent process variations. In this investigation, the technical robustness was insured by the additional maximization of the distance between a point and the border of the Pareto domain. The expert must therefore consider this new attribute in order to provide a new classification of the subset of representative points, and a new set of decision rules is obtained. Performing once more the classification of the entire set of points of the Pareto domain, a new optimal point is obtained. For the food granulation problem, this new point, which decreases the impact of a possible instability to the process, is a temperature of 66.00°C and 2.82 cm for the best drawplate profile The results confirm the importance of an additional criterion to insure the technical robustness of the optimal solution.

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