Artificial Intelligence-Based Stepwise Selection of Bearings

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Abstract

Within a mechanical system such as an automotive the number of standard machine parts is increasing, so that the parts selection becomes more important than ever before. Selection of appropriate bearings in the preliminary design phase of a machine is also important. In this paper, three decision-making approaches are compared to find out a model that is appropriate to bearing selection problem. An artificial neural network, which is trained with real design cases, is used to select a bearing mechanism at the first step. Then, the subtype of the bearing is selected by the weighting factor method. Finally, types of peripherals such as lubrication methods are determined by a rule-based expert system.

Keywords:

Bearings selection, Expert system, Neural network, Multi-attribute decision making

Introduction

Modern mechanical systems are sophisticated and need variety of elements. It is impossible for a company to produce all the machine components by itself. As the number of standard machine parts is increasing, the selection of the machine components becomes more important than ever before. [1],[2] And artificial intelligence is efficiently applicable to machine design. [3]

Bearings are machine elements, which give critical effects on the performance of a machine. The basic functions of the bearing are to support, with enough stiffness, the load acting on between the stationary body (bearing) and the moving body (shaft), and to minimize the friction resistance in the direction of rotation. In general, bearing selection is considered as a key process in preliminary machine design.

Fagan [4] exploited the rule-based expert system in developing a support tool for bearing design. Pathak et al [5] and Rao [6] have studied on the selection of rolling bearing by means of the rule-based expert system. Rowe [7] and Cheng et al [8] use the weighting sum model (WSM) for the selection strategy, which is a typical method of multi-attribute decision-making (MADM). Other MADM methods [9],[10] have also been introduced. Chen [11] added the fuzzy rating concept to the WSM.

Butler et al [12] introduced the Dampster-Shafer theory to the bearing selection problem in order to improve the performance of decision-making.

However, many of existing studies are limited to selection of the subtypes, especially rolling element bearings. And they pay little consideration to the characteristics of each decision method used in bearing selection. [13]

In this paper we show that the bearing selection problem is divided into several steps based on design characteristics. Then, we suggest an AI-based decision model in which several artificial intelligence techniques are applied in sequence, and the usefulness of the model is verified by a sample design case.

Related Decision-Making Approaches

Part selection problem belongs to the certainty-based decision-making because the gains are already determined when an alternative is selected. Furthermore, the problem is classified as a complementary model of multi-attribute decision-making (MADM), where the alternatives have a plurality of trading-off attributes. The MADM has been a popular way of studying selection problems.

The selection problem has been a main field of artificial intelligence such as expert system and neural network, because it requires experiential domain knowledge and specialties.

MADM (Multi-attribute decision-making)

The typical MADM methods are the weighted sum model

(WSM), the weighted product model (WPM), and the analytic hierarchy method (AHM). The WSM is the simplest MADM method and still widely used. The supposition that governs this model is the additive utility assumption. The WSM should be used only when the value of each attribute is expressed in equal scale.

Expert system

Expert systems, or knowledge-based systems, are computer programs, which embody knowledge of a narrow domain to solve problems of that domain [14]. An expert system usually comprises two main elements, a knowledge base and an inference mechanism. The knowledge base contains domain knowledge, which may be expressed in any combination of 'IF-THEN' rules, factual statements, frames, objects, procedures, and cases. The inference mechanism manipulates the stored knowledge to produce solutions for problems.

Most expert systems are developed as *shells*. A shell is a ready-made expert system, which consists of inference mechanism and knowledge storage facilities, but without the domain knowledge. Sophisticated expert systems are equipped with *development environments*. They are more flexible than simple shells in that they also provide means for users to implement their own inference mechanism and knowledge representation methods.

Expert systems are probably the most mature methods. Many commercial shells and development tools are available. Consequently, once the domain knowledge to be incorporated in an expert system has been extracted, the process of building the system is relatively simple.

ANN (artificial neural network)

A neural network is a computational model of the brain. Neural network models assume that computation is distributed over several simple units called neurons, which are interconnected and operate in parallel (hence, neural networks are also called parallel-distributed-processing systems or connectionist systems) [14].

Artificial neural networks can capture domain knowledge from examples. They can readily handle both continuous and discrete data. They also have a good generalization capability. However, they do not archive the acquired knowledge in an explicit form.

The most popular neural network is the multi-layer perceptron, which is a feedforward network. All signals flow in a single direction from the input to the output of the network. Feedforward networks can perform static mapping between an input space and an output space. The output at a given instant is a function of the input at that instant.

Implicit *knowledge* is built into a neural network through training. Some neural networks can be trained with typical input patterns and the corresponding expected output patterns. The error between the actual and expected outputs is used to modify the strengths of the connections between the neurons. This method of training is known as supervised training. In a multi-layer perceptron, the back-propagation algorithm for supervised training is often adopted to propagate the error from the output neurons and compute the weight modifications for the neurons in the hidden layers.

Neural networks can be employed as mapping devices, pattern classifiers, or pattern completors. Like expert systems, they have found a wide spectrum of applications in most areas of engineering.

Comparison of Decision-Making Approaches

Part selection problem is classified as a complementary model of multi-attribute decision-making (MADM), where the alternatives have a plurality of trading-off attributes. The MADM has been a popular way of studying selection problems. And also the selection problem has been a main field of artificial intelligence such as expert system and neural network, because it requires experiential domain knowledge and specialties [5],[6].

Those decision-making approaches have their own characteristics. Thus, it is important to analyze the selection problem in terms of decision-making characteristics to find out appropriate decision method. Table 1 shows the characteristics of some approaches to be used for a selection problem.

The MADM is easy to develop and maintain because the decision-making process is based on the matrix calculation. The MADM is proper to the problem in which the knowledge on selection can be easily expressed in numeric value. The RBES uses a lot of rules. It takes many days to construct a rule base for the selection problem where many attributes are related. A strong point of the RBES is that it has excellent explanation function. The ANN learns the knowledge needed in selection through implicit mathematical processing based on real cases. The ANN is desirable for the problem where it is easy to collect cases. The weak point of the ANN is that it has no explanation function. [13]

Table 1 - Characteristics of selection approaches

Subject	MADM	RBES	ANN
Approach	Calculating	Reasoning	Learning
Source of knowledge	Expert, data book	Expert, catalogue	Database, expert
Knowledge acquisition	Easy	Difficult	Easy
Explanation	Fair	Good	None
Development time	Very fast	Slow	Fast
Maintenance	Very easy	Difficult	Easy

Stepwise Selection of Bearing

Integration of ANN and ES

Caudill [15] has suggested a concept of expert network, which means the integration of the ES (expert system) and the ANN (artificial neural network). The different characteristics of the technologies suggest that they can complement each other. It was suggested that the two technologies could be used jointly to solve problems, where each technology solves a different aspect of the problem. Madesker and Turban [16] classified the integration of the technologies into three typical models: (a) ANN supports ES, (b) ES support ANN, and (c) combining ES and ANN in parallel. In the following section, we suggest a stepwise model, a modified model of (c), that combines ES and ANN in series and apply the model to the bearing selection problem.

Bearing selection process

A bearing designer should select the bearing mechanisms before selecting the bearing subtype and also determine the peripherals such as sealing mechanisms, lubrication methods, mounting devices, and others after that. The bearing selection problem of the preliminary design may be divided into three steps as shown in Figure 1. In the first step, the main type of bearing is selected through an ANN. The second step is to select bearing subtype using the MADM. Finally, the peripherals of bearings are selected by an expert system including rules obtained from catalogs or handbooks.

A case study of stepwise bearing selection

The neural network used to select the bearing mechanism has 13 nodes, on the input layer, corresponding to the design requirements, and 6 nodes on the output layer corresponding to main bearing mechanisms. The neural network has been trained using a number of cases shown in Table 2. Each case implicates a pattern that correlates a bearing mechanism with a set of attribute values. The values of the nodes of input and output layers may be numeric value, symbolic value, or logical value.

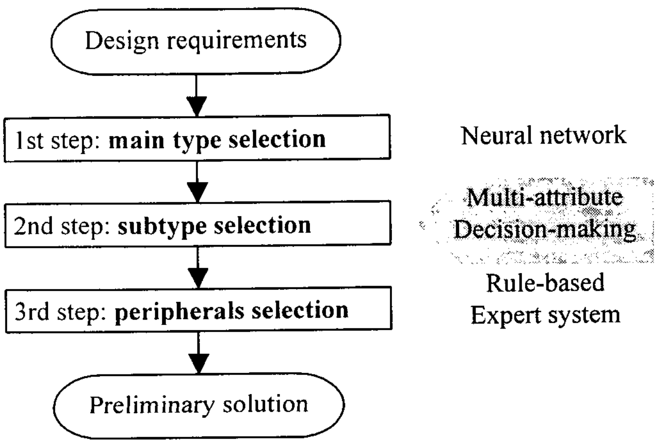

Figure 1 - Stepwise bearing selection model

Table 2 Sample patterns used to train the neural network

Case		1	2	3	Data type (Ref. unit)
Output layer[1)]		O_2	O_1	O_6	Symbolic (O_j j=1,2, ⋯,6)
I	Max. load (I_1)	1	1	10	Numeric (1000kgf)
	Max. speed (I_2)	1	1.8	7	Numeric (10000rpm)
	Stiffness (I_3)	H	H	H	Symbolic
	Accuracy (I_4)	0.1	1.0	1.0	Numeric (mic.)
	Installation space (I_5)	S	M	L	Symbolic
	Direction change (I_6)	Y	N	Y	Logical
	Frequency of start/stop (I_7)	H	M	M	Symbolic
	Temp. (I_8)	100	300	30	Numeric (°C)
	Impact load (I_9)	N	N	Y	Logical
	Cleanness (I_{10})	Y	Y	N	Logical
	Vacuum (I_{11})	N	Y	N	Logical
	Humidity (I_{12})	N	N	Y	Logical
	Noise (I_{13})	N	N	Y	Logical

1) Rolling bearings (O_1), Hydrodynamic bearing (O_2), Hydrostatic bearings (O_3), Aerodynamic bearings (O_4), Aerostatic bearings (O_5), Magnetic bearings (O_6)

The resultant bearing mechanism appropriate for the design requirements is a rolling type, because the value of node 1 is close to 1.0 while values of the other nodes are close to 0.0. It was found that the result is consistent with a real case.

The factors of rolling bearings used in the weighting sum model to select the subtype of bearing are radial load, rotational speed, impact resistance, low friction characteristics, and accuracy. The weightings are determined by the designer's preference of each attribute. Table 3 shows the results of bearing subtype selection according to a weighting combination, which considers radial load as the most important factor relative to the others. As the result cylindrical roller bearing (N, NU) is selected.

The problem of selecting bearing peripherals is different from the above two steps. There is relatively small number of factors reflecting the strategies needed in the selection. Selecting rules can be easily obtained from the guidebooks or catalogues provided by makers. In this study, lubrication method, sealing method, and mounting method of bearings are selected by a knowledge-based expert system. Figure 2 shows a result based on an input condition of rotational speed 7000 rpm, shaft diameter 70 mm, and gears included.

Table 3 - Bearing subtype selection using WSM

Alternative rolling bearings	Resultant values
Cylindrical roller (N,NU)	**0.781**
Cylindrical roller (NF,NH)	0.719
Double ball angular	0.5
Double ball deep groove	0.5
Double ball self-align	0.375
Double roller (NN)	0.75
Single ball angular	0.625
Single ball deep groove	0.625
Single ball megneto	0.469
Single ball self-align	0.344
Spherical roller self-align	0.75
Tapered double roller	0.75
Tapered single roller	0.688

It shows that four rule chains have been fired and the splash oil lubrication method has been selected through the rule chain R1_6.

Discussion

In the first step of the stepwise bearing selection process, the main type of bearing is selected using an ANN (artificial neural network), because the knowledge required for selecting the main type of bearing is difficult to represent as a numerical form or as a logic, while it is possible to collect design cases. The ANN can be replaced by other experience-based method such as case-based reasoning (CBR) and the Dampster-Shafer theory.

The MADM (multi-attribute decision-making) is suitable for the second step because the knowledge used in selecting bearing subtype is relatively clear. Furthermore, in this step, it is easy to choose attributes of bearings, and the knowledge for rating and weighting attributes is well structured.

Finally, the peripherals of bearings are selected by a rule-based expert system because the knowledge obtained from catalogues or handbooks can be easily transformed into rules, and does not change frequently. The rule-base is made up of 4 common rules and 6 main rules. The common rules are repeatedly utilized as sub-rules of the main rules. As the result, the size of rule-base is minimized.

Conclusion

In this study we suggested an AI-based decision model, which is applicable to the process of bearing selection. The bearing selection process of a machine design has been analyzed in terms of knowledge characteristics. An AI-based decision model that is appropriate to bearing selection is suggested. An artificial neural network, which is trained with industry design cases, has been used to select a bearing mechanism in the first step. Then, the subtype of the bearing has been selected using the weighting factor method. Finally, the types of peripherals such as lubrication method have been determined using a rule-based expert system.

The usefulness of the AI-based decision process has been verified by a sample bearing selection problem. The AI-based stepwise selection model adopted in this paper is applicable to other product selection problems.

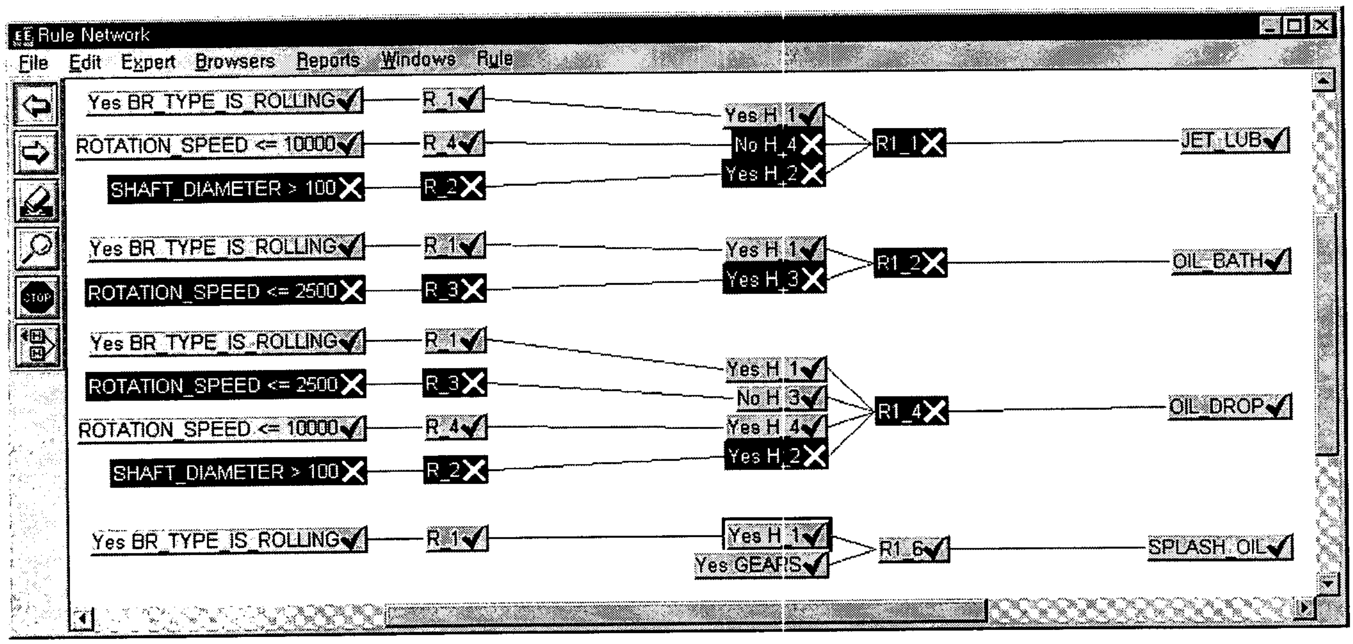

Figure 2 - Rule network showing an executed result

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