N95- 19641

34076

p. 10

A CLIPS-BASED EXPERT SYSTEM FOR THE EVALUATION AND SELECTION OF ROBOTS

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ABSTRACT

This paper describes the development of a prototype expert system for the intelligent selection of robots for manufacturing operations. The paper first develops a comprehensive, three-stage process to model the robot selection problem. The decisions involved in this model easily lend themselves to an expert system application. A rule-based system, based on the selection model, is developed using the CLIPS expert system shell. Data about actual robots is used to test the performance of the prototype system. Further extensions to the rule-based system for data handling and interfacing capabilities are suggested.

INTRODUCTION

Many aspects of today's manufacturing activities are increasingly being automated in a feverish pursuit of quality, productivity, and competitiveness. Robotics has contributed significantly to these efforts; more specifically, industrial robots are playing an increasingly vital role in improving the production and manufacturing processes of many industries [6].

The decision to acquire a robot, however, is a nontrivial one, not only because it involves a large capital outlay that has to be justified, but also because it is largely complicated by a very wide range of robot models from numerous vendors [6]. A non-computer-assisted (manual) robot selection entails a number of risks, one of which is that the selected robot might not meet the task requirements; even if it does, it might not be the optimal or the most economical one. Mathematical modeling techniques, such as integer programming, are rather awkward and inflexible in tackling this problem. The reason for this is that the robot selection process is an ill-structured and complex one, involving not only production and engineering analysis, but also cost/benefit analysis and even vendor analysis. Its ill-structured nature does not readily lend itself to tractable mathematical modeling. Therefore, nontraditional approaches, such as expert systems (ES) or artificial neural networks (ANN), seem intuitively appealing tools in these circumstances.

When the decision maker (DM) is charged with making the selection decision, he or she is being called upon to play three roles at the same time, namely (1) financial analyst, (2) robotics expert, and (3) production manager. In other words, the decision maker would need to make three different (albeit related) decisions: (1) choosing the best robots that match the task requirements at hand, (2) choosing the most cost effective one(s) from those that meet the requirements, and (3) deciding from which vendor to order the robot(s). We shall call these decisions *technical*, *economic*, and *acquisitional*, respectively. Clearly, these are very complex decisions all to be made by the same decision maker. Supporting these decisions (e.g., by a knowledge-based system) should alleviate the burden from the decision maker and bring some consistency and confidence in the overall selection process. The success of the ES technology in a wide range of application domains and problem areas has inspired its use as a vehicle for automating decisions in production and operations management [1, 19], as well as the robot selection decision [16, 17].

In this paper, a three-stage model is presented for the robot selection process. The model is *comprehensive* enough to include the major and critical aspects of the selection decision. It is implemented in a CLIPS-based prototype expert system. The rest of the paper is organized as follows. In the following section, we review previous work and, in the third section, we present our three-stage model to robot selection. In the fourth section, the implementation of the prototype expert system is discussed. Limitations of, and extensions to the prototype expert system with database management (DBMS) capabilities are provided in section five. We conclude the paper in section six.

MOTIVATION AND RELATED WORK

The application of knowledge-based systems in production and operations management has been investigated by a number of researchers [1]. In particular, the application of ES in quality control [3], in job shop scheduling [18, 19], and industrial equipment selection [11, 20] has been reported in the literature. The robot selection problem is prominent in this line of research [8, 15, 17].

In an earlier paper by Knott and Getto [9], an economic model was presented for evaluating alternative robot systems under uncertainty. The authors used the present value concept to determine the relative worthiness of alternative robot configurations. Offodile, *et al.* [14, 15] discuss the development of a computer-aided robot selection system. The authors developed a coding and classification scheme for coding and storing robot characteristics in a database. The classification system would then aid the selection of the robot(s) that can perform the desired task. Economic modeling can then be used to choose the most cost-effective of those selected robots. Other related work includes Offodile *et al.* [16], Pham and Tacgin [17], and Wang, *et al.* [21].

A review of the above literature indicates that these models are deficient in at least one of the following measures:

- *Completeness:* We suggested earlier that the robot selection problem involves three related decisions. The models presented in the literature deal invariably with at most two of these decisions. The other aspects of the selection decision are thus implicitly assumedto be unimportant for the robot selection problem. Experience suggests that this is not the case, however.
- *Generality:* the models presented are restricted to specific production functions, e.g., assembly. Many of today's production functions are not monolithic but rather a collection of integrated functions, i.e., welding, assembly, painting, etc. In particular, industrial robots are by design multi-functional and a selection model should be robust enough to evaluate them for several tasks.
- *Focus:* The focus in the literature is often more on robot characteristics (robot-centered approach) than on the task the robot is supposed to perform (task-centered approach). We posit that task characteristics should be the primary focus in determining which robot to choose, not the converse.

We propose a three-stage model that captures the overall robot selection process, with primary emphasis being given to the *characteristics* and *requirements* of the *task* at hand. The proposed task-centered model is *comprehensive* in the sense that it covers the robot selection problem from the task identification, through robot selection, to vendor selection and, possibly, order placement. The model is also *general* in the sense that it applies to a wider range of industrial robot applications. While this selection model is different from previous approaches, it incorporates in a systematic manner all the critical decisions in any sound robot selection process. The sequential order of these decisions, and the related phases, is important from a logical as well as an efficiency standpoints. We cannot, for example, separate the technical decision from the economic decision, for a robot that is technically well suited to do the job might not be economical; and vice versa. We shall present our model in the following section and in the subsequent sections discuss its implementation in a knowledge-based system.

A THREE-STAGE MODEL FOR ROBOT SELECTION

Figure 1 depicts the three-stage robot section scheme proposed in this paper. We present a general discussion of the scheme in the subsequent subsections.

- *Technical decision:* This is the first and the most critical decision to be made. It is the formal selection of one or more candidate robots that satisfy the minimum requirements and characteristics of the task to be performed. It is technical in the sense that it would normally be made by the production or process engineer upon a careful analysis of the technical characteristics of both the task and the robot. This decision is the most difficult of the three. A thorough analysis is required to arrive at the initial set of feasible robots.

- *Economic decision:* This is a decision involving the economic merit of the robot. More specifically, it is a decision about the most cost-effective robot alternative(s) considering both initial cost (purchase price) and operating costs. The purpose of the initial and operating costs is twofold: (1) to allow for a rough justification for the robot, and (2) to allow for a choice to be made among rival robots. Suppose, for example, that we had a choice of two robots from Stage One (to be described shortly)—one which is adequate for the task and costs within reasonable range; the other is more technologically advanced but costs well beyond what is considered economical for the task in question. Clearly the estimated cost of the latter would force us to choose the former robot.

- *Acquisitional decision:* This is simply deciding which vendor to acquire the robot(s) from. The choice of a vendor is based not only on purchase price, but also on service and quality.

The following three stages implement the above decisions in a systematic manner.

Stage One: *Technical Decision*

The purpose of this first stage is to determine a (possibly set of) robot(s) that most closely matches the task requirements. The starting point is the application area, or more specifically, the task itself for which the robot is needed. Thus, we need to determine in this stage the following:

1. The application area, e.g., assembly, welding, painting, etc.
2. The task within the application area, e.g., small parts assembly.
3. The task requirements, e.g., precision, speed, load.
4. The robots that most fully satisfy these requirements.
5. Whether human workers can perform the task.
6. Whether to go with robots or humans, if 5 above is true.

Identifying Application:

There is a wide range of applications, across various industries, for which industrial robots may be engaged. Both the application area and the narrow task within that application area should be identified. Thus, within welding, for example, we would identify spot welding and arc welding.

Identifying Task Characteristics:

This phase requires identification of all the task characteristics that influence the decision to employ humans or robots, and the selection among alternative, technically feasible robots. These characteristics will include, for example, the required degree of precision and accuracy; whether it is too hazardous, dangerous, or difficult for humans; and whether significant increases in productivity and/or cost savings would result.

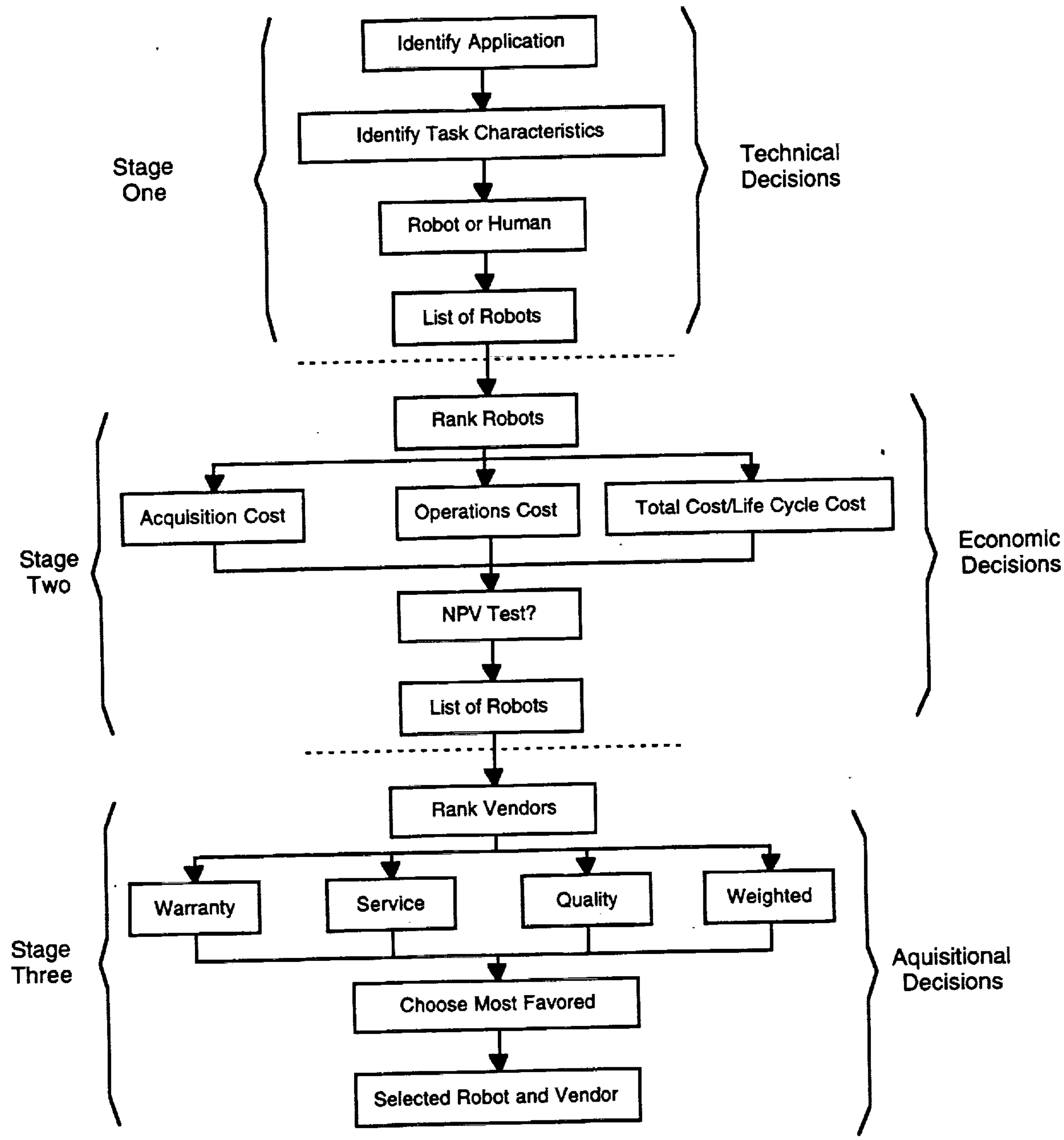

Figure 1: Three-Stage Robot Selection Model

A precise task definition might also require a task classification scheme, more fine-tuned than the one suggested by Ayres and Miller [2]. Since the desired robot is a function of the complexities of the task in question, we suggest the development of a task/robot grid (TRG) to associate specific task characteristics with relevant robot attributes. Let C_{ij} denote value j of task characteristic i, and A_{ij} denote value j of robot attribute i, i=1, 2, ..., m; j=1, 2, ..., n. Here C_{ij} is said to be compatible with A_{ij}, for particular values of i and j, if A_{ij} satisfies C_{ij}. For brevity, we denote this relationship by $C_{ij} \in A_{ij}$. Thus specifying task characteristic C_{ij} would automatically call for a robot attribute A_{ij} such that A_{ij} at least satisfies the task requirement $C_{ij}, \in i,j$.

Stage Two: *Economic Decision*

This stage can be called a cost justification stage. It utilizes the output from the first stage, which is one or more robots suited to the task at hand. The primary role of this stage is the identification of those robots that make economic sense to invest in; a present value approach is followed by the knowledge-based system to exclude all robots with net present value (NPV) less than their net cost (i.e., purchase price and operating costs). A ranking on the basis of the cost factor is then applied to the remaining robots, if any, i.e., to those passing the economic viability test. Thus, net present value analysis is used to determine whether it is profitable to employ any robot, given its net cost and the economic benefits (e.g., incremental cash flows) expected to accrue as a result of employing the robot to perform the task.

By the end of Stage Two we will have identified a subset of robots that are the most favorable in terms of performance as well as cost. Since a large number of vendors may be available, it is important to be able to get the "best" deal possible. This implies not only a good competitive price, but also acceptable quality, warranties, and a promise of support services.

Stage Three: *Acquisitional Decision*

In Stage three we have to rank, for every vendor, every robot that meets the choice criteria in Stages 1 and 2. The factors that are involved in these rankings are many. For example, Hunt [6] indicates that a certain study revealed the following factors as critical in the purchasing decisions of robots: design, performance, cost, maintenance, warranties, financial terms, and delivery terms. These can conveniently be grouped into four categories: (1) cost (purchase price and operating costs), (2) warranties, (3) quality (performance and design), and (4) service (support, financial and delivery terms). Maintenance is part of operating cost which is accounted for in Stage Two. Quality, services, warranties, and purchase price are the relevant factors in vendor selection. Purchase price has also played a role in the economic decision to determine the viability of each robot. Here, prices are used to compare vendors and rank robots accordingly. Therefore, for each vendor we rank the relevant robots on the basis of purchase price and the other three criteria (quality, warranties, services) and choose the most favorable vendor/robot combination.

THE KNOWLEDGE-BASED SYSTEM

We implemented the prototype knowledge-based system using the CLIPS expert system tool [12]. CLIPS is a forward-chaining rule-based language that resembles OPS5 and ART, two other widely known expert system tools [5]. Developed by NASA, CLIPS has shown an increasing popularity and acceptance by end users [10]. The two main components of this prototype, the knowledge base and the database, are discussed below.

The Knowledge Base

The primary focus of the selection model is the task characteristics, since it is these characteristics that determine what type of robot is needed. This emphasis is reflected in the knowledge base (KB) (or rule base) which captures the knowledge about different task requirements that are needed to justify the use of robots or humans and to specify a particular matching robot or robots. Thus, given certain task characteristics or requirements, the expert system will specify the most suitable robot configurations for performing the task.

The KB also includes knowledge about robot costs and how to manipulate these costs to justify (economically) the use of the respective robots and rank those robots that are considered justifiable. Thus, given operating and purchase costs for each robot, the expert system ranks them on the combined cost criterion. Finally, the KB also includes knowledge to help vendor selection. Subjective multiple criteria are used to compare vendors with associated robots of interest.

As a rule-based shell, CLIPS stores the knowledge in rules, which are logic-based structures, as shown in Figure 2. Figure 3 is a natural English counterpart of the rule in Figure 2.

```
;Rule No 29.
(Defrule find-robots-3rd-pass   "Technical Features"
     ?f <- (robot-2 ?robot)
          (Features (Accuracy ?v11)
                    (Repeat ?v12)
                    (Velocity ?v13)
                    (Payload ?v14)
          )
          (Robot      (ID ?robot)
                    (Accuracy ?v21&:(<= ?v21 ?v11))
                    (Repeat ?v22&:(<= ?v22 ?v12))
                    (Velocity ?v23&:(<= ?v23 ?v13))
                    (Payload ?v24&:(<= ?v24 ?v14))
          )
          =>
          (retract ?f)
          (assert (robot-3 ?robot)
)
```

Figure 2: Example Rule in CLIPS

```
Rule No 29: Finds robots matching given technical
                features.

IF        There is a robot for the application with the
          required grippers,

AND       This robot meets (at a minimum) the following
          technical features: Accuracy, Repeatability,
          Velocity, and Payload as specified by user

THEN      Add this robot to the set of currently feasible
          robots.
```

Figure 3: Example Rule in Natural English

The Database

The database is a critical resource for the ES; all details for robot configurations are contained in the database. The type of information stored for each robot includes:

- Robot class or model
- Performance characteristics
- Physical attributes

• Power characteristics

A full-fledged system would include the following additional information to permit proper comparisons among competing robots.

• Environment requirements
• General characteristics
• Operating costs

Figure 4 shows the information stored in the database for a typical robot using CLIPS syntax. As the figure indicates, each robot has a set of physical and performance characteristics (e.g., type of end effectors, number of axes, repeatability, etc.) and a set of application tasks within its capability. All of this information (and more) is supplied by robot vendors.

```
(Robot (ID RT001)
        (Control S2)
        (Power E)
        (Axes 6)
        (Accuracy .2)
        (Repeat .05)
        (Velocity 145)
        (Payload 6)
        (Effectors adjust-jaw)
        (Jobs ML PT SA EA IN)
        (Vendor "IBM Corp.")
)

(Vendor (ID VD001)
         (Name "IBM Corp.")
         (Robot-Info RT001 28500)
            (Service .95)
            (Warranty .8)
            (Quality .83)
)
```

Figure 4: "Facts" Stored as Frames in a CLIPS Database

Also contained in the database are vendor attributes such as service record, warranties, quality, robots carried and purchase prices (see Figure 3). The first three attributes are represented in the database by subjective scores (ratings), on a scale of 0 to 10. A "0" may indicate, for example, an F rating, "10" an A++ rating. This information could come from industry analysts and experts in the robotics industry.

Illustration

In this section we shall provide the results of a consultation with the prototype expert system using actual robotics data obtained from Fisher [4]. The first step in Stage One is to describe the application. For lack of space, we skip the dialogue that allows the decision maker to describe the task and its suitability for robots or human workers. On the basis of the information provided in that dialogue advice will be given as to the choice between a robot solution or human workers for the task. Next, in Stage Two, economic analysis is performed, using information elicited through a similar dialogue as in Stage one, to determine the economic merit of each robot passing the technical test. This involves calculating a net present value (NPV) for the net incremental benefits resulting from employing robotics in the task under consideration. The NPV is then compared to the net cost (price plus operating cost) of each robot, and only robots whose net cost is less than or equal to the NPV are chosen. If no robot is found to meet this test, the system offers two reasons for the failure:

1. that the task is not worth the required investments in robots, or
2. that the database includes insufficient number of robots.

In the last stage, Stage Three, the system elicits subjective input from the decision maker regarding the importance of vendor attributes, such as service or warranties. Again, the rating is on a scale of 0 to 10; "0" indicates unimportant and "10" maximally important. This information is then used to compute a subjective score for each vendor, by weighting the analyst's ratings of each vendor with the input from the decision maker. Now, robots can be ranked by both price and vendor weighted score. Figure 5 shows the final results of this consultation.

```
Indicate the importance of each of the following,
 on a scale from 0 to 10:
  1. Vendor service quality :7
  2. Vendor warranties :8
  3. Product quality :9
  4. Price :6
.....
Rank by Subjective score (S) or by Price (P)? p

Robot Index     Vendor Name                Price     Score
-----------     -----------                -----     ----
RT005           ASEA, Inc.                 $60000     17
RT007           Bendix                     $70000     13
RT011           Cincinnati Milacron        $90000     17
RT006           Automatix, Inc.            $95000     18
RT008           Bendix                     $95000     13
RT016           Kuka                      $125000     13

The net present value of cashflows:       $129036.6
```

Figure 5: Subjective Values and Final Results

LIMITATIONS AND EXTENSIONS

The description of the task as allowed by the current prototype provides only a broad definition of the nature of the task to be performed; it does not provide specific details or "tolerances." For example, to increase the chances of a match, the user may be tempted to supply larger (less tighter) values for positional accuracy and repeatability. However, this may result in a large number of robots being selected and the prototype system allows ranking only through price and vendor attributes. To rank robots for each and every attribute, however, would probably be both unwieldy and unrealistic.

Moreover, a knowledge-based robot selection system should provide a friendly interface that allows the decision maker to input English phrases to describe a particular application; the system would then use the task definition thus provided by the user to suggest applicable robot(s). Therefore, the crucial task of the knowledge-based system would be to make sense out of the English phrases supplied by the decision maker to describe the task. This implies that the knowledge-based system would have to have some natural language processing capability to properly associate the task description with meanings represented in the knowledge base. This, then, would pave the way for processing the applicable knowledge to reach a choice of a set of robots. Additionally, as mentioned earlier, the database component of the expert system needs to store a wealth of information about a wide range of robots and vendors. This information can be not only very detailed, but volatile as well, as the robot technology advances and as competition among vendor produces changes in vendor profiles. What all this amounts to is that the expert system needs to be able to survive the test of time and handle this voluminous data in a graceful manner. Current expert systems exhibit elementary data management capabilities which are inadequate for this inherently complex database. As Jarke and Vassiliou [7] indicate, a generalized Database Management System (DBMS) integrated in the ES may be necessary to deal with this database effectively. These authors sketch out four ways to extend expert systems with DBMS capabilities, not all of which are relevant in any given circumstances.

CONCLUSION

We presented in this paper a robot selection model based on a three-stage selection process; each stage feeds its output into the next stage until a final robot/vendor combination is selected. We implemented this model in a prototype knowledge-based system using the CLIPS expert system language. The prototype indicated that a full fledged expert system will be practical and can be extremely useful in providing a consistent and credible robot selection approach.

Further work is needed to improve the granularity and natural language processing capability of the system. Also needed is research into possibilities of extending the database management capabilities of the robot selection system by coupling it with a database management system.

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