Integrating an Expert System And a Neural Network for Process Planning[1]

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Abstract. This paper presents a computer aided process planner for metal furniture assembly, welding and painting using a rule based expert system integrated with an artificial neural network. The if/then rules create parts lists and process plans, while the neural network estimates standard processing times for individual product variations. Although essentially a variant process planner, the rules and neural network allows some generalization capability to new products. This development effort demonstrated that a composite intelligent approach can be useful for process planning in a real manufacturing situation.

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1. Introduction

Process planning is the activity of taking the product design or specification, which is defined in terms of size, shape, tolerances, finish, material properties, etc., and transforming it into a detailed list of manufacturing instructions such as specifications for materials, processes, sequences and machining parameters. The development of process plans and the determination of standard processing times are essential functions for most manufacturing organizations. These functions are time consuming and require significant skill and experiential knowledge to perform properly. This study used a metal furniture manufacturing environment as a test bed for the prototype system incorporating an expert rule base for process planning with a neural network for standard time estimation.

Computer-aided process planning (CAPP) systems have been devised to help simplify, improve, and provide consistency within the process planning function. Computer-aided systems have the potential to capture and retain the experiential knowledge of process planning personnel which may have taken years to develop. Furthermore, capturing this expertise in a knowledge base provides the ability to replicate process plans and expertise. There are two basic types of CAPP systems, variant and generative. The variant approach groups parts into families based on physical similarities and stores standard (core) process plans for each family. The

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standard plans can be retrieved automatically and annotated to conform to the specific product of interest. The generative approach uses detailed feature descriptions and decision logic to synthesize process plans, optimizing for each individual part and tool.

A standard process time for a given manufacturing process is the expected amount of time for a worker to complete the operation. Standard process times are usually determined using detailed time studies of the operation. Time studies involve repetitively timing the operation with various operators and making some subjective assessments concerning the operators' performance. Time studies are time consuming and tedious, however, the availability of standard process times is a valuable tool for many manufacturing organizations. Standard process times can be used to balance the flow of products through a manufacturing cell, estimate production costs, predict throughput times and evaluate operator performance.

Gupta and Ghosh [5] provided a survey of expert systems in manufacturing and process planning. Another survey of expert system approaches to process planning was published by Gupta [4] which discusses the important features and limitations of various expert systems, with respect to their part design input scheme, knowledge base representation and control strategy. Automating the CAD / CAM link has been the topic of considerable research and development efforts. Wang and Wysk [9] discuss why the expert system approach may replace algorithmic CAPP methods for various reasons. These include: 1) the organization of knowledge in an expert system (facts, rules, and control strategy) provides for much easier modification when compared to traditional computer systems, 2) decision trees and decision tables, which are often used in traditional generative CAPP systems, work effectively only for simple decision making processes, and 3) expert CAPP systems may be designed so that knowledge can be accumulated as time passes, which is not a capability of current variant and generative systems.

The majority of research in the area of automated process planning (including machine parameter and sequence planning and assembly sequence planning) has focused on the use of expert systems and algorithmic process planning techniques. More recent research has described the use of genetic algorithms [8] and fuzzy systems [10]. Also, recently some interest has occurred in using neural network technology in the development of automated process planning systems. Knapp and Wang [6] formulated an approach for the automated acquisition of process selection and within-feature process sequencing knowledge using neural networks. The authors in this reference cite several reasons why the use of neural networks are a preferable alternative to expert systems for process planning: 1) the expert system knowledge acquisition process is time consuming, costly and error prone, 2) the systems cannot adapt to change in manufacturing practice and technology, 3) expert systems are brittle in nature (i.e., with sharp boundaries of application), and 4) expert systems cannot generalize from past experience to handle new cases. Knapp and Wang [6] used a back-propagation network to map spur gear attributes or features into feasible machining operations, and the selection of only one machining operation at a time was forced using a MAXNET network. The network used a recurrent input to keep track of the previous machining operation. A similar approach was taken by Leung et al. [7] who used a bi-directional associative memory (BAM) neural network to select standard process plans from inputs describing the part features. Al-Ghanim and Cox [1] also used neural networks as pattern classifiers for process planning by inputting information about the part features, and using two neural networks to choose tool material type (three choices) and tool entry strategy (four choices), respectively. The application was milling. Chen and LeClair [2] presented another neural network approach to process planning. In this reference the authors discussed the use of an unsupervised neural network in machine setup generation. Intersecting and non-intersecting features within a setup are identified and classified using an associative memory.

One previously reported approach to process planning involving an integrated expert system and neural network approach was Chen and Pao [3]. They presented an approach to the design and planning of mechanical assemblies using an unsupervised neural network learning algorithm in the design stage to cluster similar conceptual designs which provides the input interface to the design cluster memory. The rule-based portion of the system then accesses this design cluster memory as required while performing its role in the generation of assembly plans. The system attempts to utilize the strengths of both neural network and rule-based modules to provide a more powerful single system, which is similar to the approach taken in this paper. What is novel about the research presented herein is that the neural network is used as function approximator rather than a pattern classifier, the application is a real manufacturing situation rather than a simplified “toy” problem, and the neural network is used for standard time prediction rather than choice of plans.

2. Project Objectives and Scope

The objective of this project was to develop a system which could perform process planning and process time prediction functions automatically. The result was to be a user friendly software package which utilizes expert system and neural network computing methods in a fashion which is transparent to the user. The prototype system was developed for a metal furniture manufacturer, Haskell Inc., to ensure that the problems and difficulties associated with a real manufacturing environment would be factored into the system. Haskell produces metal office furniture including pedestals, desks and file cabinets, and is considered representative because of its mainstream product line. It was determined that the final assembly area of the Cube Pedestal product line would provide a good test case for the prototype system. The Cube Pedestal is a stand alone, desk high, filing cabinet. There are significant variations available within this product line including two different heights (executive and typing), three depths (20, 24, and 30 inches), various drawer types (four drawer types are available: tray, box, file and EDP), various drawer handle and filing accessory options, several lock and support options, and many paint color choices.

Within the Cube Pedestal product line additional product variations are feasible which are not currently available and which would not require changes to the basic components which make up the assembly. Specifically, many different drawer combinations which are currently not a standard option are feasible by altering only the quantity of parts required and the assembly process. Altering the process plan to accommodate these special order cases was a good test of the process planner's ability to generalize.

As stated above, no written process plans exist for the final assembly area. Currently the specific processing steps completed for each of the 14 major processes are determined by an experienced operator. These are shown along with their required sequence in Figure 1. A brief description of each of these 14 processes in order of occurrence follows:

INSERT FIGURE 1 HERE

1. MIG WELD NUTS TO BOTTOM CHANNEL - In this process two nuts are MIG welded to each of two bottom channels. These nuts are used to attach the glides to the bottom of the pedestal. Three lengths of bottom channel exist to support the three available pedestal depths.

2. FORM WRAPPERS - In this process the pre-cut sheet metal blank is bent to form the outer surface or covering for the pedestal. Five different sheet metal blank sizes are available to support the different pedestal sizes.

3. WELD O-FRAMES - The o-frames provide the inner support structure for the pedestal. The o-frame is a rectangular structure formed by spot welding two vertical stiffeners to two horizontal stiffeners. All four stiffeners are loaded into an adjustable fixture and the welds are made simultaneously by machine. Two sizes of o-frame are available to support the two pedestal heights.

4. WELD CASE - In this process the wrapper, o-frames, bottom channels, and other stiffeners and plates are welded together to form the shell of the Cube Pedestal. An appropriate assembly fixture is used to obtain the proper alignment between the piece parts for the particular product variation being built.

5. BRAZE - In this process the top cap is positioned on the pedestal case and brazed in all four corners.

6. SPOT WELD TOP CAP - In this process the top cap is spot welded along both sides and the back of the pedestal shell. The quantity of welds depends on the particular variation of the product being built.

7. GRIND - The grind operation removes excess braze from all the externally visible brazed locations.

8. BUFF - The buff operation is also a cosmetic operation to prepare the surfaces, which have been spot welded, for the painting operation.

9. INSTALL TRACK - In this operation the runners which support the pedestal drawers and the lock bars are installed. This installation requires proper positioning of the parts based on the product variation being built, making hook and slot connections, and installing holding screws.

10. PAINT - The pedestal case and drawers are painted in this process. Due to the inaccessibility of this process it was not documented in detail and is not supported by the process planning and standard time prediction system.

11. DRAWER ASSEMBLY - When the drawers reach this process they are already assembled. In this operation various options are added to the drawers, such as the hanging mechanisms for file folders.

12. DRAWER SLIDE AND DRAWER INSTALLATION - In this operation the casters, drawer counter weight, drawer roller mechanisms, and various bumpers and sound deadeners are installed. Subsequently, the drawers are installed.

13. DRAWER ALIGNMENT - In this operation various adjustments are made to ensure that the pedestal shell is square, that proper spacing exists around all edges of the drawers, and that the drawers move in and out smoothly.

14. PACKAGING - The completed product receives a final inspection and is packaged for shipment in this operation.

3. Development of Rule Base

The overall system architecture with its major components of knowledge base, neural network and user interface (as shown in Figure 2) was devised. The first task was to develop the rule base. Each of the processes was documented via detailed interviews with the operators and observation of the process. It was observed that the operators based their decisions concerning which processing steps were required on their past experience and on basic written instruction detailing the type and quantity of final product required. During this documentation phase it became evident that each of the 14 major processes consisted of a core or standard process, which was the same for all variations of the product line, plus a small number of key processing steps which were dependent on the specific product variation selected. The specific processing steps and the reasoning behind the decision to perform that particular processing step was documented for all the major processes. For example, in the weld top cap process the operator determines the required number of spot welds to make on each side of the top cap based on observing the depth of the pedestal or by referring to a computer output for the pedestal depth. Knowing the depth of the pedestal is sufficient information to determine the required number of spot welds.

INSERT FIGURE 2 HERE

Based on the documentation acquired from the operator interviews a set of core process plans was developed, one for each of the 14 major processes. These core process plans consisted of the detailed processing steps common to all product variations within the Cube Pedestal product line plus key words which identified the required modification for each specific product variation. The type of information that is specific to the product variation selected includes machine settings, appropriate fixtures and number of welds. Each of these core process plans was stored in a separate text file. The word *VARIABLE* was used as a key word to indicate that a manufacturing step must be inserted in these locations which is specific to the product variation under consideration. An example of a plan for the install track process generated by the system is shown in Figure 3. The bold items are specific to each product variation while the rest is generic to all product variations for this process (i.e., the non-bold is the core process plan).

INSERT FIGURE 3 HERE

A set of rules was developed which conclude the appropriate processing steps to be inserted into the core process plan for each specific product variation. The rules determine the correct processing step to be inserted based on the attributes of the product variation under consideration. It was found that simple rules were sufficient to correctly select the product specific processing steps. Rules were developed which could correctly determine these product specific processing steps for two cases: 1) when the product selected was a standard or currently available product variation and 2) when the product selected was a non-standard or currently unavailable product variation. These latter rules used current options within the cube pedestal line, but provided for combinations not currently offered by the manufacturer. These rules were created by simply completing the set of physically feasible combinations from the set of current options in drawers, heights, locks, etc. A set of typical rules for the spot welding process is shown in Figure 4.

INSERT FIGURE 4 HERE

4. Development of Neural Network for Standard Processing Times

A neural network was developed which is used to predict the standard process time for the install track process. The processing time required to complete this operation varies significantly with the specific product variation selected and contain non-linearities and unspecified interactions. These qualities made a neural network a good candidate to estimate the relationship between the aspects of the product under consideration and the standard time needed for installing the tracks. The other processes demonstrated little variability in standard times for different product variations, therefore standard times were a single value for each process regardless of product option. The function of the neural network model for the install track process is to capture the relationship between the product variation selected and the associated processing time required. Figure 5 shows the neural network architecture.

INSERT FIGURE 5 HERE

A four step approach was followed to develop, train, and test the neural network.

STEP 1: Determine All Variables Which Affect The Processing Time

Based on operator interviews, observations of the install track process and engineering judgment the following seven product specific variables were determined to have a potential effect on processing time. Note that these are not necessarily statistically significant variables, but were chosen based on the expertise of the shop floor personnel.

HEIGHT -------- Height of the pedestal
DEPTH --------- Depth of the pedestal
LOCK ---------- The lock option selected
RATIO ---------- The mixture of Box/Tray runners and File/EDP runners to be installed
POS1-POS8 ---- The relative positions of the runners in the vertical stiffener
QTY B/T RUN - Quantity of Box/Tray Runners required
QTY F/E RUN - Quantity of File/EDP Runners required

STEP 2: Encode Network Input

The above identified input variables were encoded into binary (0-1) values since they were all categorical variables. A more complex process could use continuous variables, or a mix of categorical and continuous variables. The output from the neural network is a single continuous variable which represents the processing time in minutes. The encoding is detailed below.

The HEIGHT variable has two possible values, the DEPTH variable has three, the LOCK variable has three, the RATIO variable has two, the QTY B/T RUN variable has nine, the QTY F/E RUN variable has three, and each of the POS1 through POS8 variables have two possible values. Together this results in a neural network input vector with 28 bits.

INPUT = {HEIGHT, DEPTH, LOCK, RATIO, QTY T/B RUN, QTY F/E RUN, POS1, POS2, POS3, POS4, POS5, POS6, POS7, POS8}

Thus with the specific example of:

HEIGHT = Executive
DEPTH = 24
LOCK = No Lock
RATIO = All Same
Product Variation = 3 Box and 2 Tray drawers (i.e., this in turn determines the variables QTY B/T RUN, QTY F/E RUN, and POS1 through POS8)

the input vector to the neural network would be:

INPUT = {0,010,001,0,000001000,100,1,1,0,1,0,1,0,1}

STEP 3: Determine Number Of Possible Product Variations

Not all of the product options have an impact on the install track process (e.g., the color of paint option has no impact on this process). It was determined that only the pedestal height and depth, lock and drawer configuration options would impact the process, as described in Step 1. Evaluating the possible combinations of these options resulted in a total of 72 product variations that could impact the process. Therefore there are potentially 72 different standard process times for this process. This only includes the currently available product variations. If the feasible yet non-standard product variations are considered the total number of product variations increases dramatically.

This case illustrates the potential benefit of using a neural network to predict standard process times. In theory a neural network model could be developed which can generalize the timing data collected on only a small sample of the total possible product variations to all the remaining variations. This could eliminate the need to perform time studies on all product variations while still providing accurate standard time data for each individual product. Furthermore, standard process times for new products could be predicted with the system prior to building the new product.

STEP 4: Develop And Train Neural Network

All networks developed for this study used fully connected multi-layer perceptrons trained with the error back-propagation algorithm with 28 input neurons, 5 hidden neurons in each of 2 hidden layers and a single output neuron. The complete set of data consisted of 72 data points of which 20%, or 14 data points, were withheld for testing. Three metrics were used to evaluate the performance of the network: 1) mean absolute error, 2) maximum absolute error, and 3) number of test points that were predicted with errors exceeding 0.333 minutes. These three metrics provide a good overall measure of network performance. The mean error is a good indication of the consistency of performance of the network, maximum absolute error gives insight into worst case predictions of the network, and the number of errors which exceed an established limit gives some indication of the amount of confidence the user can place in the network predictions. The limit of 0.333 minutes for the third metric was established based on judgment. The limit corresponds to a network standard time prediction error of 20 seconds. The data of the processing times for the members of the product family ranged from 1.80 to 6.73 minutes. A 20 second error in prediction of standard times is considered acceptable for this range because this level of potential error could easily be masked by other system variables such as particular operator. Using the three performance metrics the network performed as shown in Table 1 over the test set of 14 observations. Figure 6 shows the predictions of the neural network versus the actuals for the test set.

Table 1. Test Case Error Summary

MAX ERROR (minutes)	AVG ABS. ERROR (minutes)	# ERR > 0.33 minutes
0.950	0.195	2 of 14

INSERT FIGURE 6 HERE

There are two readily identifiable alternatives to the neural network estimation of standard process time. One is making time studies for all product variations. This would take a considerable commitment of resources to achieve, where a neural network was developed using a subset of the data and performs quite well. A second alternative is use a simpler model such as linear regression to estimate the standard times. Since most inputs were naturally categorical rather than continuous, linear regression would be awkward. Additionally, a linear regression model would demand adherence to standard assumptions, such as appropriateness of a linear relationship, no multi-collinearity of input variables and normal distribution of residuals.

5. Integrating the System Together

A software system was developed centered on an interactive expert system that acts as user interface, procedural data base, inference engine and system integrator. Exterior to the expert system are the neural network component and external data files. The system has three primary functions: 1) develop detailed process plans, 2) develop parts lists, and 3) determine standard process times for each major process. Each of these functions are customized for the specific product variation selected. The expert system utilizes both forward and backward chaining reasoning together with developer designed procedures to accomplish the specified system tasks. The expert system development software used was Level 5 Object version 2.5, running under Windows 3.0, and the neural network development software used was BrainMaker Professional, version 2.0. The neural network uses the “Runtime.C” option of Brainmaker to compile the trained network into C code. Figure 7 shows the program flow diagram for the system.

INSERT FIGURE 7 HERE

The **User Interface**, which is a user friendly set of input screens with radio buttons and pull down menus, can set current facts in the knowledge base or activate methods. **Facts** are simply attributes for which the current values are known with certainty. For example, when the attribute “height” of the Cube Pedestal class is selected by the user to be 24 inches this is stored as a Fact in the working memory. The Fact can then be accessed throughout the consultation when the value of that attribute is required. A **Method** is a developer designed procedure which can perform various tasks and/or set attribute values based on a series of If/Then clauses. The Methods in this system perform four functions: 1) access and read/write to external data files, 2) access, provide input vector and run the neural network, 3) activate the expert system Inference Engine, and 4) perform various tasks required by the system, such as printing files. The **Inference Engine** is either activated by a Method to pursue a given attribute's value by backward chaining or is activated in a forward chaining mode when certain attribute values are changed by the user. The knowledge base consists of a set of backward chaining rules (called **Rules**) and a set of forward chaining rules (called **Demons**). **User Objects** are developed defined variables in the system with specified attributes. There are 37 Demons, 121 Rules, 45 Methods and 26 User Objects in the expert system.

6. Concluding Discussion

Neural networks and expert systems are complementary computing tools for the problem domain of automated process planning and standard processing time prediction. An integrated approach has the potential to provide a system with capabilities that exceed the capabilities of either approach taken independently. The integrated approach was shown to be feasible in an actual manufacturing application and performed well for all test cases tried as evidenced by:

- Consistently providing correct process plans and parts lists for both current and non-current products.
- Consistent prediction of standard process times for both current and non-current products to within a 20 second tolerance.

The use of a neural network to estimate standard processing times is effective and can significantly reduce the time invested in determining standard times. This is particularly true when the product family of interest is large and the product family members have highly variable processing time requirements. A neural network could be created for each processing step which could estimate the standard process time across all product variations. A similar approach could be used to estimate the variance of the standard process time for each step if management targeted time variance as an important aspect. The overall rule base and neural network for approximation of the standard time process could be integrated with other new techniques, such as fuzzy rules and neural networks for product classifications.

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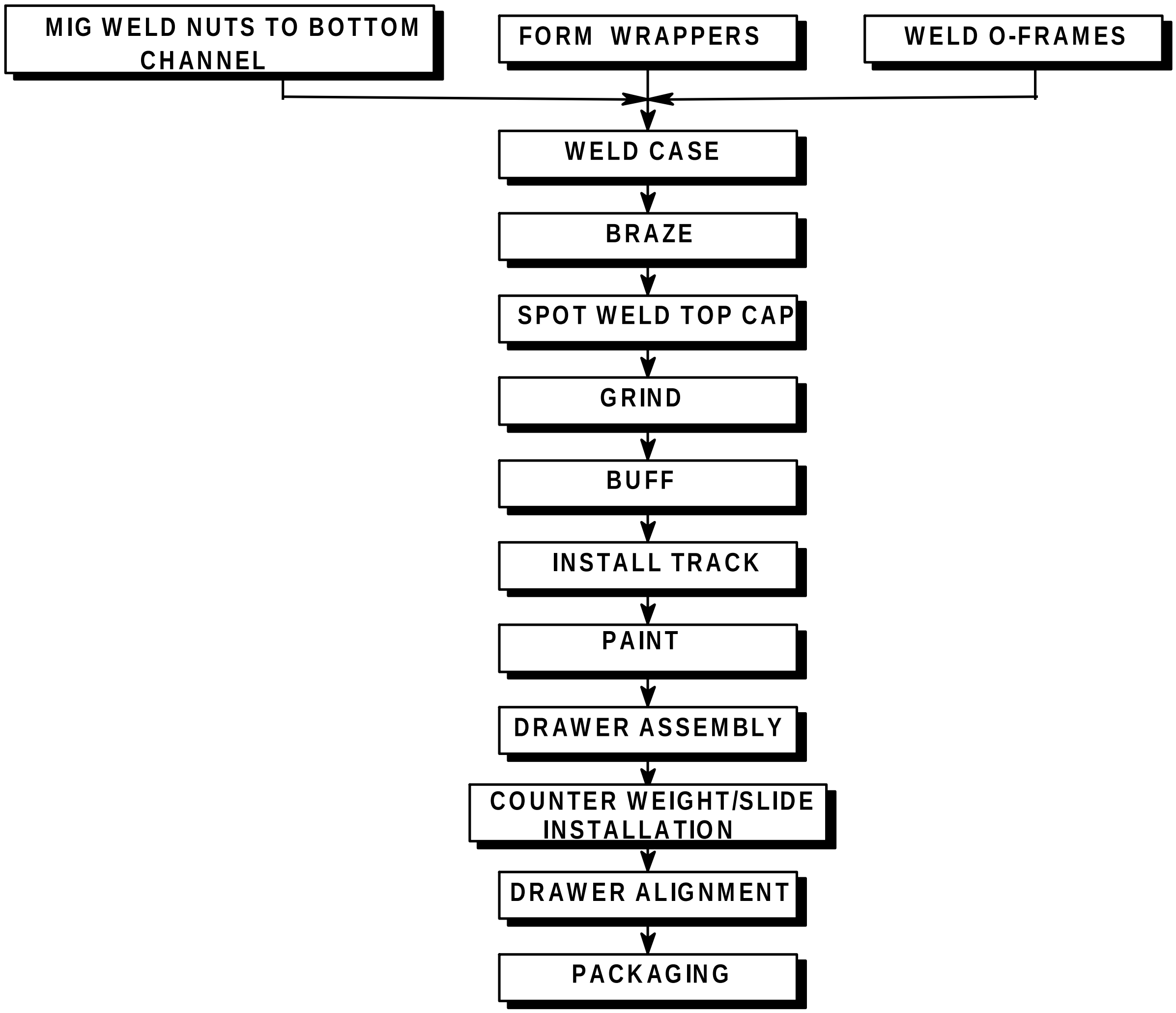

Figure 1. Overview of Cube Pedestal Process.

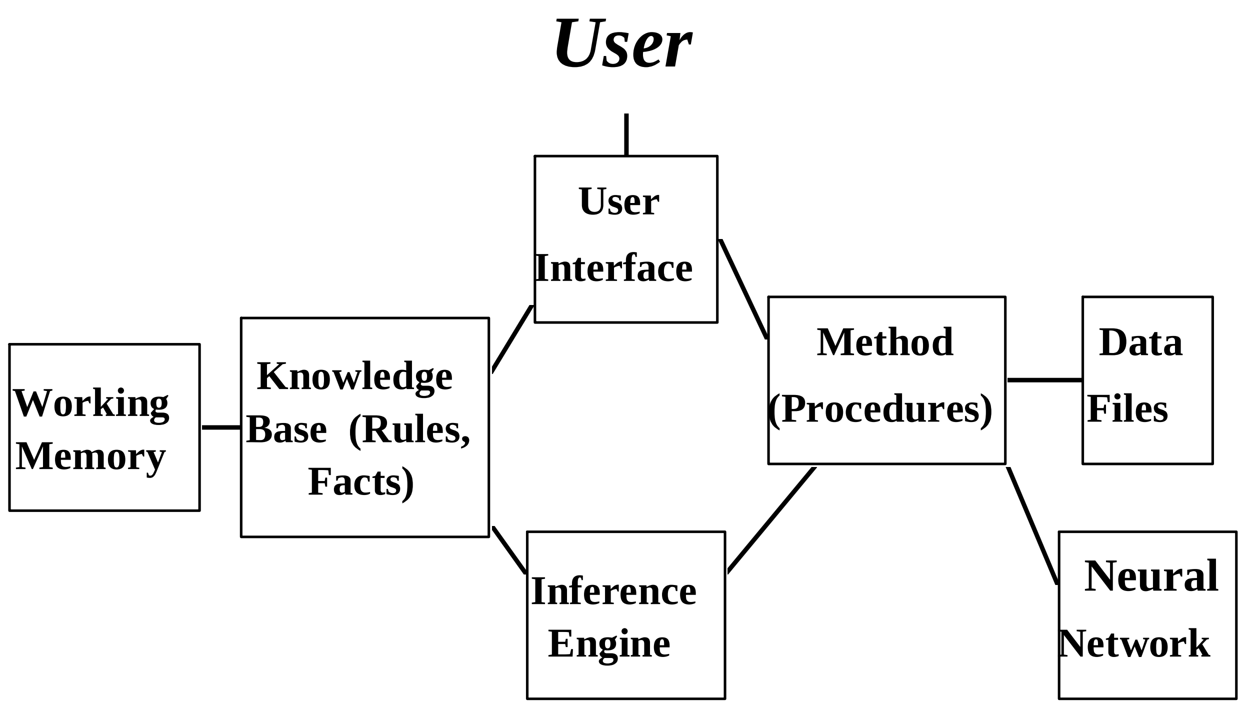

Figure 2. System Architecture.

MACRO PROCESS -- INSTALL TRACK

DETAILED PROCESS:

1) FROM PARTS LIST OBTAIN THE REQUIRED QUANTITY AND TYPE OF DRAWER RUNNERS AND LOCK BAR.

2) **LOCK BAR *VARIABLE***
THIS PEDESTAL REQUIRES ONE LOCK BAR TO BE INSTALLED ON THE RIGHT HAND SIDE POSITION LOCK BAR(S) INSIDE OF DRAWER RUNNERS. TABS ON LOCK BAR SHOULD POINT TOWARD THE CENTER AND FRONT OF THE PEDESTAL.

3) THE TECHNIQUE FOR INSTALLING DRAWER RUNNERS IS THE SAME FOR ALL PEDESTAL VARIATIONS. HOWEVER, THE LOCATION, TYPE, AND QUANTITY OF RUNNERS IS DIFFERENT BETWEEN PRODUCT VARIATIONS. THE FOLLOWING PROVIDES A STANDARD RUNNER INSTALLATION TECHNIQUE AND THE PRODUCT VARIATION SPECIFIC LOCATION OF THE RUNNERS.

4) STANDARD TECHNIQUE:

A) HOOK FRONT TAB OF RUNNER INTO SLOT ON LOCK BAR FOR EACH RUNNER TO BE INSTALLED (LOCATION PER BELOW).

B) HOOK REAR TAB OF RUNNER INTO SLOT IN REAR VERTICAL STIFFENER (LOCATION PER BELOW). USE HAMMER TO TAP RUNNER INTO SLOT TO OBTAIN PROPER SEATING.

C) REPEAT STEPS (A) AND (B) FOR OPPOSITE SIDE OF PEDESTAL IF TWO LOCK BARS ARE REQUIRED. IF ONLY ONE LOCK BAR IS REQUIRED THEN REPEAT STEPS (A) AND (B), HOWEVER, INSERT FRONT TABS OF RUNNER INTO SLOTS ON FRONT VERTICAL STIFFENER (VS. INTO LOCK BAR).

PRODUCT VARIATION SPECIFIC LOCATIONS:

TYPE OF RUNNER	LOCATION
Tray/Box	**1**
Tray/Box	**2**
Tray/Box	**3**
File/EDP	**8**
Not Applicable	**0**
Not Applicable	**0**
Not Applicable	**0**
Not Applicable	**0**

PRODUCT *VARIABLE*

Figure 3. Typical Process Plan.

```
RULE num spot welds weld case 1
IF case depth OF cube pedestal = 20
THEN spot welds OF weld case variables IS WELDS 3

RULE num spot welds weld case 2
IF case depth OF cube pedestal = 24
OR case depth OF cube pedestal = 30
THEN spot welds OF weld case variables IS WELDS 4
```

Figure 4. Typical Set of Rules for Spot Welding.

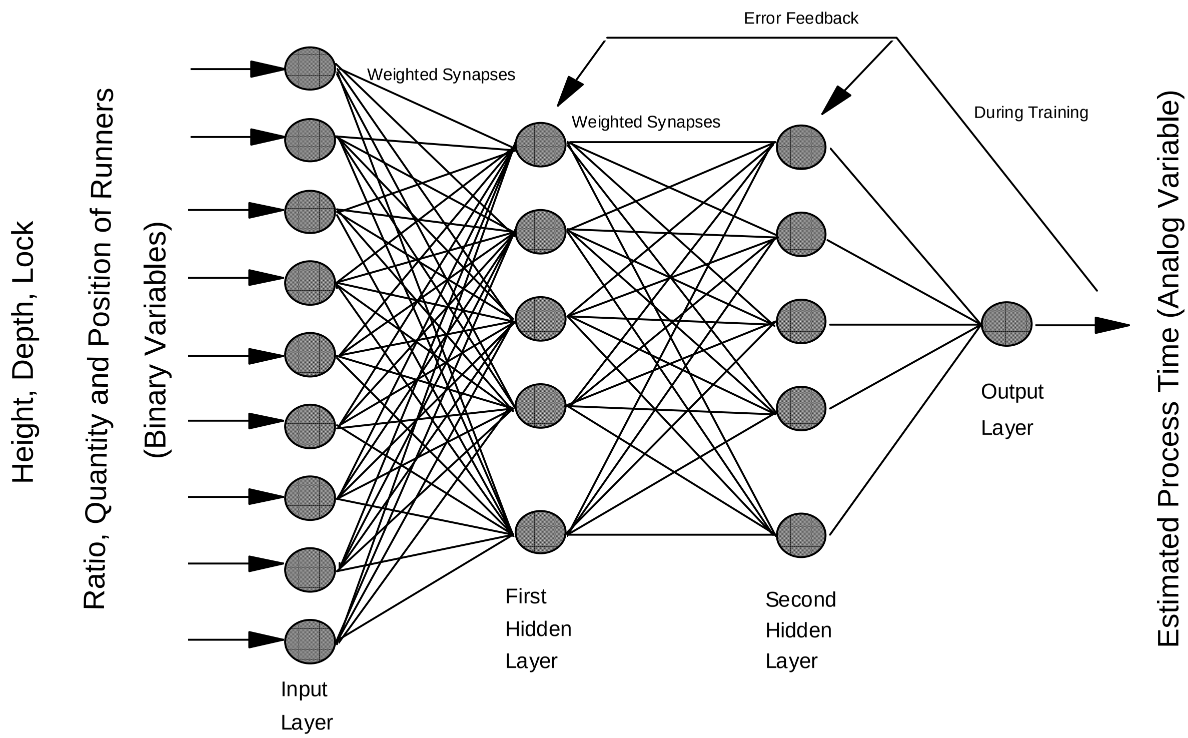

Figure 5. Neural Network for Standard Processing Time Estimation.

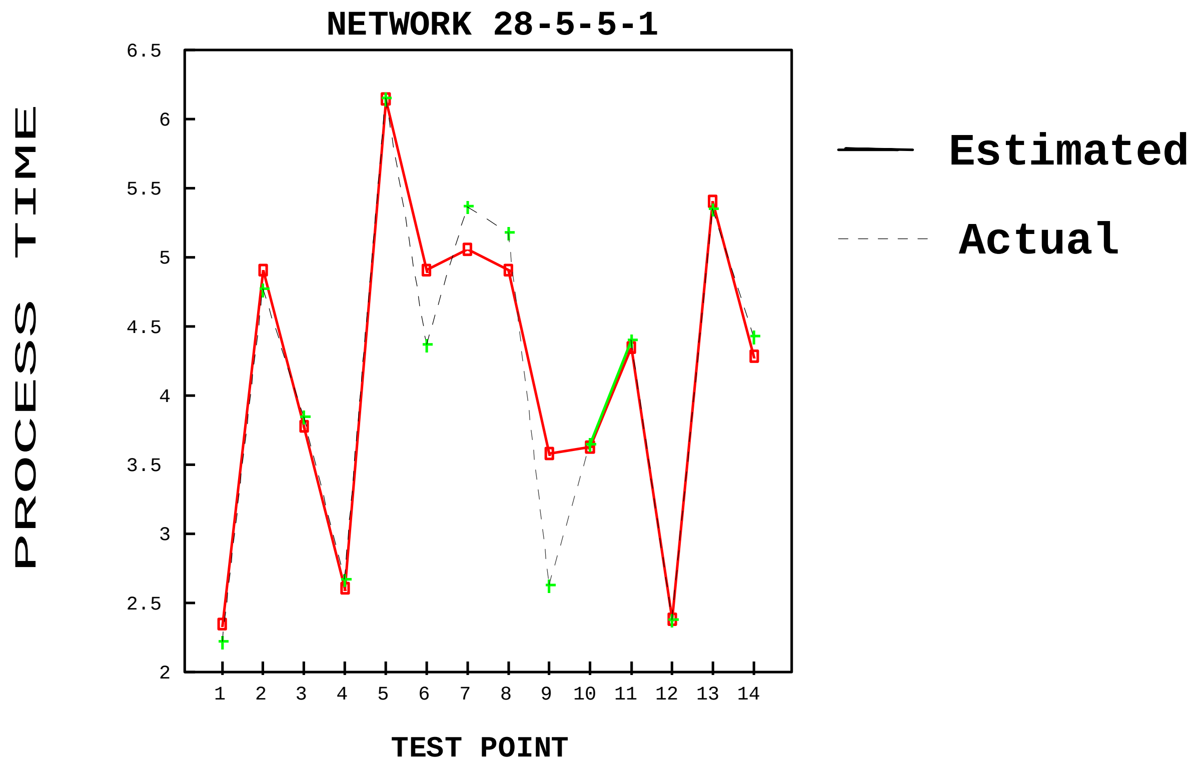

Figure 6. Estimated Standard Process Times versus Actuals for Test Set.

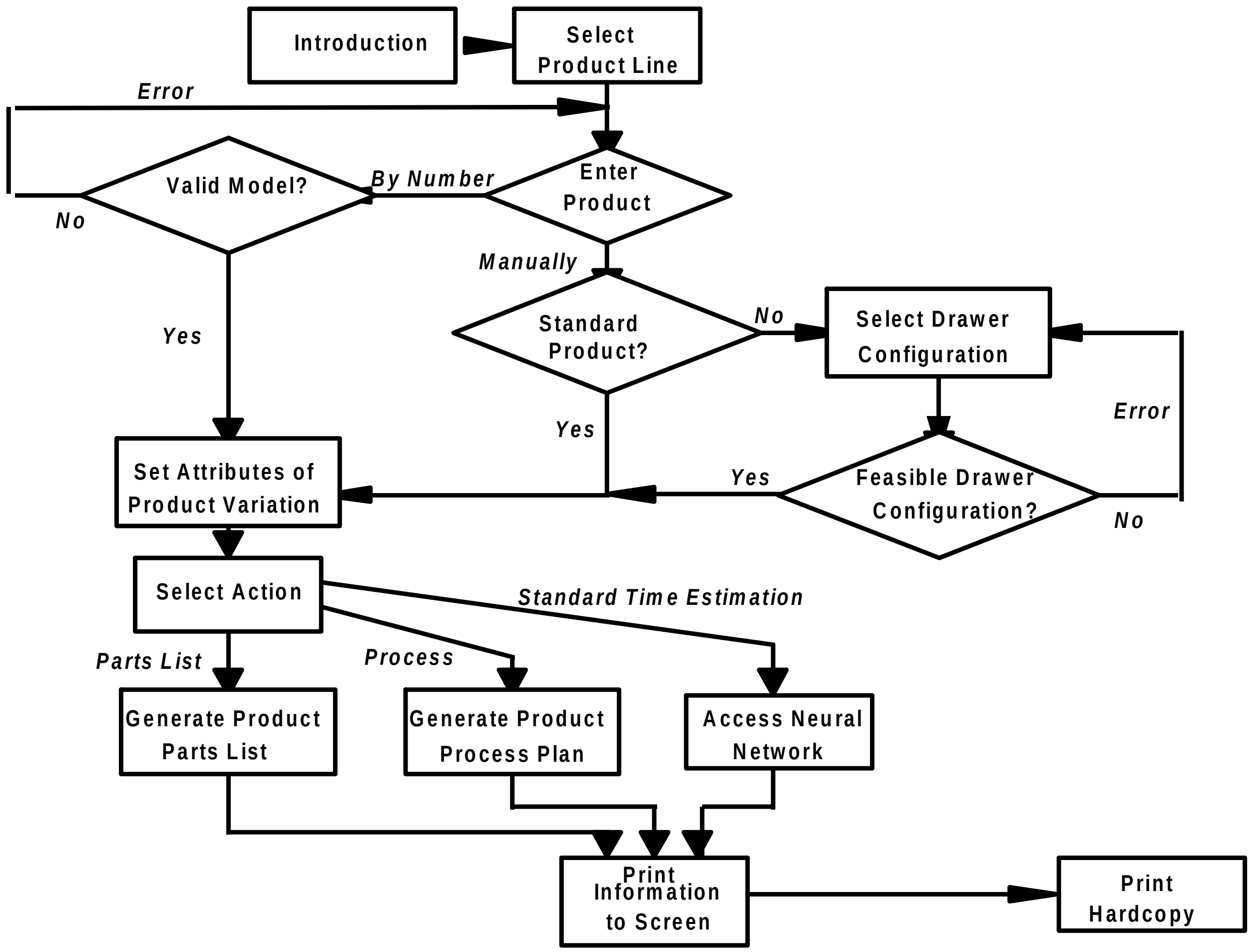

Figure 7. Flow Chart of User Consultation.