The QuenchMiner™ Expert System for Quenching and Distortion Control

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Abstract

The QuenchMiner™ Expert System is an enhancement over the original Web-based Data Mining tool developed at CHTE, WPI for analysis of quenching data. The goals of this Expert System are predicting results obtained under given quenching conditions, thereby supporting decision making to improve performance. It thus assists Heat Treating users. It is fed with the knowledge an expert has in the user domain. For example, a human expert knows that higher agitation implies greater distortion tendency; cooling rate of a quenchant affects distortion more than the carbon content of the part alloy etc. These facts are converted into rules with priorities and relative weights. The Expert System uses these rules to analyze cases submitted by the user and estimates parameters of interest. The focus is on Quenching Media and Distortion Control. There is considerable use of Artificial Intelligence in QuenchMiner™, primarily Rule Interpreter and Forward Chaining techniques.

Keywords

Quenching, Heat Treating, Data Mining, Artificial Intelligence, Decision Support.

1. Introduction

Data gathered from experiments in Quenching [1] and the related technical and scientific literature are potential sources of knowledge useful in making engineering decisions. This knowledge needs to be discovered from raw data and applied in such a way that it can be used to assist the decision making of a Heat Treating user. This is the goal of the Expert System [2] QuenchMiner™. It provides Decision Support [3] in Heat Treating with the aim of optimizing the processes involved [4]. Users submit cases, and the system analyzes them using domain knowledge to output suggested decisions. Note that this is only to *support* or *assist* the users' decision making process.

Figure 1 shows the QuenchMiner™ Logo that summarizes its functions. Heat Treating users pose queries to the system. The system does Data Mining [5] and unlocks or discovers knowledge from raw data. It uses Artificial Intelligence [6] to perform analysis similar to a domain expert and conveys the answers or suggested decisions to the user through a Web interface.

Figure 1: Logo for QuenchMiner™

QuenchMiner™ is developed at the Center for Heat Treating Excellence (CHTE), WPI. It started as a Web-based tool for analysis and retrieval of Quenching experimental data. This was the first phase of QuenchMiner™ [7] that was incremental to QuenchPAD [8], the Quenchant Performance Analysis Database, also developed at CHTE, WPI. It was then enhanced into an Expert System for Decision Support of Heat Treating processes. This is the second phase, and is being described in this paper. The third phase, has two research components, for Visualization and Graph-based Data Mining [9] respectively. These are part of our ongoing work, and will be used to further enhance QuenchMiner™, for more complex decision making. The resulting system will also serve as an Intelligent Tutoring System [10] in Quenching.

Section 2 of this paper gives an overview of Expert Systems. Section 3 outlines the goals and functions of QuenchMiner™ for Decision Support. Section 4 describes the system architecture. Section 5 provides a demonstration of the system. Section 6 explains the techniques used in the design of QuenchMiner™. Section 7 focuses on the application of the system to Distortion Control. Section 8 gives the conclusions.

2. What is an Expert System

An Expert System is a computer program that represents and reasons with knowledge of some specialist subject with a view to solving problems or giving advice [2]. In the context of this paper, QuenchMiner™ is an Expert System because it has the knowledge of the subject "Heat Treating" [4], and it reasons using that knowledge to make decisions that serve as solutions or advice to cases in Quenching.

2.1 Characteristics of an Expert System

An expert system is identified by the following features that distinguish it from a normal computer program.

- It simulates *human reasoning* about a problem domain, rather than simulating the domain itself [2].
- It performs reasoning over *representations of human knowledge*, in addition to doing numerical calculations or data retrieval [2].
- It solves problems by *heuristic or approximate methods* which unlike algorithmic solutions are not guaranteed to succeed [2].

All the above criteria are satisfied in QuenchMiner™. Note that it does not simulate the Heat Treating experiments, but rather analysis made using relevant inputs. Also, in addition to serving as a search engine for querying and data retrieval, it reasons using rules derived from that data (representing knowledge of the domain). Moreover, the goal here is only to assist the users' decisions by giving suggestions or analysis. It is not algorithmically making decisions for the user. This disclaimer has been stated throughout the development of the tool.

Also, an expert system is different from other types of Artificial Intelligence [6] programs in the following aspects.

- It deals with subject matter of *realistic complexity* that normally requires a considerable amount of human expertise [2]. This is analogous to the different between an intelligent human being and an expert on a subject.
- It must exhibit *high performance* in terms of speed and reliability in order to be a useful tool [2]. Not all Artificial Intelligence software is fast.
- It must be capable of explaining and justifying solutions or recommendations in order to convince the user that the reasoning is in fact correct [2].

QuenchMiner™ fulfils these requirements as well. Knowledge of the Heat Treating domain has been derived using Data Mining [5] techniques. This forms an integral part of the system and is analogous to the knowledge a domain expert gains through study and experience. Also, the execution time of the system is a fraction of a second per case, which is fast for the given application. In addition to that, QuenchMiner™ outputs not just the decisions but the factors that led to the decision. Thus, it is able to justify its answers similar to a human expert.

2.2 Components of an Expert System

As noted in the characteristics, the essential aspects of an expert system are the knowledge of the subject, and the ability to analyze or infer using that knowledge. This implies two primary components, namely a Knowledge Base and an Inference Engine. The structure of an Expert System [2] is shown in Figure 2.

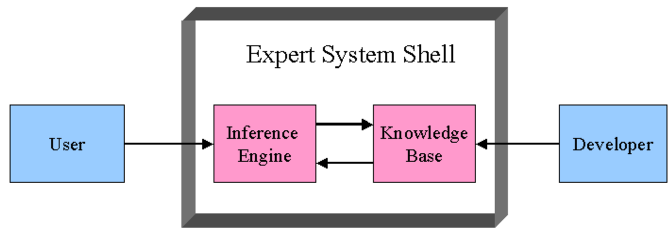

Figure 2: Structure of an Expert System.

The users interact with the system through the inference engine. This has the logic required for analysis. The inference engine uses the knowledge put in the knowledge base for answering questions, solving problems or offering advice. The knowledge base has both rules and declarations and is populated by the developers. In QuenchMiner™, the inference engine or decision making unit uses the Forward Chaining techniques [6] of Rule Interpreters [11]. More on this in Section 6. The knowledge base has declarations about the quenching template with all its required slots representing details of the quenchant, part and quenching conditions. It also has rules representing tendencies in quenching such as "Excessive Agitation Velocity of the quenchant implies high Distortion Tendency of the part. These rules are derived by Data Mining [5] in the user domain. For details refer to [7] that describes the development of QuenchMiner™ in its early stages.

Information on the above components, namely the knowledge base and inference engine with respect to QuenchMiner™ is in Section 4 on system architecture.

3. Decision Support in QuenchMiner™

As stated earlier, QuenchMiner™ serves as a tool to *support* or *assist* the users decisions in selecting suitable quenchants, parts and conditions to achieve a desired output for quenching in the industry. It analyzes user cases addressing problems such as distortion.

More specifically, there are certain parameters of interest that a user wants to determine in a given case. The user submits the case in the form of input conditions used to carry out quenching experiments. QuenchMiner™ uses domain knowledge to estimate the possible values or tendencies in these parameters, without actually performing the experiment. It conveys the estimated response to the user with analysis that identifies the causes of the tendencies. This supports the user in making decisions to optimize quenching processes.

For example, the user submits quenching conditions through the Web, and asks the system what the tendency for distortion is in the given case. The system responds with a predicted value such as high, moderate or low. The user can alter input conditions, e.g. select a different quenchant category and resubmit the case. The system may return a different response this time. It also outputs the reasons for the estimated decision, e.g., "Quenchant with low viscosity implies high distortion tendency". Thus the user also receives a diagnosis of the case, in addition to the suggested decision.

3.1 Parameters for Analysis

There are several parameters of interest. QuenchMiner™ focuses on the analysis of the following as listed below. These are selected based on feedback provided by the CHTE users and the Quenching team at WPI.

- *Desired Suspension:* This indicates manner in which the part should be oriented in the quenchant for the best results in quenching, whether vertical or transverse or near the thickest section. If the actual part suspension as input by the user is not the same as the desired suspension, this could adversely affect the quenching results. The desired suspension depends mainly on the geometry of the part [12].
- *Cooling Rate:* This parameter represents the average cooling rate range in the experiment, whether fast or moderate or slow. Predicting this would be analogous to taking the statistical average of the time temperature data obtained from the experiment and categorizing it into the appropriate range. The cooling rate is affected by various factors such as the viscosity of the quenchant, the agitation velocity and the oxide layer part surface [12].
- *Cooling Nature:* This refers to the uniformity of the cooling process, whether uniform or non-uniform or partially uniform (in between the two extremes). This would be similar to the conclusion a heat treating expert would draw on observing a cooling curve. The nature of cooling depends on the grain nature of the part material, the roughness of the part surface and other factors [12].
- *Heat Transfer Coefficient:* This indicates the average heat transfer coefficient in the experiment representing the heat extraction capacity of the process, whether high, medium or low. This characterizes a given quenching experiment. Predicting this average is analogous to calculating the mean heat transfer coefficient (hc) from a plot of hc v/s temperature, and grouping it into a range. The hc is affected by the cooling rate, density of the part, specific heat and other variables [13].
- *Residual Stress:* This represents the extent to which the part undergoes stress after the quenching process, whether negligible or moderate or high. This parameter is influenced not only by the factors in the quenching process such as the quenchant temperature and the part area also by the conditions prior to heat treatment such as manufacturing processes e.g. welding, stamping, cold plastic deformation [14].
- *Hardness:* The refers to the level of hardness achieved by the part after quenching, whether high, medium or low. The hardness is on the higher side, i.e. we are not likely to get soft parts in this process. This is affected by factors such as the cooling rate, carbon content and quenchant type [15].
- *Distortion Tendency:* This indicates the likelihood of the part to get distorted during quenching. The tendency for distortion could be low or moderate or high, depending on the input conditions. Distortion depends on the cooling rate, cooling nature and residual stress in the part. Thus it in turn depend on the inputs affecting these parameters [16].
- *Cracking Potential:* This parameter indicates whether cracking is likely to occur, i.e. an extreme case of distortion. Since this is dependent on the degree of distortion in the part, the variables affecting distortion tendency are the same as those affecting cracking potential [16].

3.2 Input Variables

The inputs to QuenchMiner™ depend on the parameter(s) selected. These provide information about the quenchant, part and quenching conditions. The complete list of all the possible the input variables is as follows.

- *Quenchant Category:* The type of quenchant used e.g. water, oil, polymer.
- *Quenchant Temperature:* The temperature at which the quenchant is maintained at the beginning of the experiment, whether high, medium or low.
- *Agitation Velocity:* The level of agitation provided for the quenchant, whether absent, insufficient, moderate or excessive.
- *Viscosity:* The viscosity of the quenchant, whether high, medium or low.
- *Agitation Type:* The device used for agitation, e.g. pumps, nozzles, impellers.
- *Speed Improvers Used:* Whether speed improvers are added to the quenchant for faster cooling [17].
- *Aging:* The age of the quenchant, whether old or not [12].
- *Polymer Foaming:* Whether the polymer quenchant foams [12].
- *Polymer Degradation:* Whether the polymer quenchant degrades [12].
- *Part Material:* The material used in the part, e.g. alloy steel, plain carbon steel.
- *Geometry:* The shape of the part, e.g. cylinder, plate, L-shaped, irregular.
- *Part Area:* The Cross-sectional area of part, whether thick or thin.

- *Part Volume:* The volume of the part whether small or large.
- *Density:* The density of the part material, whether high or low [13].
- *Specific Heat:* The specific heat of the part material, whether high or low [13].
- *Oxide Layer:* The presence and thickness of the oxide layer on the part surface, whether absent, thick or thin.
- *Surface Roughness:* The roughness of the part surface, whether smooth, medium or rough.
- *Suspension:* The orientation of the part in the quenchant, whether vertical or transverse or near the thickest section.
- *Carbon Content:* The carbon content of part material, whether high, medium or low [15].
- *Grain Nature:* The uniformity of the grains in the part material whether uniform or non-uniform.
- *Grain Size:* The fineness of grains in the part material, whether fine or coarse.
- *Welding:* Whether welding is used in part manufacturing [15].
- *Stamping:* Whether stamping occurs during part manufacturing [15].
- *Cold Plastic Deformation:* Whether cold plastic deformation occurs during part manufacturing [15].
- *Fixture Type:* Whether the fixture type used to store the part is proper or improper.

Note that only the variables relevant to the respective case have to submitted by the user. The impact of the input variables on the output parameters is analyzed based on the case information, and the decision is conveyed to the user. Details of the methodology used in analysis are outlined in Section 6.

4. Architecture

The architecture of the QuenchMiner™ Expert System is shown in Figure 3.

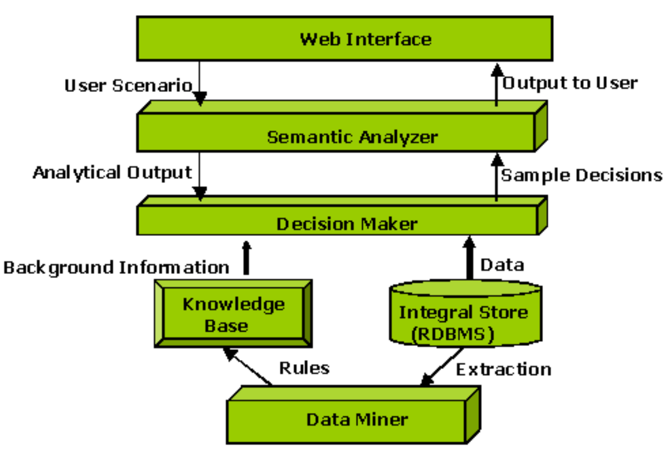

Figure 3: System Architecture

This includes the major components, a Decision Maker and a Knowledge Base, corresponding to the inference engine and knowledge base in an Expert System [2] respectively.

The user submits a scenario through the Web Interface. This is a plain-text description of the case.

The system needs to understand the semantics of the information provided by the user based on the domain and convert this into an appropriate form for analysis. This is the responsibility of the Semantic Analyzer.

The output of the Analyzer is fed into the Decision Maker that interacts with the underlying Integral Store (database with all relevant data) and Knowledge Base to obtain a sample set of decisions. The Integral Store is the Quenching Data Mart [7] as built in the first phase of QuenchMiner™.

The output of the Decision Maker is then sent to the Semantic Analyzer to get the Web output in plain text as needed by the user.

The functioning of the system is clearly depicted through examples, as shown in the following section.

5. Demonstration of System

QuenchMiner™ serves as a good tool for Heat Treating users to retrieve experimental data at a glance and analyze it to make decisions for process optimization. Its capability is demonstrated by sample screen-dumps shown here. These were taken during the experimental evaluation of the system.

5.1 Menu with Case Categories

Figure 4 shows the opening menu screen that is presented to the users. This has case categories based on the parameters outlined in Section 3.1. The users may choose to analyze one parameter at a time or a combination of parameters.

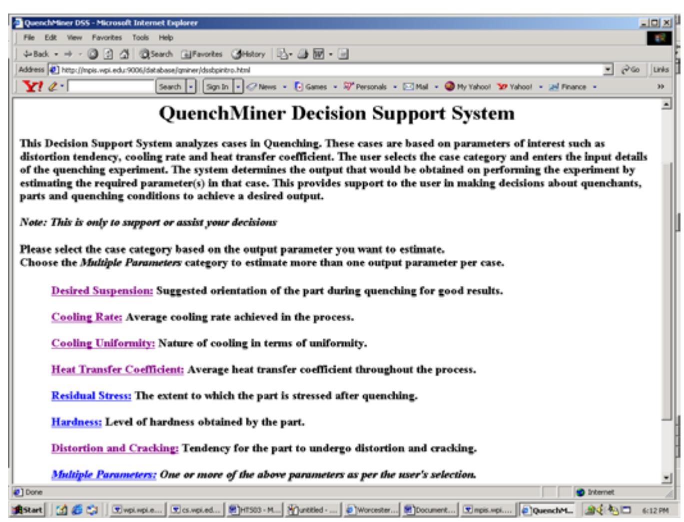

Figure 4: Menu for Decision Support

Consider the following case: *Estimate the average cooling rate achieved in the given quenching process*. To execute this case, the user selects "*Cooling Rate*" in the above menu.

5.2 Case Input

On selecting the required parameters, an input screen appears for the given case category as shown in Figure 5.

The user is required to specify the input conditions for quenching in this case. The user enters the following input conditions:

- Quenchant
    - Category: Water
    - Temperature: High
    - AgitationVelocity: Insufficient
    - Viscosity: Blank
    - Speed Improvers: Blank

- Part
    - Area: Thin
    - Volume: Blank
    - Oxide Layer: Thick
    - Surface Roughness: Rough

Note that the user does not need to specify all the fields. However, the more input the user provides, the greater is the accuracy of the output. Certain fields are inferred by the system. For example, in this case the quenchant type used is water, which implies that the viscosity is low. This is deduced using domain knowledge.

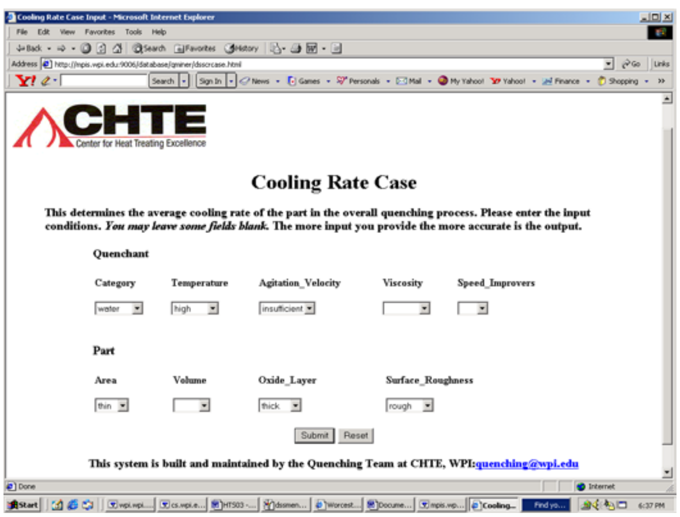

Figure 5: Cooling Rate Input Screen

5.3 Case Output

The system processes the input and displays the analysis and decisions as the output to the user. This is shown in Figure 6.

The system estimates that the average cooling rate in this quenching process is fast. This is conveyed as a decision to the user. The analysis involved in making that decision is also displayed. In this case, the analysis is as follows.

- Quenchant with low viscosity implies fast cooling.
- Insufficient agitation implies cooling on the slower side.
- Thin part area implies fast cooling.
- Thick oxide layer implies cooling on the slower side.
- Rough surface implies cooling on the faster side.
- High quenchant temperature implies cooling on the slower side.

Figure 6: Cooling Rate Output Screen

Thus, on the whole, it is estimated that the average Cooling Rate is "fast". Thus the system has determined the causes of the effects. It has identified the input that led to faster cooling, and the ones that led to slower cooling.

The user is allowed to alter one or more parameters in the case, and observe the effect. For example, consider that the user alters the Quenchant Type to "oil", and Viscosity to "high", and resubmits the case.

The system now infers that "Quenchant with high viscosity implies slow cooling". The Quenchant Type and Viscosity have a significant impact on the Cooling Rate. Thus, it is estimated that the average cooling rate is "moderate". This decision is conveyed to the user. Hence the system enables the user to observe the changes in the tendencies of the parameters as the input conditions change.

QuenchMiner™ does this analysis and decision making based on the knowledge of the domain and the logic coded into it for inference. This is similar to the way human beings analyze information. They use their knowledge of the subject and their capacity to reason and answer questions or make decisions.

The details of the methodology used in QuenchMiner™ for analysis is outlined below. It uses Artificial Intelligence techniques.

6. Techniques used in Design

The input variables in QuenchMiner™ listed in Section 3.1 have an impact on one or more output parameters. The impact of the input variables on the output parameters is analyzed through Fishbone Diagrams [18]. These help to estimate tendencies in the output. The extent of the impact is represented by numeric priorities assigned to each variable. The priorities and tendencies are taken into account in making decisions about the estimated value of the parameter(s) of interest selected by the user. Rule Interpreters [11] and their Forward Chaining [6] techniques are used in this analysis. The details of each step are presented below.

6.1 Fishbone Diagrams

There are input variables storing details about the quenchant, part and quenching conditions. These are entered by the user. Also, some parameters such as Cooling Rate affect other parameters such as Distortion Tendency. Thus for the analysis of Distortion Tendency, Cooling Rate also serves as a variable in addition to the user-specified input variables. Such variables are referred to as intermediate or binding variables [11].

The impact of the input and intermediate variables on each output parameter is represented through Fishbone Diagrams [18], so called due to their resemblance with the bones of a fish. They are also known as cause-effect diagrams because they represent causal relationships, i.e. they indicate which variables cause certain effects on .parameters of interest. Another name for them is Ishikawa diagrams after their creator. Each fishbone diagram focuses on the analysis of one parameter. Figure 7 shows the Fishbone diagram for Cooling Rate.

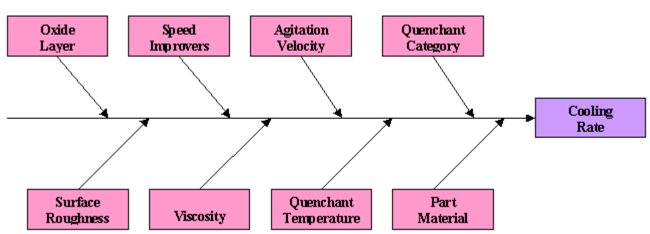

Figure 7: Fishbone Diagram for Cooling Rate

From this, it is clear that Cooling Rate is affected by the following variables.

- Oxide Layer
- Speed Improvers Used
- Agitation Velocity
- Quenchant Category
- Surface Roughness
- Viscosity
- Quenchant Temperature
- Part Material

These serve to identify tendencies. On studying the data in the databases, it can be inferred statistically, for example, that experiments having high agitation velocities, also have high cooling rates. On combining this information with the impact represented by Fishbone Diagrams, it is clear that agitation affects cooling rate and not vice versa, i.e. there is a causal link from Agitation Velocity to Cooling Rate. Thus, this leads to a rule "High Agitation implies Fast Cooling Rate".

Moreover, there are parameters with no causal links. For example, if there are experiments where Welding occurred during part manufacturing, and the corresponding part when quenched showed fast cooling, it can be inferred that this is simply a coincidence. Since Welding is not one of the factors that affects Cooling Rate, there is no causal link between them. Thus, such an occurrence does not lead to a rule.

Rules of this type are termed as Association Rules [19,5] since they represent associations between the different variables and parameters. More information on the derivation of these rules in QuenchMiner™ can be found in [7].

In addition to the impacts, the extent of the impact is also important. For example, in the parameter Cooling Rate, the impact of the variable Quenchant Category is stronger than that of Oxide Layer. The extent of the impact is represented by priorities. Rule Interpreter techniques [11] enable this representation, as explained below.

6.2 Rule Interpreters and Forward Chaining

A Rule Interpreter is a software that is designed to apply a given set of rules to perform analysis and make decisions [6]. The Rule Interpreter technology used in QuenchMiner™ is Jess, The Java Expert System Shell [11]. Jess uses a *Forward Chaining* [6] mechanism for execution.

Forward Chaining: *This is a method that finds every conclusion possible based on a given set of premises [11]*. In the Forward Chaining approach, there are no queries. Instead inference rules are applied to the knowledge base, leading to new assertions. This process repeats forever, until some stopping criterion is met. The system stores the facts (in our context, quenching input conditions) in a memory called the Working Memory. It stores the rules in a Knowledge Base. In each cycle, the system computes the subset of rules whose left-hand side is satisfied by the current contents of the Working Memory. It then decides which of these rules should be executed, taking into account specificities, conflict resolution and weights as described below. The final step in each cycle is to execute the action(s) on the chosen rule(s) [6].

Jess uses a special algorithm called *Rete* [11] to match the rules to the facts. The Rete algorithm first compiles the memory into a network that eliminates duplication between the rules. Rete networks also eliminate duplication over time [6].

As mentioned in Section 6.1, there are priorities assigned to rules, based on the extent of impact. Also intermediate variable such as Cooling Rate and Residual Stress affect parameters such as Distortion Tendency. Accordingly weights have to be assigned to these variables. Also at times, rules may lead to conflicting results. Finally, it is crucial to decide when the rule application stops, since the knowledge base is filled with rules. If the rules keep getting applied continuously, the system will be in an infinite loop. These issues are addressed in the Jess Rule Interpreter as follows.

- *Specificity*: The specificity of a rule is its relative importance with reference to the situation [11]. For example, cooling rate is affected more by quenchant category than by surface roughness. Accordingly numeric specificities are assigned.
- *Conflict Resolution*: This refers to the course of action to be taken when conflicting conditions occur [11]. For example, if one rule states that under the given conditions, the tendency for distortion is greater and the other one states that it is less, this presents a conflict. The simplest conflict resolution strategy is selecting the rule with the highest priority.
- *Weights*: The RHS of one rule may serve as the LHS of another. For example, the cooling rate during quenching is affected by viscosity and agitation. Cooling rate in turn affects the tendency for distortion. There have to be relative weights assigned to intermediate parameters, so that they can be used to determine the final outcome [11].
- *Termination*: It is crucial to decide when the application of rules stops. Since rules affect each other, just one pass over the set of rules is not enough. One of the most common strategies is to remove a rule from the list once it fires, and continue to check the remaining rules. Thus there is no threat of infinite loops, and it is ensured that all rules are examined [11].

These are the techniques used in analysis and decision making in QuenchMiner™. The actual process is outlined in the next subsection.

6.3 Decision Making Process

The functioning of the Decision Maker Unit in QuenchMiner™ is summarized in the flowchart shown in Figure 8.

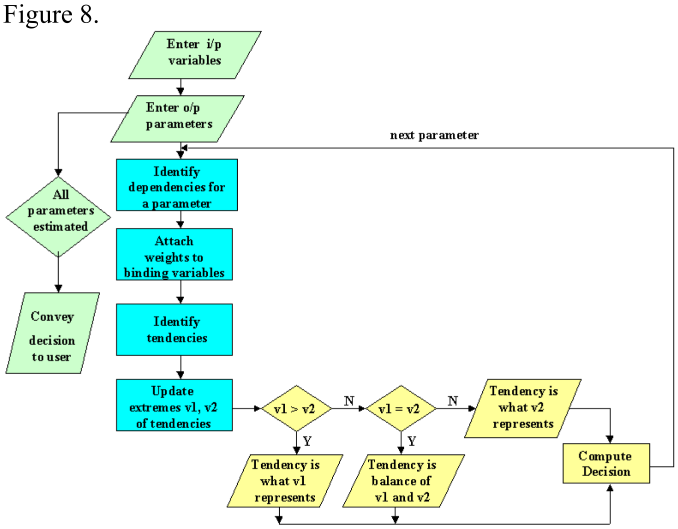

Figure 8: Flowchart for Decision Making

This flowchart is based on a combination case, i.e. where multiple parameters are analyzed. For analyzing each individual parameter, the flowchart will be a subset of the above. The logic of this flowchart is as follows.

- The user enters the input variables pertaining to the given case.
- The user selects the output parameters of interest in that case.
- The system identifies the dependencies based on the cause-effect relationships.
- Weights and priorities are assigned to the variables based on the extent of impact.
- Tendencies are identified based on the rules that are stored in the knowledge base. These represent the statistical inferences drawn on studying the data in the databases.
- Two extremes v1 and v2 represent the two extreme natures of a given binding variable. For example, in case of Cooling Rate, they represent the extremes of “slow cooling” and “fast cooling”. Based on the rules that fire, these values get updated. For example, if Quenchant Category is “water”, v2 representing fast cooling gets updated by the corresponding weight. This updating is done for every rule that gets fired.
- Finally, the extremes v1 and v2 are compared. If they are equal, the estimated tendency is the balance of the two. For example, if the all rules that fire for fast cooling and slow cooling update the two respective variables by the same extent, then it is predicted that the cooling rate will be “moderate”, which is the balance of fast and slow. If v1 and v2 are not equal, the final tendency is the one that is greater. Thus if more rules (in terms of extent of impact) fire for “fast cooling”, the estimated tendency is “fast”.
- Likewise, decisions are computed for every parameter.
- Once all the parameters are computed, the list of decisions is conveyed to the user. This represents the estimated values of all the parameters of interest in the given case.

This is how QuenchMiner™ analyzes cases and conveys the corresponding decisions to the user. Note that these are only estimations, based on heuristics, as is typical of Expert Systems.

7. Application to Distortion Control

Distortion is one of the biggest problems in Quenching. It is the tendency of a part to get deformed in shape and or size during the cooling process [16]. Extreme distortion can lead to cracking where the part is likely to break at certain regions during quenching [16]. The control of distortion is important to the users and is an issue of concern.

QuenchMiner™ addresses Distortion Control by predicting the distortion tendency in a given experiment using the input conditions. It estimates whether the distortion is likely to be high, low or moderate and gives reasons for that. On observing the analysis, the user is able to understand what factors caused distortion, if any, in the given case. The user can alter the input conditions and resubmit the case, and observe the effect of changing some of the input variables.

For example, if in a given case, the Agitation Velocity is "excessive", and the system analyzes that this is one of the factors responsible for "high" Distortion Tendency, the user can resubmit the case with the velocity changed to "moderate". If this time the system returns Distortion Tendency as "low", this is one solution to the problem. Likewise, there be one or more factors that can be adjusted for Distortion Control.

The screen-dumps below present a Distortion Case and its analysis by QuenchMiner™. The user wants to estimate the potential for distortion and cracking in a given case. The steps are as follows.

7.1 Case Selection

The user selects the Case Category below from the Decision Support System Menu of QuenchMiner™.

- Distortion and Cracking: Tendency for part to undergo distortion and cracking.

This presents the corresponding Case Input screen to the user to enter the quenching conditions for the experiment.

7.2 Case Input

The input screen for the "Distortion and Cracking" Case is shown in Figure 9. This has the input fields representing the details of the quenching experiment.

The user enters the following input values.

- Quenchant
  - Category: Oil
  - Temperature: High
  - AgitationVelocity: Moderate
  - Viscosity: High
  - AgitationType: Impellers
  - Improvers: No
  - Aging: Blank
  - Foaming: Blank
  - Degradation: Blank

- Part
  - Geometry: Cube
  - Area: Thick
  - Volume: Blank
  - Oxide: Thick
  - Surface: Rough
  - Carbon: Medium
  - GrainNature: Non-uniform
  - GrainSize: Coarse

- Manufacturing Details
  - Welding: Yes
  - Stamping: No
  - ColdPlasticDeformation: Blank
  - FixtureType: Proper

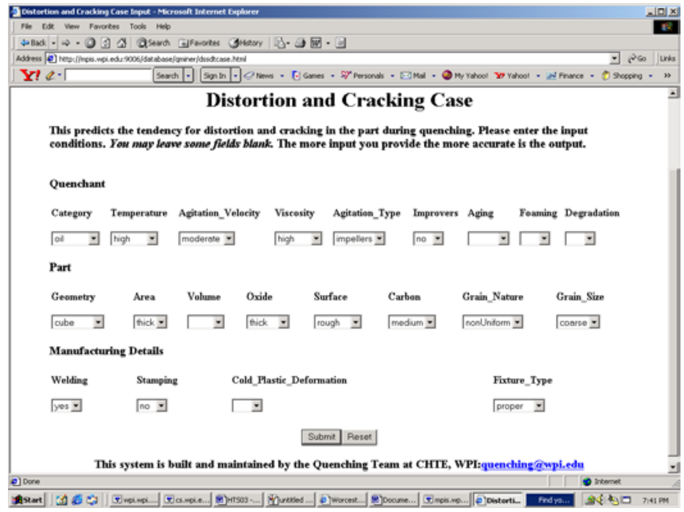

Figure 9: Distortion Case Input

7.3 Case Output

The system analyzes the given input to deduce the corresponding output. The output is shown in Figure 10. The analysis is as follows.

- Quenchant with high viscosity implies low distortion tendency
- Moderate agitation implies low distortion tendency
- Use of impellers for agitation implies low distortion tendency
- No speed improvers implies distortion tendency on the lower side
- Thick part area implies low distortion tendency
- Thick oxide layer implies distortion tendency on the lower side
- Rough surface implies distortion tendency on the higher side
- High quenchant temperature implies distortion tendency on the lower side
- Cubical geometry implies distortion tendency on the lower side
- Coarse grain size implies distortion tendency on the higher side
- Non-uniform grain nature implies distortion tendency on the higher side
- Welding implies distortion tendency on the higher side
- Stamping implies distortion tendency on the higher side
- Proper fixture type implies distortion tendency on the lower side.

On the basis of this analysis, the decisions, i.e. the estimates about distortion and cracking are,

- Distortion Tendency: Low
- Cracking: Not Likely

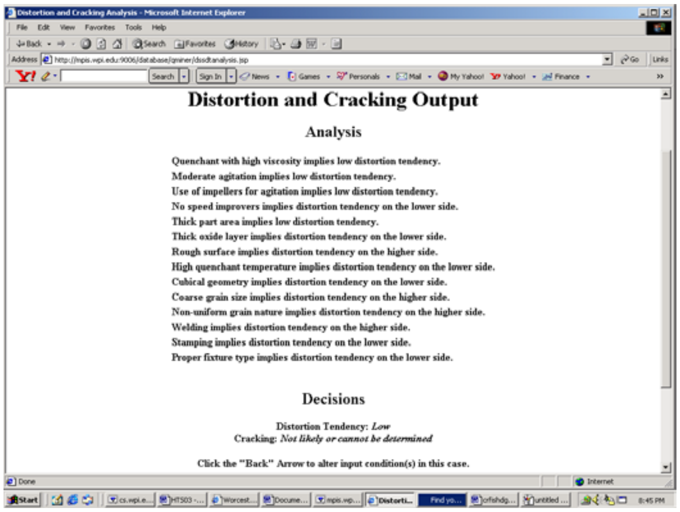

Figure 10: Distortion Case Output

Thus, by studying this case, the user knows that the given quenching conditions would most probably not cause distortion and cracking, and hence are suitable for the quenching of the desired part.

Likewise, several other examples yield interesting results, and serve to address the issue of Distortion Control.

8. Conclusions

QuenchMiner™ has been designed as an Expert System that provides Decision Support in the Heat Treating of Materials. Its focus is on Quenching and Distortion Control. It serves as a tool for users to retrieve quenching experimental data and analyze it to assist decision making, with the goal of process optimization. The system is ready for use and is available to the authorized users of CHTE at the MPI (Metal Processing Institute) Web-site at WPI. Ongoing research and improvements suggested by users will be applied to further enhance the system.

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