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Application of Machine Learning Techniques in the Process Modeling of WEDM

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Abstract- Wire-EDM is a highly complex process, which is characterized by non-linear behavior. Owing to unique capabilities of machining complex shapes and hard materials with high accuracy and fine surface finish, WEDM is used in various manufacturing industries. There has been on-going research to develop automated capabilities for WEDM by understanding the interaction mechanism of various input parameters to get the requisite output measures like MRR, Surface Finish etc. To get the desired output measures, WEDM depends mainly on the operator's experience and trial and error methods. To overcome this, a standard method for predicting output measures based on the input parameters in WEDM is yet to be established, which is a key requirement for developing Automated Process Control System and Expert System for WEDM. As a part of research, data mining technique applied to model the WEDM process, to select the input parameters for the desired output measures. The model was built trained, tested and validated with the Experimental data and with additional data. It is observed that the model built using data mining approach results-in with desired accuracy.

Index Terms- CRT for WEDM, CHAID for WEDM, Classification, Data Mining for Wire EDM, Modelling, Machine Learning.

I. Introduction

Wire Electro Discharge machining (WEDM) is one of the important non-traditional machining processes which are used for machining difficult to machine materials like titanium, nimonics, zirconium, etc.Wire-electro discharge machining (WEDM) widely used in the aerospace, nuclear and automotive industries. This is because the WEDM process provides an effective solution for machining hard materials with intricate shapes, which are difficult to machine through conventional machining methods. [4,5]

In WEDM the cost of machining is rather high due to high initial investment for the machine and cost of the wire–electrode tool. The WEDM process is more economical, if it is used to cut difficult to machine materials with complex, precise and accurate contours in low volume and greater variety. WEDM provides high accuracy, repeatability, and a better surface finish but the tradeoff is a very slow machining rate. Due to the slow machining rate in WEDM, machining tasks take many hours depending on the complexity of the job. Due to this, there is a need for the users of WEDM to estimate /predict machining time (in other words the machining rate) along with requisite surface finish, by selecting suitable input parameter values with a pre-programmed system, which may be termed as Expert System for WEDM. Selection of suitable cutting parameters plays an important role for obtaining higher cutting speed or good surface finish. Improperly selected parameters may result in serious consequences like short-circuiting of wire and wire breakage and in turn reduces productivity. [14,15]

Various investigations have been carried out by several researchers for improving the surface finish and cutting speed of WEDM process. Even though up-to-date CNC-WEDM machines are available, the problem of selection of cutting parameters in WEDM process is not fully solved, since so far there is no established standard method for predicting machining rate based on the input parameters because of the complex machining mechanism of WEDM. In addition to this the recommended input parameter values of the Manufacturers will not yield optimum machining conditions. Hence, there is a heavy dependency on the operators/skilled persons who have hands on the system. Thus the inability to predict efficient automated machining rate has been one of the major obstacles in developing automated process control systems and expert systems for WEDM.[16]

Due to its inherent complexity it is difficult to model WEDM. A limited success is achieved to model WEDM with latest techniques like artificial neural networks, fuzzy logic, etc. Hence, there is a requirement of set of rules to generate with IF. Then, if possible, to make the WEDM process into a Knowledge base system, or Expert System. The data mining technique, relatively a new technique, an attempt is made in this research to generate the simplest IF…THEN rules, with a very high overall accuracy. In the process, the experimental data is classified and analyzed with machine learning algorithms coupled with categorizing methods.

II. EXPERIMENTAL DETAILS

Hot die steel H13 has been considered in the present set of research work. In the recent past H13 gained dominance, where high strength and/or hardness are required at elevated temperatures. Brass wire of 0.25 mm diameter was used as tool electrode in the experimental set up. All the experiments were conducted on SPRINTCUT (AU) WITH PULSE GENERATOR ELPULS 40A DLX CNC Wire-cut EDM machine[8]. In this machine, all the axes are servo controlled and can be programmed to follow a CNC code which is fed through the control panel. All three axes have an accuracy of 1μm. The size of the work piece considered for experimentation on the wire-cut EDM is 25 mm x 5 mm x 5 mm. A small gap of 0.025 mm to 0.05 mm is maintained in between the wire and work-piece. The high energy density erodes material from both the wire and work piece by local melting and vaporizing. The di-electric fluid (de-ionized water) is continuously flashed through the gap along the wire, to the sparking area to remove the debris produced during the erosion. Nine Input process parameters such as Pulse On time (TON), Pulse Off time (TOFF), Peak Current (IP), Spark gap Voltage Setting (SV), Wire tension setting (WT), Wire Feed rate setting (WF), Servo Feed Setting (SF), Flushing pressure of dielectric fluid (WP) and Material Thickness (THICK) used in this study.[3,4,8,9,10,14,15,16]

Table 1

Sl.No.	**PARAMETERS**	**SYMBOL**	**LEVEL1**	**LEVEL2**	**LEVEL3**	**UNITS**
1	Pulse On time	TON	111	121	131	μsec
2	Pulse Off time	TOFF	63	53	43	μsec
3	Peak Current	IP	70	150	230	Ampere
4	Spark gap Voltage Setting	SV	30	50	70	Volts
5	Wire tension setting	WT	4	8	12	Kg-f
6	Wire Feed rate setting	WF	4	5	6	m/min
7	Servo Feed Setting	SF	1100	1600	2100	mm/min
8	Flushing pressure of dielectric fluid	WP	9	12	15	Kg/cm2
9	Material Thickness	THICK	24	35	49	mm

The input parameters and their range of values have been carefully chosen based on the literature and by experimental evaluation of one factor at a time method. The results of the experiments given in Table 2 are based on Experiments planned using a Custom Design option of IBM SPSS software. IBM software is statistical design software. Data mining techniques does not require following any statistical design. The use of statistical design of experiments was chosen for the simple reason that if the data is not indicative of the domain, then the machine leaning may not find patterns that may be present in the domain.[12,13]

Table 2

EXPNO	TON	TOFF	SV	IP	WF	WT	SF	THICK	WP	MRR(Mgs/sec)
1	111	63	150	50	12	12	1100	35	15	0.542
2	111	63	150	70	12	12	2100	24	12	0.574
:	:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:	:
15	111	43	70	50	6	4	2100	49	15	1.331
16	111	63	70	50	9	4	1600	49	9	1.378
17	111	53	230	70	12	8	1600	24	12	1.401
:	:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:	:
34	121	63	70	50	9	4	1600	49	9	2.418
35	121	53	70	50	6	8	1100	24	9	2.463
36	111	43	70	30	12	4	1100	35	9	2.564
37	131	43	70	50	6	12	1600	49	12	2.677
:	:	:	:	:	:	:	:	:	:	:

:	:	:	:	:	:	:	:	:	:	:
48	131	53	70	50	12	4	1600	24	15	3.369
49	131	43	150	70	9	8	2100	49	9	3.391
50	121	63	230	30	12	8	1100	24	12	3.451
:	:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:	:
71	131	63	150	70	12	12	2100	24	12	5.086
72	131	53	230	70	12	4	1100	49	12	5.138

III. METHODOLOGY

The obtained experimental results were analyzed by using data mining approach. The data mining system applies induction rule to analyze the results.[10] The data mining system constructs the models from the experimental data and enables rules to be automatically learnt from training data. Then the system validates the obtained trained, tested data from the experimental data. The system uses top down induction of decision tree method to analyze the data. The advantage of decision tree method is that decision trees represent rules that can be easily understood by everyone and gives the actual process knowledge to develop a knowledge base system. A set of rules can be derived from this decision tree stating the relationship between the various input parameters of WEDM like, Pulse on, Pulse off, Thickness of material etc. and the output measures namely surface finish and material removal rate [11,12].

3.1 THE DATA MINING PROCESS

Data mining process has the following four steps to follow:

1. *DATA PREPROCESSING:* Data collection, Data Cleaning, and Data Transformation are the three steps used to gather data, clean the data and to transform the collected data for further processing.
2. *PATTERN SEARCH:* To find and compare the patterns in data this method was used. This is the most crucial part of the data mining process. Neural networks, Machine Learning and statistical methods are the different data mining algorithms that are used for this purpose.
3. *ANALYSIS*. The output of the pattern search is analyzed and investigated to decide to stop or to perform a revised search.
4. *INTERPRET*. The final investigated findings are further interpreted.

3.1.1. DATA PREPARATION

Data preparation is an essential step in the data mining process. The data must be reformulated in terms that can be handled by the data mining algorithm. The following classification strategy is used:

(a) The targeted out puts of the WEDM process are surface finish "*R*a" and cutting speed "CSPEED", Material Removal Rate MRR. The *R*a and CSPEED, MRR are treated separately. This is done by firstly analyzing the effect of the input parameters on CSPEED and then repeating the exercise for surface finish Ra. For the present paper only the MRR is considered.

(b) A set of attributes/input parameters with their ranges are predefined as shown in table1.

(c) The experiments are carried out with the predefined number with the input parameters and their ranges. The resultant MRR values are calculated with the output cutting speed values taken from the machines display screen for each experiment and by using the following formula

$MRR = k\ t\ vc\ \rho$ *(mgs/sec)*

Where, k is the Kerf width (mm), t is the thickness of work piece (mm), VC is the Cutting speed (mm/min). *ρ(row) is the density of the work piece material*

(d) The input parameters/attributes values in WEDM can only be changed on the machine in a step-wise manner; hence they will be treated as categorical data. The target values are categorized into four (2, 3, 4, 5) classes by using an incremental categorization approach. The incremental approach is something like a common man's language which helps in classifying the data based on whether the output is below or above a threshold value. The categorizations of target values were performed by the above two, three, four, and five classes using the mean and standard deviation method. There are several such methods to process the data in data mining.

(e) In the standard deviation method the threshold values are chosen with the aid of mean and standard deviation by applying some

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of the basic statistical rules to the outputs in the training set, testing set and validation set.

3.1.2. SEARCH FOR PATTERNS

3.1.2.1. DATA MINING ALGORITHM: There is several rule induction algorithms for classification, and C4.5, ID3, CHAID, CN2 and CART, MARS are examples of such algorithms. Some studies have compared the prediction accuracy, complexity and training time of different classification algorithms. In the present study Chi-squared Automatic Interaction Detection CHAID, Classification and Regression Trees CART algorithms have been chosen for the following reasons:

One of the main differences between these algorithms is the method of splitting criteria that they use in selecting attributes for root and internal decision nodes in building the decision tree. Also, another difference is that whether an algorithm can split the node into two or more child nodes.

In CHAID, the decision tree is constructed by splitting the data into two or more Child nodes, beginning with the entire data. The attribute that has the strongest interaction
With the target variable measured by Chi-square statistics will be chosen as a node for Splitting. Categories of each independent attributes are merged when there is insignificant difference between them with respect to the target variable. The significance of a difference is measured by the p-value obtained from a statistical test. The type of statistical test used in this process depends on the type of target variable. The F-test is used if the target variable is continuous, and the Pearson chi-squared test is used if the target variable is categorical CHAID maximizes the significance of a chi-square statistic at each partition of dependent variable.

In CART, the data is partitioned by a sequence of binary splits starting at a parent Node. The splits take place using a variety of impurity or diversity measures such the Gini Index, towing, and least squared deviation. At each split, the impurity of all sub-partitions is summed up to choose the attribute that causes the maximum reduction in impurity. The process of partitioning data at each node is based on the concept that each node must be more homogenous than the original parent. The goal is to produce subsets of the data that are as homogeneous as possible with respect to the target variable.

Then after the 2,3,4,5 classification, the model was built using data from Table 2. Then the data was subjected to the two data mining methods (learning methods to validate the applicability of the rules to the pattern found in the data though the training, testing. The software provides the option of selecting a part of the data for training and another part of data for testing and some another part of the data for validating the suitability of algorithm, classification etc. This is in terms of %. The following % allocation of data chosen by the author as per the standards: For eg.,for training set as 70%, for testing 20% and for validation 10% of the data provided in Table 2 chosen by the software at random basing on allocation. The results are tabulated in Table3, Table 4.

IV. RESULTS AND DISCUSSIONS

Table 3

			SD			
2CL	CHAID					
'Partition'	1_Training		2_Testing		3_Validation	
Correct	52	100.00%	8	100.00%	12	100.00%
Wrong	0	0.00%	0	0.00%	0	0.00%
Total	52		8		12	
	CRT					
'Partition'	1_Training		2_Testing		3_Validation	
Correct	52	100.00%	8	100.00%	12	100.00%
Wrong	0	0.00%	0	0.00%	0	0.00%
Total	52		8		12	

			SD			
3CL	CHAID					
'Partition'	1_Training		2_Testing		3_Validation	
Correct	52	100.00%	8	100.00%	11	83.33%
Wrong	0	0.00%	0	0.00%	2	16.67%
Total	52		8		12	
	CRT					
'Partition'	1_Training		2_Testing		3_Validation	
Correct	52	100.00%	8	100.00%	11	91.67%
Wrong	0	0.00%	0	0.00%	1	8.33%
Total	52		8		12	

			SD			
4CL	CHAID					
'Partition'	1_Training		2_Testing		3_Validation	
Correct	49	94.23%	7	83.33%	10	83.33%
Wrong	3	5.77%	1	16.67%	2	16.67%
Total	52		8		12	
	CRT					
'Partition'	1_Training		2_Testing		3_Validation	
Correct	49	94.23%	8	100.00%	10	83.33%
Wrong	3	5.77%	0	0.00%	2	16.67%
Total	52		8		12	

			SD			
5CL	CHAID					
'Partition'	1_Training		2_Testing		3_Validation	
Correct	46	88.46%	6	75.00%	9	75.00%
Wrong	6	11.54%	2	25.00%	3	25.00%
Total	52		8		12	
	CRT					
'Partition'	1_Training		2_Testing		3_Validation	
Correct	48	92.31%	7	87.75%	10	83.33%
Wrong	4	7.69%	1	12.25%	2	16.67%
Total	52		8		12	

Table 4

2CL SD			
	1_Training	2_Testing	3_Validation
CHAID	100.00%	100.00%	100.00%
CRT	100.00%	100.00%	100.00%

3CL SD			
	1_Trainin	2_Testing	3_Validation
CHAID	100.00%	100.00%	83.33%
CRT	100.00%	100.00%	91.67%

4CL SD			
	1_Trainin	2_Testing	3_Validation
CHAID	94.23%	83.33%	83.33%
CRT	94.23%	100.00%	83.33%

5CL SD			
	1_Training	2_Testing	3_Validation
CHAID	88.46%	75.00%	75.00%
CRT	92.31%	87.75%	83.33%

	2CL			3CL			4CL			5CL	
	CHAID VAL	CRT VAL		CHAID VA	CRT VAL		CHAID VA	CRT VAL		CHAID VAL	CRT VAL
SD	100.00%	100.00%	SD	83.33%	91.67%	SD	83.33%	83.33%	SD	75.00%	83.33%

From the decision trees it is seen that TON, TOFF, IP, SV,SF, WF and Thickness of the material are the important parameters influencing the MRR.

Table 5

2CLSD			
	1_Training	2_Testing	3_Validation
CHAID	100.00%	100.00%	100.00%
CRT	94.23%	100.00%	91.67%

Table 6

3CLSD			
	1_Training	2_Testing	3_Validation
CHAID	100.00%	100.00%	91.67%
CRT	100.00%	100.00%	91.67%

Table 9

2CL		
	CHAID VAL	CRT VAL
SD	100.00%	100.00%
3CL		
	CHAID VAL	CRT VAL
SD	91.67%	91.67%
4CL		
	CHAID VAL	CRT VAL
SD	83.33%	83.33%
5CL		
	CHAID VAL	CRT VAL
SD	75.00%	83.33%

Table 7

4CLSD			
	1_Training	2_Testing	3_Validation
CHAID	94.23%	83.33%	83.33%
CRT	94.23%	100.00%	83.33%

Table 8

5CLSD			
	1_Training	2_Testing	3_Validation
CHAID	88.46%	75.00%	75.00%
CRT	92.31%	86.75%	83.33%

From the results of data mining with four classes, it is seen that material thickness (THICK) is influencing the material removal rate. As the thickness is increasing the MRR is increasing. The result is obtained from both the CART and CHAID confirms this. After the Thickness equally important parameters which influence the MRR are TON, IP, SF,SV, WF,WP in the order written in CART algorithm. In CHAID the Order differs but the final conclusion is agreeable with CART.

It may be noted from the trees and also from the above tables 5, 6, 7, 8 that as the number of classes are increasing the importance of accuracy in pattern search is increasing as result the validation and the misclassifying the training and test data is also increasing. Hence it may be worth noting that as the classification increase into number of classes then the categorizing methods followed should be more math oriented and care should be taken in framing the rules for classification. There are total 8 models (Table 9) for the 4 classes(2,3,4,5 classes) with standard deviation method and 2 data mining machine learning algorithms. Out of 8 models 2 models yield 100% , 2 models yield 91.67% 2 models yield 83.33%.Whereas for the last class one model yields 83.33% and one model for 75%. Thus an overall basis the success rate is 7/8=85% (75% and above is considered as threshold). Thus if such a model is developed then the trial and error methods to be adopted by the operator will reduce and the machining time reduces and increases productivity and the can be more compatible to CAPP and knowledgebase system. The invalidated cases in the classification is 16.33% up to 16 to 25% in case of CHAID and it is 16.33% in case of CART. It is also to be noted from the results that data misclassifying is only to the tune of 7 to 11.54% (table3)of the cases hence it is presumed that the model performed reasonably well on the test data misclassifying only 16.33% of the cases.

V. CONCLUSION

In this paper WEDM domain was dealt as classification problem. The data mining approach provides the important decision parameters that are useful in obtaining the desired output results and making the WEDM process much more automation process to incorporate into CAPP. The CHAID, CART algorithms has been used to automatically learn rules from WEDM data. Similarly other algorithms can also be tried with suitable categorization, classification approaches. This approach can be applied to any manufacturing process and can significantly reduce cycle times by increasing the level of automation and also providing insight into the process. For improved performance and prediction accuracy Hybrid approaches in combination of artificial neural networks and decision trees may also be employed. However there will be question when to use CRT and when to use CHAID analysis. CHAID analysis is especially useful for data expressing categorical values instead of continuous values whereas CRT analysis is useful for data sets consisting of categorical or continuous values for the dependent (response or target values). Hence the users must be aware how the target values are distributed (categorical or continuous) and then use the respective machine learning algorithm to get better results.

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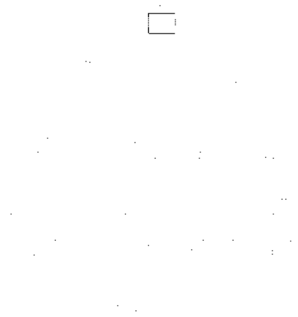
DECISION TREES FOR CART ALGORITHM



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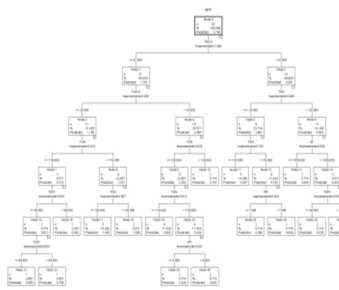

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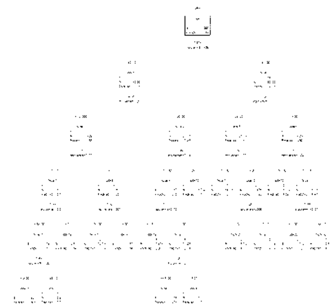

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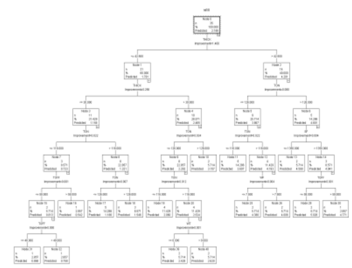

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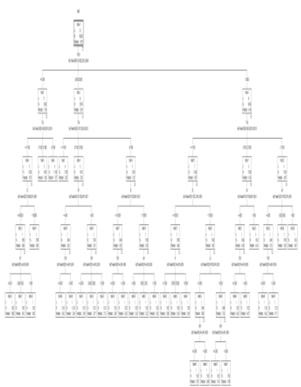
DECISION TREES FOR CHAID ALGORITHM



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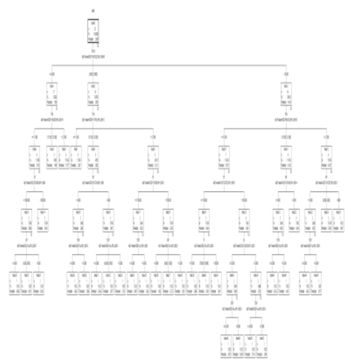

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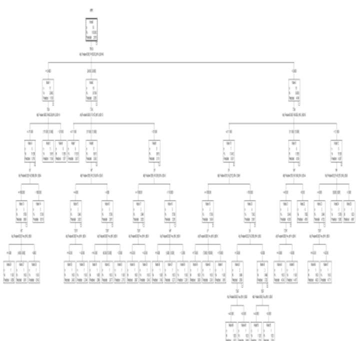

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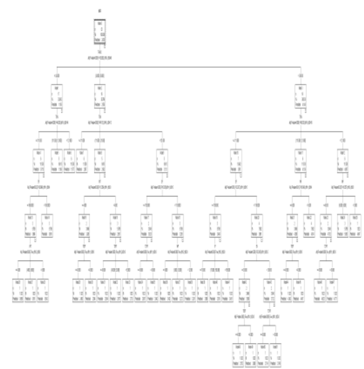

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