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# APPLICATION OF NEURO-FUZZY SYSTEMS AND GENETIC PROGRAMMING FOR MODELLING SURFACE ROUGHNESS IN ELECTRICAL DISCHARGE MACHINING

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**Abstract**: This paper reports the development of two intelligent models for the electric discharge machining (EDM) process using adaptive-neuro-fuzzy-inference system (ANFIS) and genetic programming (GP). Experiments were conducted by varying the pulse duration and discharge current and the corresponding values of surface roughness ($R_a$) were measured. The values of surface roughness predicted by these models are then compared. Both models show good agreement with experimental results. The results indicate that the genetic programming technique gives slightly smaller deviation of the measured values of model than neuro-fuzzy model.
**Keywords**: neuro-fuzzy systems, genetic programming, surface roughness

## 1. INTRODUCTION

Electrical discharge machining (EDM) is a very common type of machining in manufacturing industries. The manufacturing industries strive to achieve either a minimum cost of production or a maximum production rate, or an optimum combination of both, along with better product quality in machining [1, 2]. Increasingly, research in manufacturing processes and systems is evaluating processes to improve their efficiency, productivity and quality. The quality of finished products is defined by how closely the finished product adheres to certain specifications, including dimensions and surface quality. Surface quality is defined and identified by the combination of surface finish, surface texture, and surface roughness. Surface roughness ($R_a$) is the commonest index for determining surface quality [3, 4].

EDM process do not allow achieving the theoretical surface roughness due to defects appearing on machined surfaces and mainly generated by deficiencies and imbalances in the process. Due to these aspects, measuring procedures are necessary; as it permits one to establish the real state of surfaces to manufacture parts with higher accuracy. To know the surface quality, it is necessary to employ theoretical models making it feasible to do predictions in function of response parameters [5].

Recently, some initial investigations in applying the basic artificial intelligence approach to model machining processes. Wang et al. [6] development and application of a hybrid artificial neural network and genetic algorithm methodology to modelling and optimisation of electro-discharge machining. An adaptive neuro-fuzzy inference system (ANFIS) model has been developed for the prediction of the white layer thickness (WLT) and the average surface roughness achieved as a function of the process parameters by Çaydas [7]. Yilmaz et al. [8] presented a intelligent system for the selection of electro discharge machining parameters which lead to less electrode wear, better surface quality and more erosion rate according to the selected operation (finishing, roughing, etc.). Rao et al. [9] developed mathematical model for predicting die-sinking electrical discharge machining of aluminium alloy characteristics such as the metal removal rate (MRR), the tool wear rate (TWR), the surface roughness ($R_a$ value) and the hardness(HRB) using fuzzy mathematical method. Multi-objective optimisation of electrical discharge machining of metal matrix composite using non-dominated sorting genetic algorithm were explained by Golshan et al. [10]. In this research, the influence of electrical discharge machining (EDM) on surface roughness and material removal rate (MRR) in metal matrix composite was investigated. Kuriakose et al. [11] presented work, a multiple regression model is used to represent relationship between input and output variables and a multi-objective optimization method based on genetic algorithm is used to optimize Wire-EDM process. From the review of literature, it is observed that artificial intelligence techniques including neuro-fuzzy system and genetic algorithm have found wide applications in modelling of process parameters and controlling the EDM system components.

In this study, discharge current and pulse duration as machining conditions were selected. A neuro-fuzzy and genetic models were developed and compared using these machining parameters. Contribution of this paper is that not only modelling is done by neuro-fuzzy system and genetic programming, but comparison of two modelling methodologies. Comparative observation showed that the genetic programming gives slightly smaller deviation of the measured values of model than neuro-fuzzy model.

## 2. DESIGN OF EXPERIMENTS

Evolutionary Experimental investigation was conducted on an EDM machine tool ″FUMEC – CNC 21″ in South Korea. The work material used in the experiment was manganese-vanadium tool steel, ASTM A681 (0,9% C, 2% Mn, and 0,2% V), hardness 62 HRc. The tool was made of electrolytic copper with 99,9% purity and 20×10 mm cross-section. The dielectric was petroleum. Due to small eroding surface and depth, natural flushing was used.

The machining conditions included variable discharge current and pulse duration. The range of the discharge current was $I_e$=1÷50 A (current density 0,5÷25 A/cm$^2$), while the pulse duration was chosen from the interval $t_i$=1÷100 μs to accommodate the chosen current. The rest of the parameters of electric impulse were held constant, according to the manufacturer's recommendations (open gap voltage $U_o$=100 V, duty factor τ=0,8 and positive tool electrode polarity).

The experiments were conducted according to the specified experiment plan. Input parameters were varied and the resulting machining parameters of EDM process were monitored and recorded. Measured parameter was surface roughness $R_a$. Surface integrity was assessed by measuring surface roughness and research of the surface layer properties. ″PERTHOMETER S5P″ of Mahr, Germany was used to measure the arithmetic average deviation of the assessed profile (ISO 4287) [12].

## 3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The acronym ANFIS derives its name from adaptive neuro-fuzzy inference system. Fuzzy inference system (FIS) is a rule based system consisting of three components. These are:

- a rule-base, containing fuzzy if-then rules,
- a data-base, defining the Membership Functions (MF) and
- an inference system that combines the fuzzy rules and produces the system results.

Using a given input/output data set, the ANFIS method constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone, or in combination with a least squares type of method.

For this model, main parameters for the experiments are discharge current Ie, pulse duration ti (input data set) and surface roughness Ra (output data set) (Figure 1). The training dataset and testing dataset are obtained from experiments. The input/output dataset was divided randomly into three categories: training dataset, consisting 18 of the input/output dataset, checking dataset, consisting 5 of the data and validation (unknown to model) data set, which consists 5 of data.

Training process is accomplished by using Mat Lab 6.0. In order to determine the optimal network architecture, various network architectures were designed; different training algorithms were used. The number and type of membership functions, method optimization hybrid or back propagation, and number epoch were changed. Then the best adaptive network architecture was determined. The training epoch for each network is 500, hybrid method optimization, the best results given 3 membership functions Gaussian type. When the network training was successfully finished, the ANFIS was tested with validation data.

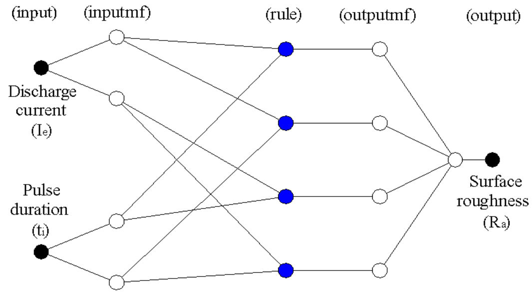


Figure 1. Basic ANFIS architecture

**4. GENETIC PROGRAMMING (GP)**

Evolutionary algorithms, with genetic programming being a subclass, as their name is suggesting are based on principles of evolution and natural selection. Each solution to the problem is considered to be one individual which is evaluated by fitness function. Results of evaluation are directly determining each individual’s probability of mating and thus transferring his genetic material onto next generation.

Fitness function which will be used to evaluate quality of generated solution is mean square error function:

$$\Delta = \frac{1}{28}\sum_{i=1}^{28}\left(P(i)\quad D(i)\right)^2 \tag{1}$$

where P is experimentally obtained value and D is modelled value for every parameter.

For practical realization of model software GPdotNET was used [8]. At the beginning six random constants were generated from the interval 0÷10. These will be used in equations forming as supporting members. Not to be confused, those constants don’t have to be in final solutions. They are just available there for algorithm to use them. Sometimes solutions are found to be better without some constants. Number of individuals in every generation was 500. Elite count was 16, which means that from every generation 16 individuals with best fitness were automatically moved to next generation. Whole modelling procedure lasted for 500 generation. During that time evolution operators were executed with probabilities: 0,7 for crossover to happen, mutation 0,1, 0,2 for reproduction and 0,05 for permutation. Only arithmetic operators, respectively “+”, “-“, “*” and “/”, are used to form membership functions.

**5. RESULTS**

Numerical values of average percent deviation, for modelled results from experimentally obtained results, are shown in Table 1.

Table 1. Values of average percent deviation of results

| ANFIS Error (%) | GP Error (%) |
|---|---|
| 4,01 | 2,6 |

Figure 2 describe the comparison of experimental, ANFIS and GP results for the surface roughness, respectively. It proved that the methods used in this paper are feasible and could be used to predict the Ra in an acceptable error rate for EDM. The compared lines seem to be close to each other indicating with good agreement.

**6. CONCLUSION**

In this paper an ANFIS and genetic programming (GP) are used to estimate surface roughness in EDM. Figure 2 shows the compared predicted values obtained by experiment and estimated by ANFIS and GP model and show a good comparison with those obtained experimentally.

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One of the most important advantages of GP of modelling is that specific equations are obtained and models can be used independently. Because of the scarcity of space and slight complexity of generated membership functions, they are not shown within this paper. They are although available on request from corresponding author.

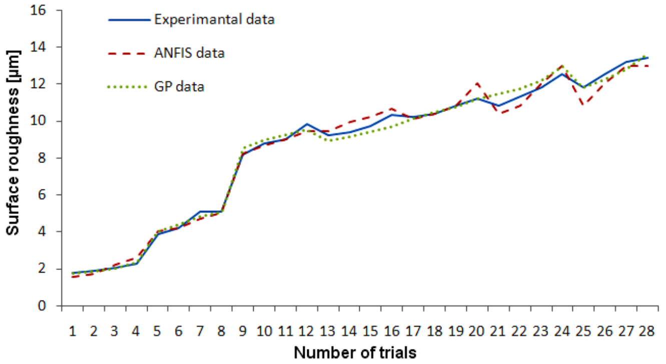


Figure 2. Correlation between experimental, ANFIS and GP surface roughness value

The adequacy of models are checked and is found to be adequate for ANFIS model is 95,9% and GP model is 97,6 % confidence level and the both models can be used for predicting the surface roughness in EDM. The effectiveness of the models is only within the range and factors studies. The model adequacy can be further improved by considering more variables and ranges of parameters.

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