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Analytical research of artificial intelligent models for machining industry under varying environmental strategies: An industry 4.0 approach

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A R T I C L E I N F O

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Response surface methodology (RSM)
Environmental conditions

A B S T R A C T

Since the introduction of Industry 4.0, manufacturing industries have adopted smarter automation systems enabling better interconnection amongst various aspects of the production industry. Application of industry 4.0 furnishes better performance and efficiency with improved reliability and robustness. The present research provides a novel framework which takes in consideration the complexity and flexibility of the working environment within the factory premises, previously not explored. Smart systems equipped with sensors and communicators are responsible for monitoring information and detecting malfunctions pre-hand which eventually boosts the system performance. Furthermore, the research explores the concept of predictive maintenance in industry 4.0 setup which apprehends any system failure based on atmospheric related changes. A novel algorithm is explored in this research which takes in consideration multisource diverse dataset based on varying environmental conditions and simultaneously furnishing inputs for predictive maintenance in Industry 4.0 implementation, thereby providing a transparent and effective manufacturing method. The framework for Industry 4.0 is validated and deemed feasible with quantitative comparison with previous prediction models which can further predict any future malfunctions in the industrial machines. The productivity values are validated with models developed with the help of intelligent hybrid prediction techniques such as adaptive neuro-fuzzy inference system (ANFIS) and response surface methodology (RSM). The input parameters considered are atmospheric conditions whereas the required output response is productivity of the machines. Error rates were evaluated lowest error rate for triangular membership functions for both machining models.

1. Introduction

The prediction interval is a potential tool for measuring and resolving the output data uncertainties accompanied in the model. With application of a successful prediction interval model, these uncertainties are bound to get reduced with each iteration. Anticipation of future model-based uncertainties within the system result in a more sound and efficient building power supervision choices [12]. The inputs comprising of higher prediction uncertainty can be introduced with certain constraints, eventually resulting in better performance of the anticipated cooling system. Furthermore, the faults within the system can be pinpointed and discovered, if the required or predicted cooling or heating conditions which differ from the actual conditions. Finally, through these prediction techniques it can be interpreted that a wider range of prediction loads furnishes high uncertainties in the system, while a narrow range of prediction loads display lower uncertainty level. A reliable and improved performance is shown in latter system as compared to the former system [3–5].

Modern industries are incorporating Industry 4.0 concept to accelerate the productivity of machines with the aid of artificially intelligent techniques [6]. Basically Industry 4.0 is completely altering the conventional industrial setups since these are capable of supporting appreciable production flexibility and creativity in a cost-effective manner [7]. It integrates features of communication, data generation and artificial intelligence in one capable setup known as Industry 4.0 [8]. The immense potential of Industry 4.0 has been validated by previous researches also as it has established substantial innovation and growth potential at other platforms also, thereby refining the existing industrial framework of sustainability [9].

Chiller cooling capacity is often affected by condenser scale formation, coolant leakage, and formation of non-condensable fumes [6]. These shortcomings can be estimated if the pre-estimated cooling loads comprehensively vary from the actual cooling loads. The observed de-

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Nomenclature

ACH	Number of air changes per hour
RSM	Response surface methodology
ANFIS	Adaptive neuro-fuzzy inference system
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
CLF	Cooling load factor
HVAC	Heating, ventilation and air conditioning
IR	Infrared
DBT	Dry bulb temperature
WBT	Wet bulb temperature
RH	Relative humidity
WS	Wind speed
MT	Mean temperature

fects, on the other hand, would be inaccurate if the pre-estimated cooling loads evaluated were improper. Thereby, quantitative explanation of the errors present in the pre-estimated cooling loads is helpful in assessing only if the observed faults are reliable [7–9]. Henceforth, a generic framework for quantifying the instabilities within the anticipated cooling loads must be suggested. More effective building power arrangements and precise fault recognition approaches may be devised where the quantitative instabilities are taken into consideration.

Through extensive literature review process, it can be concluded that in past seldom findings have been reported on generic based interval procedure for examining pre-estimated cooling loads. Nevertheless, the assertions restrict its implementation as the residual forecast of other algorithms for cooling load prediction may not be based on the zero mean Laplace distribution. The current research suggests a universal method of evaluating the pre-estimated cooling loads which will further furnish the pre-hand uncertainties within the system. Unlike traditional approaches for estimating interval predictions, the novel framework does not assume any predictive residuals distribution. Theoretically, it is ideal for all major prediction-based algorithms for cooling load estimation as pre-hand considerations unassumed [10–13].

Prime factors such as consistency and safety are considered as one of the most significant aspects in smart automated industries. These parameters are continuously evolving due to the complexity and diversity of the required system. Incorporation of big data analysis in an industrial setup will furnish exceptional benefits, such as boosting framework management, attaining near zero maintenance and further guaranteeing pre-estimated based maintenance system [14–16].

Uncertainties associated with the anticipated cooling loads in a specific area are inevitable owing to the nature of cooling loads. Analyst estimated that the uncertainties may affect the performance of cooling load prediction-based power saving procedures considerably. The efficiency of the system might be poor if the anticipated cooling requirements deviate from the estimated cooling requirement. This was evident through past literatures [17], which concluded that uncertainties considerably diminished the overall performance of the cooling load-based programming procedures [18]. Moreover, these machine errors, impact the optimised combined processes such as simultaneous heating, cooling and energy production arrangements incorporated within the building structure, monitored regularly by forecasted cooling requirement. Additionally, these errors may arise during false detection estimation procedure when the system displays lower efficiency and performance.

Utilizing special spatiotemporal characteristic to describe or represent industrial data analytics helps the system to be more effective and efficient. furthermore, this furnishes more reliable attributes for data mining in an automated production industry setup. In order to understand the relationship of various inputs over several outputs, artificial neural network is applied which predicts the productivity of machines. This effectively reduces number of experimental runs, thereby reducing running cost and time. In previous productivity related studies various researchers have employed ANN technique to reduce the number of operations with appreciable results [19]. Moreover, response surface methodology (RSM) technique is employed so as to obtain accurate nearer experimental results. The present research is based on evaluation of the productivity of various machines in a factory which may have degraded over the years. The evaluation process mainly includes a fluke metre setup which detects the ambient conditions on day to day to performance to predict machine performance in advance. This a handheld camera is employed in measuring the temperatures at various points in the machines.

With respect to the above trends, the authors have coined following perspectives presented below;

- Application of ambient based productivity estimations, prove to be a viable and feasible option due to its simple operation and environmentally friendly nature.
- Exploration of machine productivity for various atmospheric conditions while employing soft computing techniques such as ANFIS and RSM have never been addressed in any previous literature.
- Predictive maintenance developed for taking environmental parameters in consideration yields values quite close to those obtained while experimentation.
- Previous studies (other fields in machining) have highlighted the importance of combining soft computing prediction models for energy monitoring, yielding accurate productivity characteristics with reduced effort, cost, labour, time and energy [14,15].

The current research applied a handheld camera auditing system, which detects machine productivity as output prediction and further predicted with artificial intelligence technique known as adaptive neuro-fuzzy interface system (ANFIS) and response surface methodology (RSM) approach. Hence impact of several input variables (DBT, wind speed, and relative humidity) can be studied with these models in a cost-effective manner. The predicted responses of ANFIS were compared with those obtained in experimental and theoretical evaluations and were found to be quite precise. The application of soft computing techniques coupled with optimization of machine monitoring technique will yield revolutionary results in the current industrialization era.

2. Material and method

Industrialized nations have introduced many productions boosting programs to encourage the merging of industries with artificial intelligence. This will eventually speedup financial regain and furnish new scopes for advancement in manufacturing industries. Preliminary functional procedures such as predefining the input and output variables is performed to maximize the end result. The experiment and analysis were conducted by selecting three inputs DBT, WS and RH. It is upon this benchmark that the input proposed will be evaluated for maximum productivity of machines with minimum effort. Some hybrid approaches have been presented in this paper to compare the experimental and predicted data explained in four successive steps: (i) Accumulation of the acquired experimental data and clustering the data based on training and testing, (ii) Based on the environmental conditions theoretical data generation (iii) Identifying the best performance model in ANFIS data structure for evaluating the performance of machine fixture, (iii) Comparative analysis amongst the results of ANFIS, experimental and theoretical models for best productivity determination amongst them and (iv) Finally, generalization and validation of the results with previous models.

2.1. Data compilation

Availability of reliable data has always been a revolution in development of any product into business industry since the evolution of smart

Table 1
Technical details of experiment setup.

S.No.	Properties of Camera	Specification
1	Model of Camera	Handheld Camera FLUKE metre
2	Field of view	23° x 17°
3	Thermal sensitivity	≤0.1 °C at 30 °C (100 mK)
4	Spectral range	7.5 μm to 14 μm
5	Detector type	160 × 120 focal plane array, uncooled microbolometer
6	Visual camera	640 × 480 resolution
7	Object temperature range	-20 °C to +350 °C
8	Accuracy	± 2 °C or 2 % (whichever is greater)

systems. The following sources of industrial big data are the most popular;

- Data from the design of a product or equipment.
- Data from the system operation and control module.
- Data from workforce actions such as task records and videos of employees' work activities.
- Data from production method & procedures.
  Data from transportation & supply chain.
- Data from environmental factors like climate, workspace temperature, humidity, and sound levels.
- Data from equipment/machine health checking & its failure diagnosis.
  Data from standard of production & each manufacturing station's malfunctioning or faulty rate.
- Data from product utilization & consumption like accessibility & maintenance frequency
- Data from Clients or buyers like feedback/response on product, client characteristics.

The experimental and theoretical dataset for developing the prediction ANFIS model was acquired from the drone-camera test setup. Subsequent sections comprise of the complete description of the steps followed in data evaluation. Fluke camera setup technical ratings are given below in Table 1.

amongst many similar technologies, the most significant comprehensive strategies that have ignited a new interest throughout the globe in high tech production is Industry 4.0, being actively implemented in countries such as United states and Germany.

Once industrial big data has been processed, the result is a set of dimensions, transformations, patterns, scores, and pre-hand estimations. This data-processing procedure can be roughly broken down into many phases such as data formatting, dimensionality elimination, secret pattern detection, and evaluating accuracy and prediction. Artificial intelligence and non-traditional statistical techniques are typically adopted for industrialized signal processing and data extraction, using time-frequency modelling for mechanical vibration data acquisition with high ambient noise. This eventually is performed with the aid of analytical simulation which encompasses the most influential subset of the inputs with low dimensionality. Nevertheless, the primary obstacle in signal processing while applying industrial big data is countered by the "5V" properties of the available data (volume, velocity, variety, veracity, and value). Fig. 1 displays the flow chart for data accumulation and experimentation.

2.2. Modelling through artificial intelligence

Basic modelling method employed in the study was the first order Takagi-Sugeno artificial neuro-fuzzy interface system (ANFIS). The experiment was structured on the above model as depicted in Fig. 2 so as to evaluate the machine productivity values. Similar models have been earlier established in previous literatures for modelling various unclear and difficult thermal engineering applications with limited, nonlinear, and uncertain database. Recently ANFIS models have gained substantial popularity due to its capability to build effective fuzzy rules, facilitating efficient surface plots between various input and output responses. Practically, there is an urgent desire to implement such artificial neural techniques in machine productivity evaluations since this methodology may prove as a perfect alternative to the conventional experimental techniques, thereby furnishing outcomes with enhanced reliability. General model of ANFIS comprises of six major layers with initial layer of input parameters, followed by fuzzification layer, rule consequent layer, rule strength normalization layer, rule consequent layer, and finally the rule inference layer. Constructing a feasible ANFIS structure indicates the presence of the Fuzzy Theory and membership frameworks.

Table 2
ANFIS framework for training model.

Parameters	Specifications
Total number of nodes	193
Number of linear parameters	81
Number of non-linear parameters	36
Number of training data pairs	45
Number of rules that are fuzzy	81
Membership function	Triangular

Approximately 32 set of input variables and data patterns were generated from the experiments categorizing them randomly into two subsets, i.e., 24 (≈75%) and 8 (≈25%), data for the training and testing ANFIS models, respectively. The framework of the single ANFIS model is explained in Table 2**.**

The following equations of ANFIS were applied to generate different responses by modelling;

Layer 1- Fuzzification layer:

$$Q_{1,i} = \mu_{A_i}(x),\ for\ i = 1,2\ or \tag{1}$$

$$Q_{1,j} = \mu_{B_j}(y),\ for\ j = 1,2 \tag{2}$$

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \tag{3}$$

Layer 2- Product Layer:

$$Q_{2,i} = \bar{w}_i = \mu_{A_i}(x)\mu_{B_i}(y),\ for\ i = 1,2 \tag{4}$$

Layer 3- Normalized Layer:

$$Q_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2},\ for\ i = 1,2 \tag{5}$$

Layer 4- Defuzzied Layer:

$$Q_{4,i} = \bar{w}_i\, f_i = \bar{w}_i\left(p_i x + q_i y + r_i\right),\ for\ i = 1,2 \tag{6}$$

Fig. 1. Flow chart of data accumulation and experimentation work.

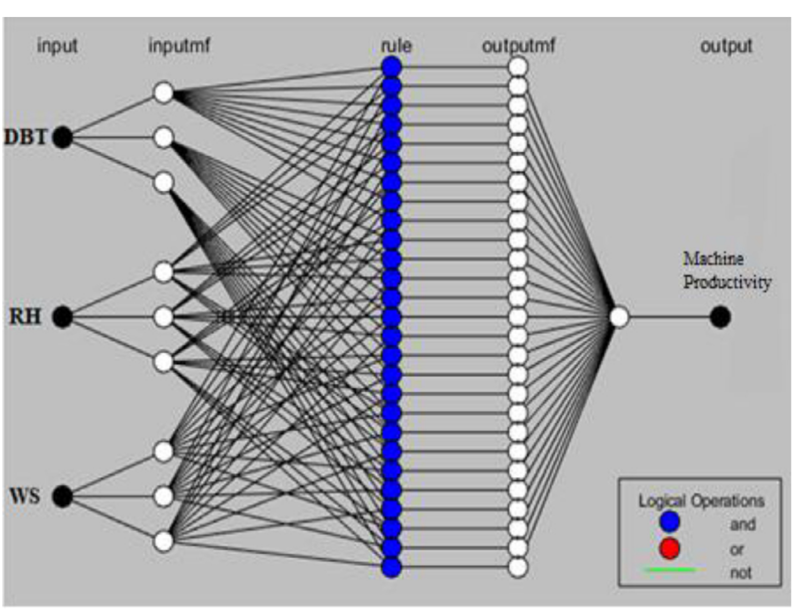

Fig. 2. Framework of ANFIS Model.

Layer 5- Total Output Layer:

$$Q_{5,i} = overall\ output = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{8}$$

$$f = \bar{w}_i (p_1 x + q_1 y + r_1) + \bar{w}_2\ (p_2 x + q_2 y + r_2) \tag{9}$$

$$f = (\bar{w}_1 p_1 x + \bar{w}_1 q_1 y + \bar{w}_1 r_1)\ + (\bar{w}_2 p_2 x + \bar{w}_2 q_2 y + \bar{w}_2 r_2) \tag{10}$$

Generally, machine characteristics-based modelling begins with developing a precise objective function which complies with the complexity of problem statement. Conventional methods employed to generate objective function for several input and output parameters consumes considerable time and labour. However, the ANFIS technique furnishes an acceptable objective function due to its capability to generate the data without the requirement of any previous model history. Estimations and predictions determined from ANFIS technique can be further fine-tuned with improved precision and efficiency by employment of genetic algorithm in output responses.

Often it is seen the ANFIS technique may not may be 100 % accurate as the outcomes are caught within the local optima. Also, the conflicting outputs complicates the model development. To overcome this complexity, RSM technique is developed which takes in all the complexities of the environment and are employed to solve complex machine related problems quickly and effectively.

2.3. Response surface methodology

The RSM technique provides an initial approach in solving and linking the input parameters with output parameters. A custom design of CCRD with 32 test runs was carried to determine the outputs and fits equation. Furthermore, the developed architecture furnishes fresh extreme values (low and high) for each variable. Input variables are derived by data obtained from past literature confirming their feasibility by experimental results. Ranges developed for input parameters strongly influenced the output responses beyond which the effects became marginal. The environmental parameters such as DBT was varied between 2–41 °C, RH was varied 20–90% for a maximum WS of 10 Km/hr. The experiment was conducted for different building walls having different geometries at various environmental conditions (DBT, RH and WS) so as to obtain the best amongst them based on output responses. For a particular set of input variables, three readings were taken simultaneously in order to develop fool proof values with minimum uncertainty. Finally, their average value was considered as end responses for further analysis. The fits equation for each output constant was derived and specified in subsequent sections. The research includes several control factors, numerical and coded values employed in the custom designed CCRD array, comprising of a total of 32 runs. Complete set of data under different environment conditions is furnished in appendix 1.

2.7. Uncertainty analysis

Data mining and knowledge acquisition are made feasible by the "5V" qualities of industrial data analytics, which furnish comprehensive and holistic based information. Given below are a few details which are acquired via data extraction technologies;

- Malfunctions in plant equipment
- Deficiencies in design process
- Fault in the manufacturing process
- Customer attitude, traditions, and requests
- Employee behaviour and work ethics.

Table 3
Errors and uncertainties associated with all instruments.

Measurements	Instrument	Range	Accuracy
DBT	Fluke metre	0 -100^0 C	± 0.4
WS	Fluke metre	0 -15 Km/hr	± 0.8
RH	Fluke metre	0 -100 %	± 0.5
Calculated results			**Uncertainty**
Machine 1 yield		0–1	± 0.1 %
Machine 2 yield		0–1	± 0.1 %

The examination of uncertainties evaluates the errors in the corresponding coefficient points. Errors are involved in all calculations; however, we typically aim to make them as modest as possible. Also, we require an accurate assessment of their size. The uncertainty in various parameters is primarily sourced by different factors such as instrument error, measurement error, surrounding conditions, methodology of measurement and type of instrument. In order to attain a sense of credibility, each parameter was measured 3 times for all test machines.

Often measurement of several performance parameters (DBT, WS and RH) and output productivity yield carry a small error in the displayed value. Hence each instrument has its own level of uncertainty which has been taken in consideration to remove any variation in the measured value. The uncertainty analysis was performed using submission of squares of each individual parameter measured during the analysis. All errors in measuring instruments are prescribed in Table 3. If numerous distinct causes impact an outcome, so errors in the predictor factors are reasonably plausible, and therefore, an overall inaccuracy may be estimated as follows.

The total percentage of uncertainty is determined in this experiment by applying the equation 11 provided below:

$$U = \left(\left[\frac{\partial R}{\partial x_1} W_1 \right]^2 + \left[\frac{\partial R}{\partial x_2} W_2 \right]^2 + \ldots\ldots + \left[\frac{\partial R}{\partial x_n} W_n \right]^2 \right)^{1/2} \tag{11}$$

The total percentage uncertainty (U) = square root of [(uncertainty of DBT)^2 + (uncertainty of WS)^2 + (uncertainty of RH)^2 + (uncertainty of reflected)^2 + (uncertainty in measurement machine 1)^2 + (uncertainty in measurement machine 2)^2]$^{1/2}$

The total percentage uncertainty = Square root of $[(0.4)^2 + (0.8)^2 + (0.5)^2 + (0.2)^2 + (0.1)^2 + (0.1)^2 + (0.2)^2]^{1/2}$

The total percentage uncertainty = ± 1.15 %

The total uncertainty evaluated for the entire test is approximately ± 1.15 %, thereby lying-in standard range.

3. Experimental setup

Conventionally, the analytical process for a typical manufacturing system doesn't account for unseen aspects/elements such as health facility/status within the industrial premisses, operator's capacity, environmental information (weather-based prediction data), workstation temperature, and noise criteria. Due to extreme segregation and complex sensor measurement, these parameters are seldomly used. Practically, generation of various relationships amongst the above parameters can be achieved with application of an integration between industrial big data and artificial intelligence, which furnishes an effective interaction between man-machine-environment. Consequently, error estimations in the industrial processes can be evaluated and validated so as to comprehend a production process in detail. Big data in the industrial sector enable the ability to describe the condition of a production process completely. Performance of the system decision criteria is considerably enhanced with integration of artificial intelligence and pre-estimated conditions within the industrial premises.

The following assumed the given data as prescribe below;

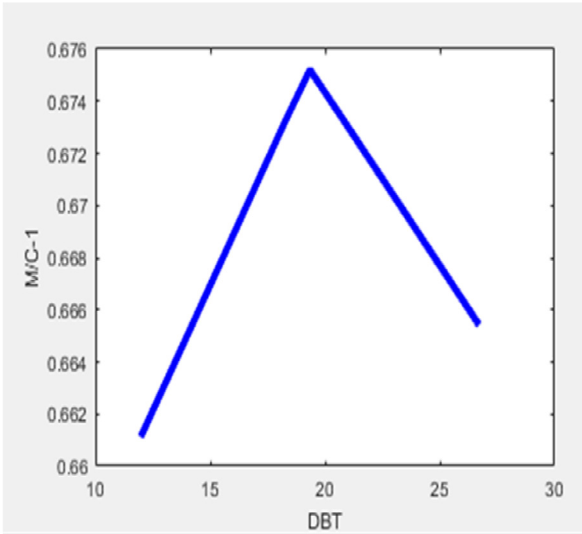

Fig. 3. Variation of machine 1 with DBT.

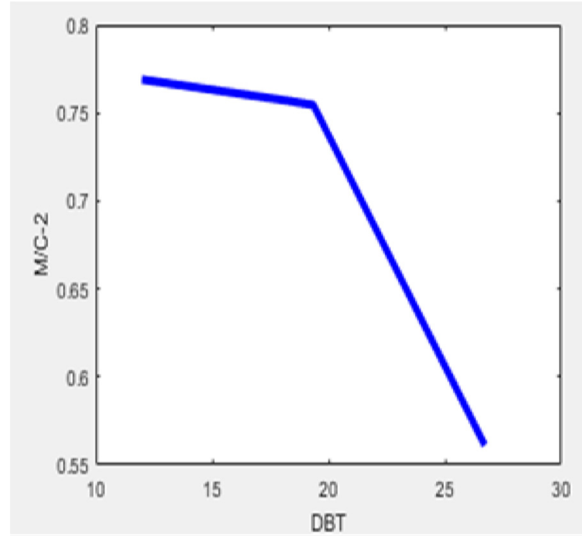

Fig. 4. Variation of machine 2 with DBT.

- Ambient conditions were monitored during experimentation and kept in ranges varying between values such as rain possibility, wind speed, temperature and moisture content. The humidity ranged between 20- 90 %, wind speed about 10 km/hr, and DBT ranged between 2–45 °C.
- The machine handling and variation parameters were studied in machine manual.
- The data estimated was later on transferred into the software for further computations in the productivity of machines.

4. Result and discussion

Excessive industrial noise, harsh ambient conditions and improper lighting distributions are crucial factors that might influence employees job performance and wellbeing. Furthermore, this eventually leads to substantial degradation on manufacturing productivity, power usage, and equipment performance. Availability of surplus data aids in developing smart models which can describe the consumption behaviour, anticipate deuteriation of the system, excessive power usage, eventually suggesting a feasible monitoring system based on responses achieved by optimizing the prime factors within the system. Implementation of these feasible models leads to enhanced quality of mass production processes. This particular section highlights the importance of enumerating the importance of predictive maintenance while estimating machine productivity for an industrial setup. The environmental parameters were obtained with utmost precision and are based on a set of parameters such as direction, concentration, thermal clarity, thermal span and reach.

4.1. Impact of dry bulb temperature (DBT) on machine yield

Dry bulb temperature (DBT) or ambient temperature is one of the primary parameters which affects the machine yield and can be corrected by using the above correlations. Often high temperatures create hurdle in machine yield may result in heightened temperature of the tool which eventually wears faster. Conversely, presence of cold air draft furnishes a lower temperature on the tool, increasing machine life. Consequently, presence of air draft brings relief in tool wear properties easing stress on tool cutting point. The relationship between both the machines can be understood with the Fig. 3 and Fig. 4 provided below;

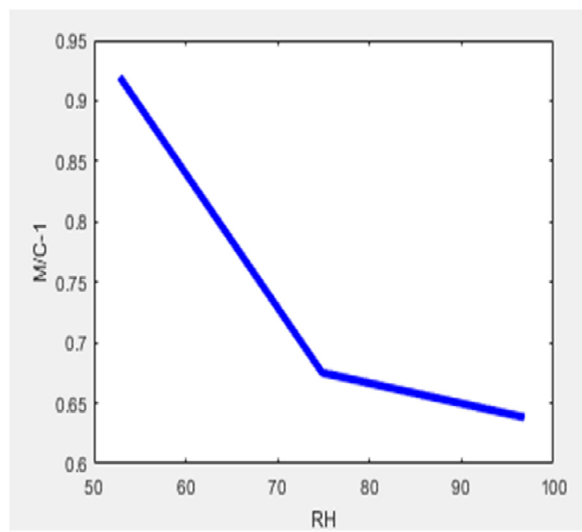

Fig. 5. Variation of machine 1 with RH.

4.2. Impact of relative humidity (RH) on machine yield

Variation in relative humidity while monitoring machine performance with the aid of ANFIS arrangement plays a vital role in machine yield. Presence of high moisture content in ambient air results in faster tool wear due to water droplet formation. Furthermore, a layer of moisture forms over the surface where tool geometry often gets distorted. These inherent droplets lower machine yield and can be nullified or avoided by maintaining humidity levels in the machining area. The relationship of machine yield ratio with RH can be understood by the Fig. 5 and Fig. 6 provided below;

4.3. Impact of wind speed (WS) on machine yield

Positive wind draft is an essential parameter while measuring yield ratios in tool temperature estimation. At high wind speed machining becomes stable since faster heat removal rate occurs eventually lowering tool wear. Although average values are taken in the analysis but this still may require the tool to be positionally straight in the direction of the

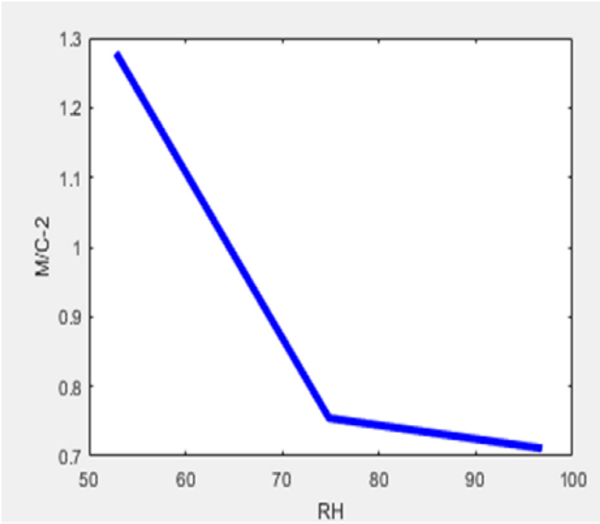

Fig. 6. Variation of machine 2 with RH.

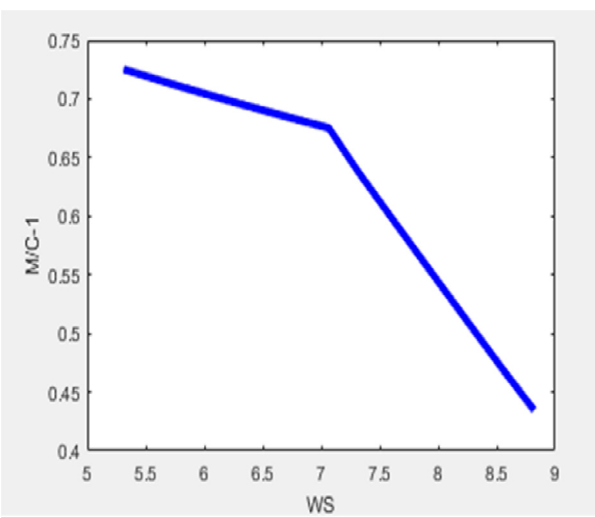

Fig. 7. Variation of machine 1 with WS.

wind draft. The relationship of the machine yield constants with WS can be understood by the Fig. 7 and Fig. 8 provided below;

4.4. Predictive maintenance with artificial intelligence (ANFIS)

ANFIS prediction method is applied to analyse a logical correlation amongst machine yield ratios and climatic conditions, including DBT, WS, and RH in this study. Experimental results for multiple machining conditions were achieved under varied climatic factors.

The assumed input features contribute to a suggestively to a wide group of facts that offers vast experimental results that involve time, work, energy, and fuel. The learning recommends that an AI approach (ANFIS) be implemented that enables a practical and reliable response prediction with minimal data input inaccuracy, including limited data inputs. Training and validation of the given data produced via RSM is surveyed using the Sugeno-type fuzzy inference structure, which principally functions on an erudite method that employs the regression investigation modelling and the gradient descent method of the back-propagation.

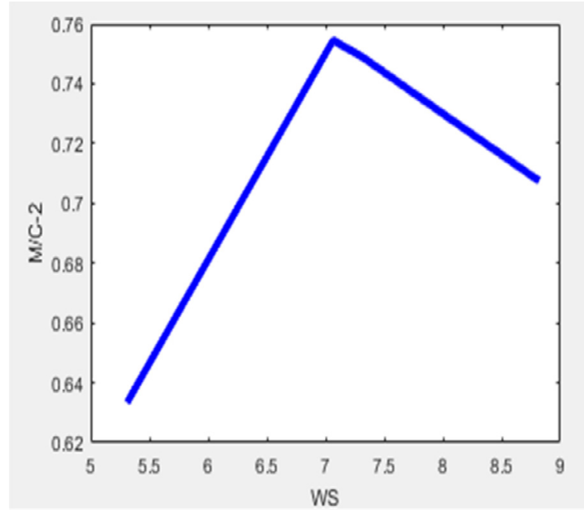

Fig. 8. Variation of machine 2 with WS.

Table 4
Comparative error percentage results of ANFIS modelling for various relationship functions.

Relationship function	M/c 1-Error %	M/c 2-Error %
Triangular	0.00005	0.00003
Trapezoidal	0.00776	0.01225
Cubic	0.00006	0.00007
Gaussian 1	0.00009	0.00024
Gaussian 2	0.00008	0.00308
Polynomial	0.00902	0.01699
Generalized Bell	0.00048	0.00286
Sigmoidal	0.00048	0.00286

Algorithm-based fusion is supported out to boost the massive functionality of the structure developed for the testing machine yields. Former studies have shown the effectiveness of ANFIS architectures comprising of 3 training data inputs and four stages to be applied effectively in well-defined, complicated technical situations. For each response function, the FIS (fuzzy interface system) is separately developed for three ANFIS training input data functions. About 27 rules were created inside the system deemed appropriate network topology when uniting the experimental constraints with the essential factors. The rules established for both constants machine 1 and machine 2 are represented in Fig. 9 and Fig. 10.

During the Fuzzy Interface System (FIS) modelling, the declarations furnished about the ANFIS fuzzy algorithm are configured with the Sugeno framework, which establishes its parameters based on contemporary factors consequent from the input data sets. That makes it easier to plot the association amongst input-output reactions to all climatic situations (heat and cold), as shown in the Fig. 11-16 displaying various plots between environmental parameters and machine yield. The average square deviation was evaluated for each algorithm and network topology created in Sugeno following training and testing sets of the data in the ANFIS modelling. For different types of membership functions, error percentage is achieved so as to contemplate the best working model amongst them as evident from Table 4. Minimum error was achieved in case of triangular membership function for both machine yields. All error percentage for different membership functions are displayed in Table 4 with minimum error rates highlighted in yellow. Using the ANFIS method, reliable values have been projected similar to former theoretical produced data sets used to train and test all response parameters [20–22]. The forecasted values examined after ANFIS model understand

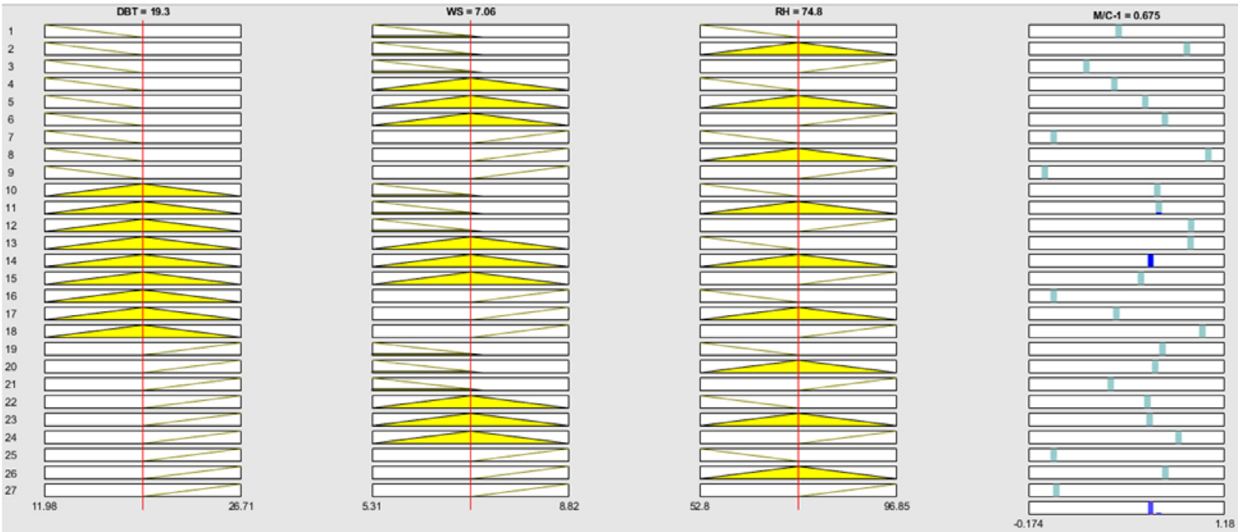

Fig. 9. Rules developed in ANFIS model for machine 1.

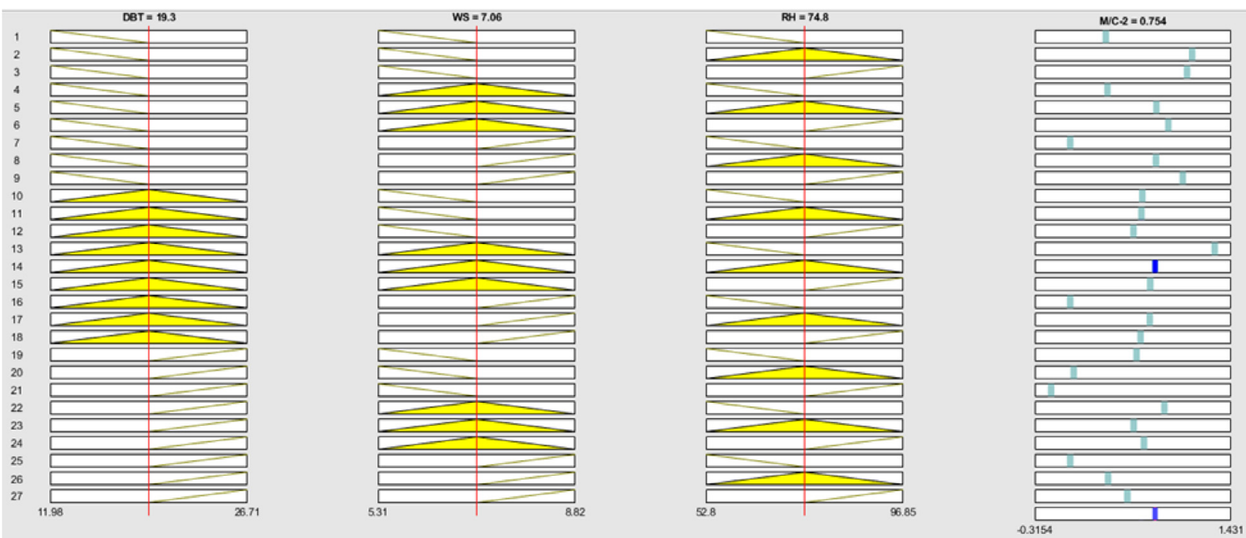

Fig. 10. Rules developed in ANFIS model for machine 2.

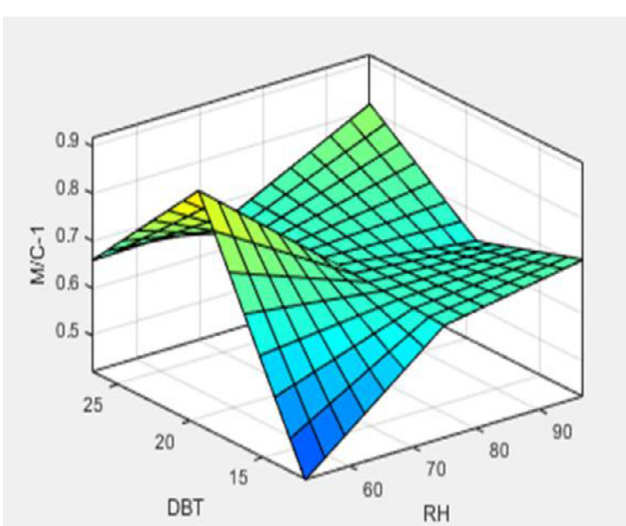

Fig. 11. Machine 1 vs DBT vs RH.

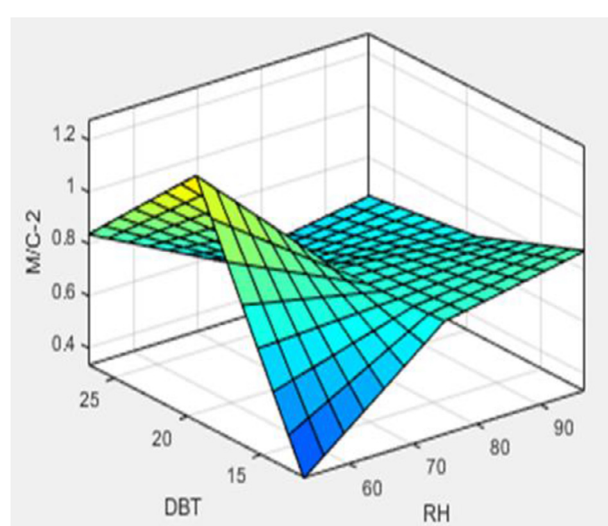

Fig. 12. Machine 2 vs DBT vs RH.

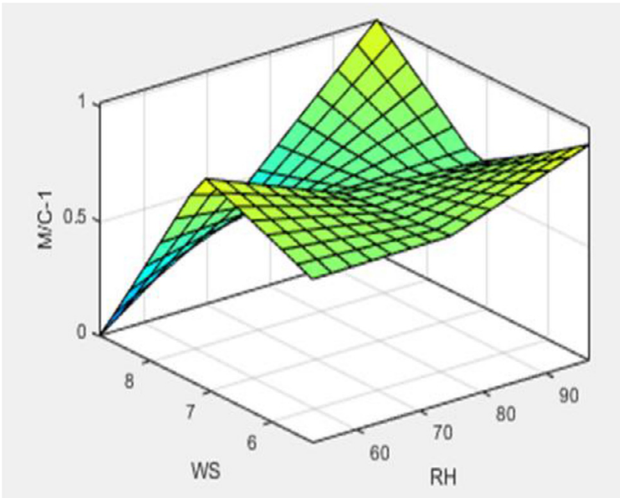

Fig. 13. Machine 1 vs WS vs RH.

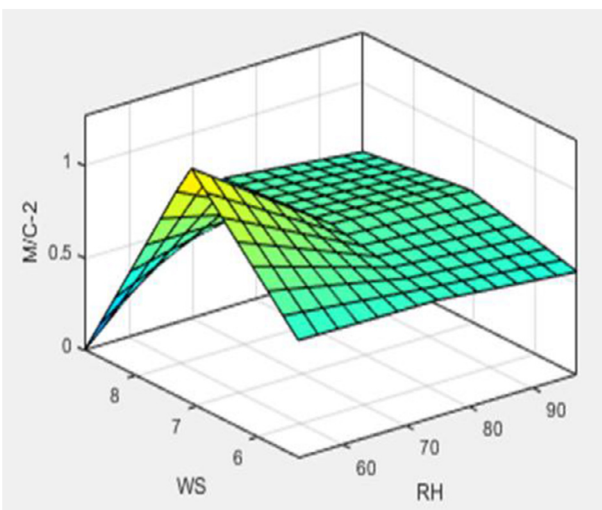

Fig. 14. Machine 2 vs WS vs RH.

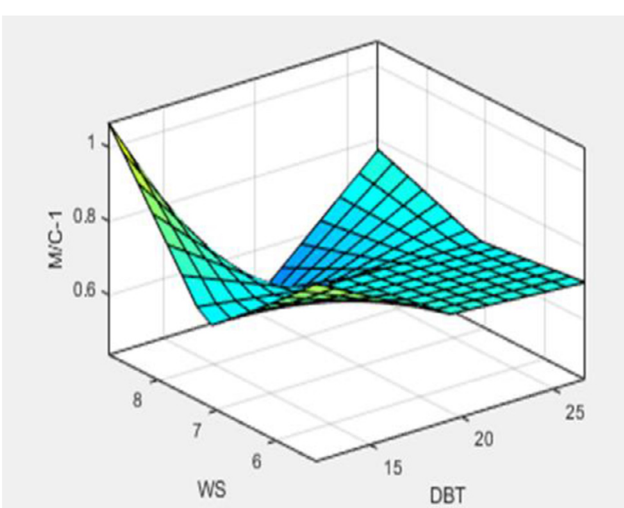

Fig. 15. Machine 1 vs DBT vs WS.

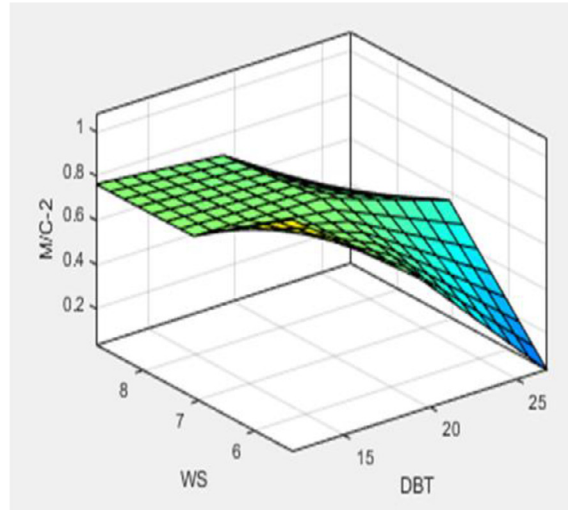

Fig. 16. Machine 2 vs DBT vs WS.

relationship and shows the validation of the proposed formula as values attained are quite close to those attained in the formula.

4.5. Application of response surface methodology

RSM is a set of predictive mathematical tools used for simulation and control challenges to optimize the reaction affected by many variables. RSM is used to simulate, control and optimize the system in this study. The test results have been evaluated using reaction surface regression [23–25].

Machining experiments using both machines were accomplished and the equivalent DBT, WS and RH were used as the input responses. Moreover, contribution of environmental factors is not only an intricate process but also holds a certain degree of uncertainty involving non-linear relationship amongst the variables, a second order model was recognized to demonstrate the relationship amongst the input parameters and the outcomes. The equations established the relationship between various environmental parameters and machine yield.

M/C-1 =1.236 - 0.01036 DBT - 0.047 WS - 0.00347 RH + 0.000094 DBT*DBT + 0.01002 WS*WS + 0.000074 RH*RH - 0.00042 DBT*WS + 0.000117 DBT*RH - 0.00156 WS*RH

M/C-2 =1.535 - 0.0395 DBT + 0.003 WS - 0.0075 RH + 0.000320 DBT*DBT - 0.0051 WS*WS - 0.000010 RH*RH - 0.00030 DBT*WS + 0.000159 DBT*RH + 0.00091 WS*RH

The necessity of this investigation is to capitalize and bring their value near to 1. The first group of plots are for machine 1 displayed in Fig. 17 which essentially is a resolution of simulated results attained through response surface methodology approach. Principally the histogram in above figure predicts the productivity ratios to be quite close to the required ideal values. Subsequently showing minimum error rate. Simultaneously the Fig. 18 displays error rate established in case of machine 2 and further comprises the yield ratios for these simulation results for which too is quite low as error values are closely aligned in the central part of the histogram which is a favourable characteristic [26–28].

5. Conclusions

Machine breakdown and minor production plant delay can lead into significant financial damages for any company. Efficiency deterioration prototype of different categories of equipment as well as the same category of equipment with distinct man-machine-environment elements

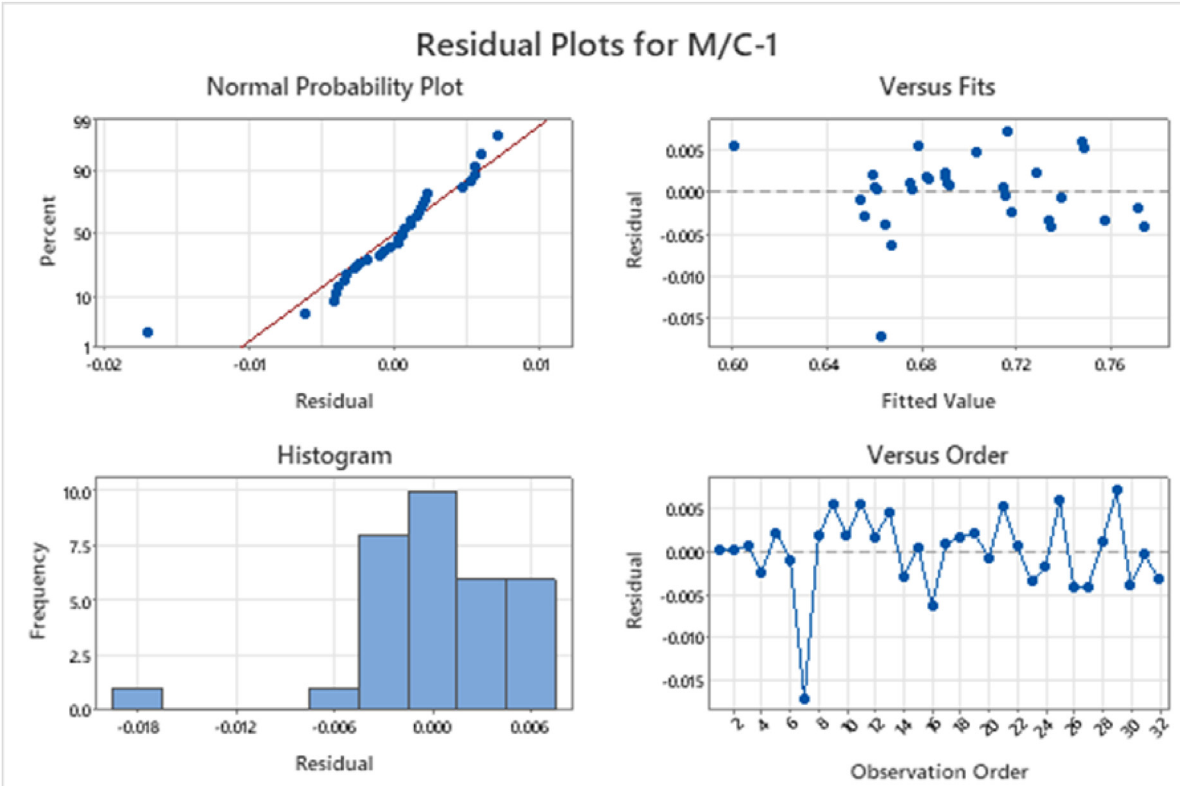

Fig. 17. Simulation results of machine 1 yield with RSM approach.

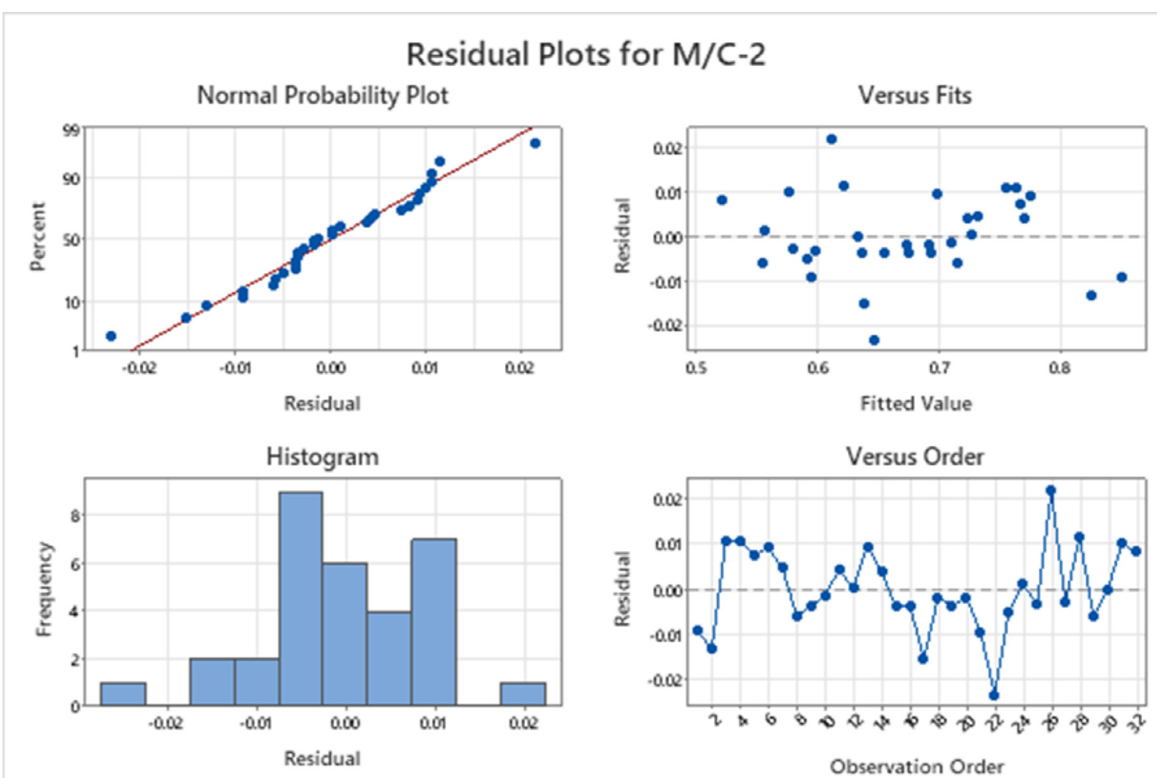

Fig. 18. Simulation results of machine 2 yield with RSM approach.

might be built depending upon the amount of equipment depreciation and data mining of various environment-based parameters. The ideal restoration scheme can be identified by evaluating the efficacy of various maintenance plans, associated expenses, resources, and so on. Operational tools that are stationary while awaiting the next upcoming job consumes considerable energy from the perspective of manufacturing operations. The introduction of a machine incubation system if machine tools are stationary, will aid in minimising power usage. The contemporary research explored the potential of machine monitoring in building structures for various ambient conditions such as DBT, WS and RH. The experimental responses were obtained and compared with those obtained by computed data. Generation of individual experimental outcome with different combinations environmental conditions becomes a tedious job [29,30]. Henceforth, the current work explores and confirms the superior predictive accuracy of machine performance by incorporating the variations in environment for accurate data. Furthermore, the integrated method of ANFIS-RSM yielded best possible outputs closer to experimental values. Major outcomes of the study are listed below;

- In order to reduce the energy requirements of machining and tools which have gone under deterioration over the years for which several parameters are responsible for degrading any building.
- The present study was performed to evaluate the heat losses through machine elements such as tools. Proper modifications in these elements over these elements may lower the energy transfer and increase overall life of tool.
- Hence this study helps us in pin pointing the exact location of the discrepancy and further improvise and solve the problem by modifying or completely replacing the machine element.
- Current study would aid future auditors to predict and evaluate the tool wear in advance under varying environmental conditions in a cost-effective manner where machine audit was earlier not possible, thereby boosting up the sustainability and energy efficiency of the industrial setup.

Numerous techniques might be successful in reducing energy usage, including turning off lights, unplugging appliances, optimizing tools on machinery, and limiting the power consumed by heating, ventilation, and air conditioning (HVAC) setups. Application of HVAC integrated with AI results in maintaining a pleasant setup within the workplace. This will eventually result in effective monitoring of workshop thermal conditions by correlating the actual and predicted conditions in the manufacturing space. Moreover, the dynamic weather measurement stored in the big data which prepares a comparative analysis between actual-predicted data can be implemented to reduce the overall power usage. Artificial intelligence techniques are applied to strengthen make-span and power consumption parameters within the data processing system, eventually discovering energy savings options for product development.

6. Limitations and future scope

The primary limitation of this integration study is requirement of considerable data sets at various climatic conditions. Although the ANFIS model can facilitate any number of inputs but its accuracy levels keep on decreasing with increase in number of inputs beyond nine (9). In future researchers can employ a wider range data set for various climates across the world so that users can select their required model based on their country's climate. This will remove the level of uncertainty in various industrial setups providing comfortable ambient conditions to the machines in the building.

Appendix 1

S.No.	DBT (°C)	Wind speed (km/hr)	Relative humidity (%)	Yield ratio M/C -1	M/C -2
1	11.98	7.38	87.47	0.66	0.84
2	13.19	7.02	85.44	0.68	0.81
3	16.52	6.66	80.43	0.69	0.77
4	17.31	6.21	67.20	0.72	0.77
5	16.41	6.75	76.27	0.69	0.77
6	15.99	7.47	91.73	0.65	0.78
7	18.42	7.29	84.69	0.65	0.74
8	19.69	7.38	88.53	0.66	0.71
9	20.85	6.93	83.73	0.68	0.69
10	19.74	6.84	83.09	0.68	0.71
11	16.52	8.82	96.85	0.61	0.77
12	18.63	6.66	79.47	0.69	0.73
13	20.27	6.39	71.79	0.71	0.71
14	18.89	7.47	83.63	0.65	0.73
15	21.96	7.38	81.49	0.66	0.67
16	22.85	7.29	76.16	0.66	0.65
17	24.28	7.02	77.65	0.68	0.62
18	20.74	6.84	76.69	0.68	0.69
19	23.96	5.85	58.99	0.73	0.63
20	21.96	5.67	57.71	0.74	0.67
21	26.71	5.31	52.80	0.75	0.59
22	23.38	6.12	64.85	0.72	0.62
23	27.23	5.04	55.89	0.75	0.59
24	29.56	4.68	47.89	0.77	0.56
25	26.81	5.31	64.00	0.75	0.60
26	25.81	5.58	62.51	0.73	0.63
27	28.18	4.77	60.27	0.77	0.58
28	25.65	6.66	77.23	0.69	0.63
29	30.08	6.03	64.75	0.72	0.55
30	25.76	7.38	87.25	0.66	0.63
31	27.76	6.12	59.63	0.72	0.59
32	31.93	5.58	54.29	0.73	0.53

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