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Hardness Prediction Model for En Grade Steels Subjected to Different Heat Treatment Processes

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A B S T R A C T

It is more often witnessed that the hardness of the steel depends on environment conditions, type of heat treatment adopted, composition and morphology. The selection of process parameters plays a vital role in obtaining the required hardness. It opens up scope for extensive research to map the relationship between the process parameters which is coherent with hardness of the steel. In the present investigation, an attempt has been made to accomplish this task with the help of a support vector machines (SVM) model for mapping process parameters with hardness. The basis for the development of SVM prediction model for the hardness at any condition within the conducted domain has been obtained by the data base comprising of set of input variable such as process, temperature, metal grade and output variable such as hardness. This is achieved by conducting several experimentations at different temperatures for various heat treatment processes such as annealing, normalizing, hardening and quenching using two different grades of steels namely EN19 and EN24 (with and without nickel). The presence of Nickel, which is an austenite stabilizer, promotes the formation of needle like fine grain martensite phase and its effect on hardness has been reported.

1. Introduction

Alloying and heat treatment are two methods which are extensively used for controlling material properties and it is already inferred that the heat treatment can undergo morphological changes to obtain different mechanical properties. As a tailor made process for having different mechanical properties, heat treatment has gained wide attention. In the present work, an attempt has been made to study the effect of simultaneous variation of process parameters such as temperature, type of heat treatment process and the type of material on the hardness during heat treatment of two different grades of steels. The objective of this work is to develop the base for a support system for the operator to predict the hardness of a material for any process at any temperature for any material within the operating domain. The work is presented for the development of a prediction module using an artificial intelligence based support vector machines (SVM) using Matlab that predicts the hardness given the input values of process parameters. This will provide the operator to automatically predict the hardness and serve as a support for the operator by without conducting experimentation. The purpose of adopting this approach is to minimize experimentation time and avoid multiple heat treatment operations to achieve the desired hardness thereby enhancing productivity.

2. LITERATURE REVIEW

Brinksmeir and Brockhoff [1] have significantly worked on utilization of grinding heat as a new heat treatment Process. Guo and Sha [2] correlated between processing parameters and properties of maraging steels using artificial neural network. Jaroslav [3] took the help of finite element analysis and simulation techniques to study about quenching and other heat treatment processes elaborately. Małgorzata and Gestwai [4] studied about the uses of aqueous polymer quenchants for hardening of carbonitrated parts, and a conventional quench oil were evaluated to harden carbonitrated parts and resulting microstructures were compared. Mazumder and Steen [5] developed a heat transfer model for CW laser material processing. Mohammed and Sudhakar [6] have taken the help of

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artificial neural networks to develop a back propagation model to find the fracture toughness in micro alloy steel. Myllykoskia et al. [7] tried to develop a prediction model for mechanical properties of batch annealed thin steel strip using artificial neural network modelling. Smoljan et al. [8] did a computer simulation of working stress of heat treated steel specimen. Sorkhabi and Rafiazadeh [9] considered the effect of coating time and heat treatment on structures and corrosion characteristics of electroless Ni–P alloy deposits. Tadashi [10] has worked upon the properties of stainless steel, observing its progress while treated thermo mechanically. Trzaska et al. [11]developed a computer programme for the prediction of steel process parameters after heat treatment. Waga and Hagel [12] considered 2-1/4Cr-1 Mo steel as base metal and studied the effect of trace elements, molybdenum, and intercritical heat treatment on temper embrittlement. Yoshiyuki [13] focussed on the development of mechanical properties of structural high-carbon low-alloy steels through modified heat treatment. From the above review, in summary, the approach taken in the past has been clearly in two different domains namely either prediction of mechanical properties or optimisation of process parameters, both of which have been attempted for one process only. The regression models developed operate individually. Very little work appears to have been carried out in presenting an approach for the prediction of hardness when five heat treatment process are involved for different grade of steels. In this paper therefore, a regression model is developed for the prediction of hardness using a forward mapping model for different heat treatment operations for different materials at varying temperature range.

3. EXPERIMENTAL WORK

3.1 Selection of base metals

The objective of this work is to present an approach for simultaneously handling data from various heat treatment processes with different ranges of input values yet producing similar hardness on the specimen. A conventional regression approach will not be able to predict the output accurately. To develop such an approach, a set of experiments were conducted given the available facilities and range of operating conditions as described below. The process parameters that were focused upon in the present work are temperature, material, type of heat treatment i.e . annealing, normalizing, hardening with different quenchants (water, oil and polymer) for two grades of steel i.e. EN24, EN19 were carried out in muffle type furnace. The compositions of the base metals are shown in Table 1.

Table.1: Composition (in %) of EN19 and EN24 Alloy steel

	C	Mn	Si	S	P	Cr	Mo	Ni
EN19	**0.35-0.45**	**0.50-0.80**	**0.10-0.35**	**0.040**	**0.040**	**0.90-1.40**	**0.20-0.40**	
EN24	**0.35-0.45**	**0.45-0.70**	**0.10-0.35**	**0.040**	**0.040**	**0.90-1.40**	**0.20-0.40**	**1.30-1.80**

For all of these operations, the hardness was measured using a Rockwell hardness testing machine (C-scale) for varying values of temperature, material, type of heat treatment. After scrapping out the slag from the metal pieces, the final hardness was measured on each specimen by taking the average of three hardness readings.

3.2 Generation of database

This section illustrates the generation of database for the SVM prediction model by conducting experiments on each EN19 and EN24 alloy steels under the Rockwell's hardness machine to obtain the initial hardness values. Heat treatment for considered steels (EN19 and EN24) were performed at 10 different temperatures in the range of 500°C to 950°C, having an intervals of 50^{0}C each. Different heat treatment processes such as annealing, normalizing, hardening, oil quenching using SAE40 oil, polymer quenching using soluble oil with water in 1:10 ratio at different temperatures ranging from 500°C to 950°C with an interval of 50°C. The heat treated EN19 and EN24 alloy steels under different heat treatment processes are as shown in the Fig 2.

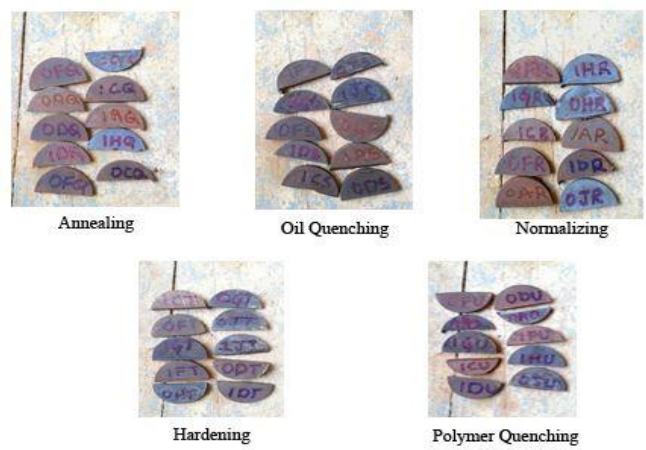

Fig. 2. Heat Treated EN19 and EN24 alloy steels under different heat treatment processes

3.3 Results and Discussion

Heat treated samples about 100 pieces under different conditions were subjected to Rockwell hardness tester. Based on the experimental work carried out, it was observed that the obtained hardness mostly varies between 10 and 60 HRC. The variation of hardness of heat treated EN19 and EN 24 alloy steel for different heat treatment processes at various temperatures are plotted in Fig. 3 and Fig. 4 respectively.

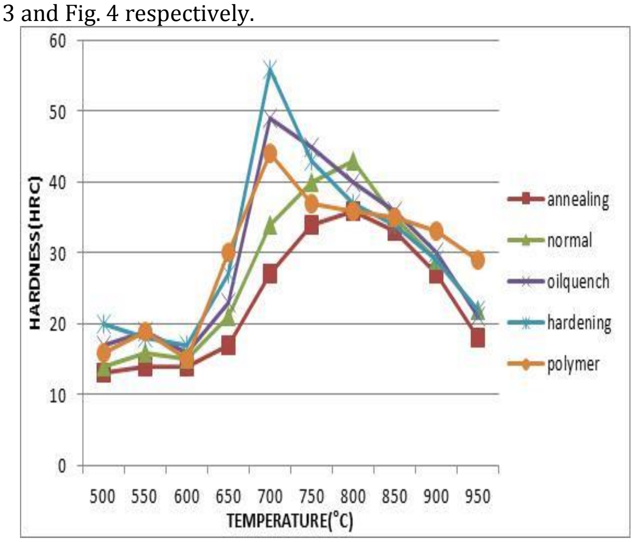

Fig. 3. Variation of hardness of heat treated EN19 alloy steel for different heat treatment at various temperatures.

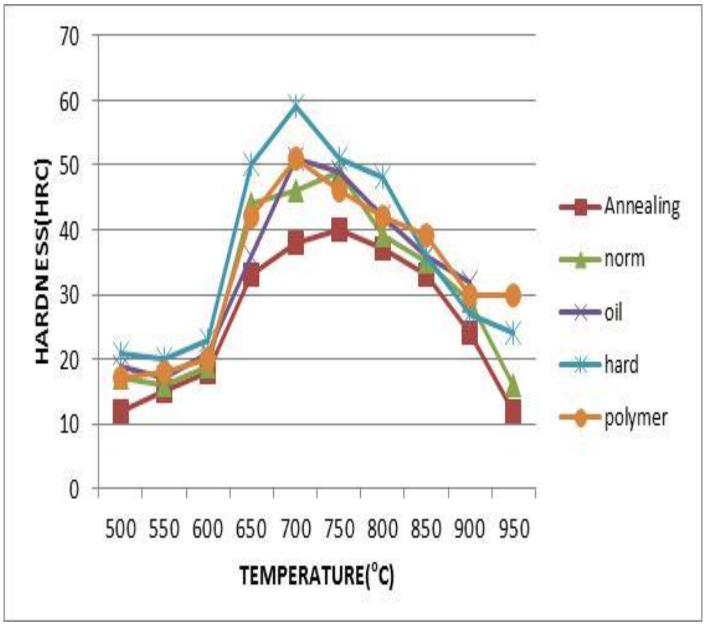

Fig. 4. Variation of hardness of heat treated EN24 alloy steel for different heat treatment at various temperatures.

From above graphs, it has been inferred that both the grades of steel exhibit maximum hardness for hardening carried out at the soaking temperature in the temperature range of 700°C - 750°C. Because of severe cooling rate during water quenching (hardening) results in the formation of martensite and presence of alloy carbides impart maximum hardness. Similarly, relieving of internal stresses and presence of ferrite results in obtaining lower hardness during annealing at 500°C for both the steels. It has also been witnessed that at higher temperature hardness decrease to larger extent and this may be accounted due to enhanced diffusion rate of various segregated phases and formation of epsilon carbides.

4. HARDNESS PREDICTION MODEL

4.1 Proposed methodology

The primary objective of this paper is to propose an approach that can handle data for four processes simultaneously, predict the hardness. In addition, the development of a prediction model to estimate hardness under given operating conditions for EN19 and EN24 steels using different heat treatments. A support vector machines (SVM) based approach using Matlab has been adopted herein. A pilot set of experiments were conducted given the available facilities and range of operating conditions. In order to simultaneously handle data related to four processes, SVM regression which predicts hardness given process parameters as input is adopted. Finally the regression model predicts the hardness for that process. The regression approach is done in Matlab using SVM as the tool for regression of the experimental data as it has been proven to be a superior technique in terms of speed and performance compared to other regression techniques as well as able to handle sparse data effectively. A detailed description of the modelling approach adopted is described in the following sections.In contrast with the modelling methodologies presented in section 2 wherein a single technique is used to map the parameters with the predicted output; a regression approach is used in this work. This is because the operating conditions adopted for various heat treatment processes in terms of temperature, material are quite different. Yet it can be seen from the results presented above that the hardness values obtained are not similar. Developing one single regression model that combines all the data to predict the surface finish will obviously produce the right result. Single support vector regression (SVR) model has been developed for all processes and the corresponding SVM regression model is used for prediction of hardness. The model has been developed in Matlab. The SVM model can easily be developed by assigning a few parameters namely the kernel function, the cost function etc. The SVM model generates a unique solution after training. The goal of SVM is to find out a function that gives a deviation of error from the actual given output and at the same time is as flat as possible. This is achieved by mapping the training patterns from the input space to a high dimensional feature space in such a way that the data which could not be separated by a linear function in the input space can be separated in the feature space. The forward mapping approach is shown in Fig. 5.

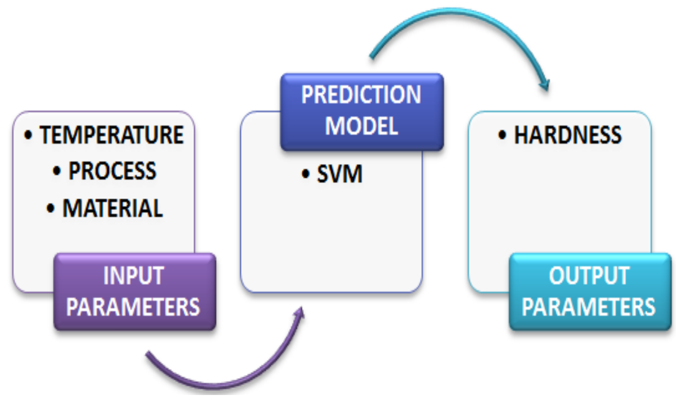

Fig 5: Forward Mapping Approach

4.2 Hardness Prediction

A single regression model has been developed, for all the heat treatment processes. Based on the experimental results, the data set is supplied as input value to the corresponding regression model and the hardness is predicted in Matlab as shown in Fig. 6.

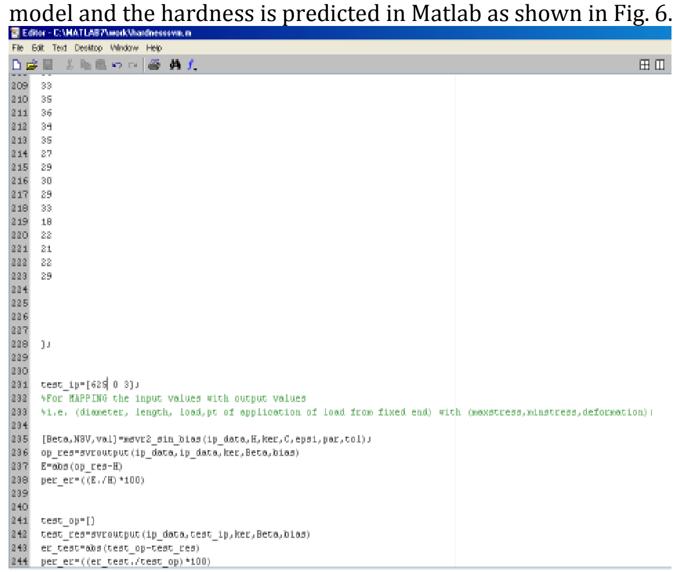

Fig.6. Determination of hardness value at specific temperature for EN24 Alloy Steel

Out of the 125 data points obtained, 100 points were used to train the model and the balance 25 was used to test the performance of the regression model. The 100 data points comprising temperature, material, and process were supplied as the input data (100 x 3 matrix) and mapped with the corresponding output data (100 x 1) matrix of hardness values. The difference between the actual hardness values obtained and the SVM predicted hardness values are shown in table 3 and 4 and plotted in Fig 7 and Fig 8.

Temperature(°c)	**Experimental hardness values(HRC)**	**SVM Predicted Hardness Values(HRC)**
625	29	27.8
725	35	34.45
875	41	42.36
930	39	38.4
948	37	40.32

Table.3: Hardness values of both experimental and SVM predicted for intermediate temperatures of EN24 alloy steel

Table. 4: Hardness values of both experimental and SVM

Temperature(°c)	**Experimental hardness values(HRC)**	**SVM Predicted Hardness Value(HRC)**
575	15	18.6
626	31	29.35
775	36	33.75
849	28	30.05
922	37	36.68

Predicted for intermediate Temperatures of EN19 alloy Steel

5. PREDITION MODEL VALIDATION

In the case of EN 24 alloy steel, it can be observed that SVM predicted values and the values obtained through experimentation are fairly close. Out of 25 values given as test values (shown in Table 3), 14 values have an error less than 1, 8 values have an error slightly greater than 1 and 3 points have an error value around 3. An error of 1 to 2 is considered to be negligible in industries especially because the overall hardness is itself of the order of 40 to 50. In the present work, the hardness values being so close and their range being less, this variation appears to be a major deviation especially when plotted in Fig 7. However, they fall very much within the acceptable range of 1-2 for hardness and so are acceptable especially given that the process is heat treatment.

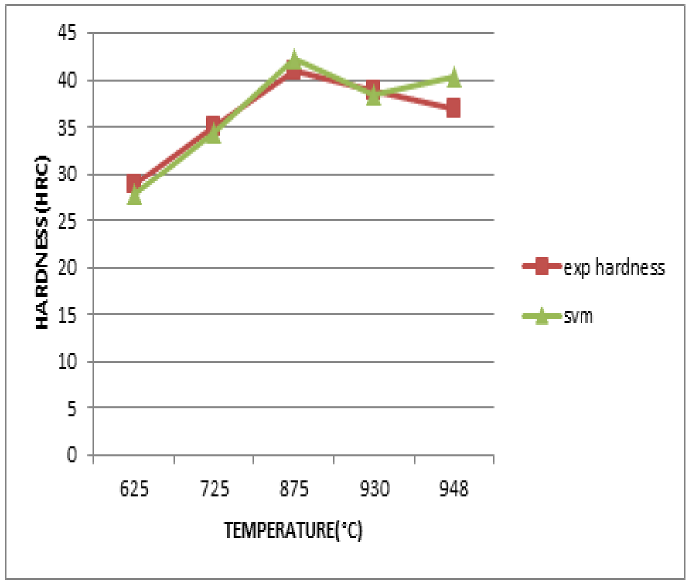

Fig. 7. variation of hardness for Experimental and SVM predicted values for heat treated EN24 alloy steel

In the case of EN 19 alloy steels, it can be observed from Fig 8 that the SVM predicted values and the values obtained through experimentation are quite close. Out of 25 values given as test data (shown in Table 4), 13 values have an error less than 1, 9 values have an error greater than 2 and 3 values show an error around 3. An error of 1 to 2 is considered to be negligible in industries especially because the overall hardness is itself of the order of 30 to 50. In the present work, the hardness values being so close and their range being less, this variation appears to be a major deviation especially when plotted (seen in Fig 8). However, they fall very much within the acceptable range of 1-2 for hardness and so are acceptable especially given that the process is heat treatment.

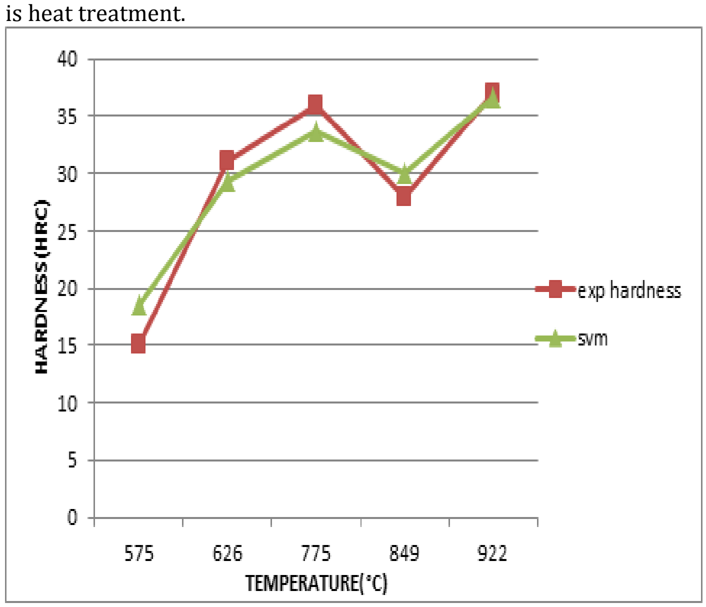

Fig 8. Variation of hardness for Experimental and SVM predicted values for heat treated EN24 alloy steel

Conclusion

The hardness EN-24 grade of steel is maximum compared to EN-19 grade of steel for all the heat treatment and it may be accounted to Nickel which acts as austenite stabilizer. There is a considerable enhancement of hardness is obtained in the temperature range of 700^{0}C-800^o C , because of alloy carbide are easily dissolved in the austenite zone and imparts hardness. Above the mentioned temperature range, the hardness decreases as the grains become coarser. Variation of hardness for both EN19 and EN24 alloy steel is being well validated with the help of graphs. An empirical relation between the temperature, grade of steel, heat treatment process and hardness has been developed using Support Vector Machine (SVM). A user-friendly database (SVM) has been developed using matlab software that readily suggests the hardness values for any given temperature and for any heat treatment processes within the given range, without necessarily conducting the experiment. To verify whether the predicted values are correct or wrong, again an experiment has been done on that specified temperatures to justify the predicted values. It was found that the experimental values obtained were almost similar to the SVM predicted values with an acceptable error. Hence SVM tool is an apt model for the prediction of unknown temperatures, without conducting the experiment.

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