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Prediction of ttt curves of cold working tool steels using support vector machine model

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Prediction of ttt curves of cold working tool steels using support vector machine model

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Abstract. The cold working tool steels are of high carbon steels with metallic alloy additions which impart higher hardenability, abrasion resistance and less distortion in quenching. The microstructure changes occurring in tool steel during heat treatment is of very much importance as the final properties of the steel depends upon these changes occurred during the process. In order to obtain the desired performance the alloy constituents and its ratio plays a vital role as the steel transformation itself is complex in nature and depends very much upon the time and temperature. The proper treatment can deliver satisfactory results, at the same time process deviation can completely spoil the results. So knowing time temperature transformation (TTT) of phases is very critical which varies for each type depending upon its constituents and proportion range. To obtain adequate post heat treatment properties the percentage of retained austenite should be lower and metallic carbides obtained should be fine in nature.

Support vector machine is a computational model which can learn from the observed data and use these to predict or solve using mathematical model. Back propagation feedback network will be created and trained for further solutions. The points on the TTT curve for the known transformations curves are used to plot the curves for different materials. These data will be trained to predict TTT curves for other steels having similar alloying constituents but with different proportion range.

The proposed methodology can be used for prediction of TTT curves for cold working steels and can be used for prediction of phases for different heat treatment methods.

Keywords : Cold working tool steel , TTT curves, Machine learning, Support vector machine

1. Introduction

Press tools are required for metal forming and cutting in the industry and the demand is ever increasing especially in automotive sector as well as other manufacturing industries. This calls for tool steel with better performance in terms of optimum wear resistance and toughness. Cold working tool steels are with high chromium and other metallic content to give better wear resistance and are easy to machine in pretreated conditions [1]. The ability to machine in pretreated conditions and obtaining desired properties in the post treatment condition is the pre requisite for any material used in press tool manufacturing. The formation of metallic carbides and the conversion of phases during the thermal treatments results in higher surface hardness and thus better tribological properties. The metal constituents and their proportions are decided on the basis of the after treatment properties required for a specific application and their proportions are decided on the basis of the after treatment properties required for a specific application. Carbon is the element that stabilizes austenite by increasing the range of austnite formation in the steel.Addition of alloying elemnts into iron carbide mixture will either expand or contract the phase boundaries.Thoug iron carbide phase diagram is useful for the prediction of transformation conditions it can't provide more details on non-equilibrium condition of steels and this can be decribed effectively with Time Temperature Transformation (TTT) diagrams. They relate to the tranfromation of austenite to the time and temperature they are subjected [2]. TTT diagram gives the changes occurring or phase transformation with respect to time and temperature and are hence useful for the design of tool steel for a specific purpose with apt alloying element, proportion and their heat treatment cycles [3].

There are two main types of transformation diagrams, time temperature or isothermal transformation and continuous cooling transformation diagrams. In case of TTT diagram the transformation takes place at a specific transformation temperature at which the cooling will be held while CCT gives the transformation by continuous cooling. TTT diagram graphically describes the cooling rate required for austenite to get converted to pearlite, bainite and martensite. This is used to determine the austenic transformation and is plotted with logarithmic scale of time on x-axis and temperature on y-axis. The correlation between the composition, phase transformation parameters and fineness of phases can be obtained by studying the TTT curves of different chemistry. Experimental determination of TTT curves in all such cases will be a very difficult exercise and hence if prediction is possible with the help of computational models, it is to be sought for modeling and simulation of TTT diagrams with various compositions and proportions.

2. Material

The cold working tool steel which is focused in this study is AISI A8 tool steel which is of air hardening grade with high content of chromium (8 %) and 0.5 % of carbon . Other alloying elements are silicon, manganese, molybdenum and vanadium. Carbon significantly aids for the formation of austenite and improves the mechanical strength. In martenstic grades it increases the hardness and strength with the formation of carbides but reduces the toughness. Chromium, Vanadium (V) and Molybdenum (Mo) which is having body centered cubic crystal structure helps in ferrite stabilization and lowers the solubility of carbon in austenite, thus increasing the metallic carbide formation. Chromium (Cr) helps to increase the wear resistance and corrosion resistance at higer concentrations. Manganese improves the hardenability and ductility and strength at elevated temperatures. Alloying elements in general have influence on kinectics and mechanism of transformation and the carbide forming elements such as Cr, Mo, V produce quantitative and qualitative changes in the isothermal transformations. In general alloying elements are classified in two categories one which promotes the formation of austenite or increase the γ - field to a wider limit such as Mn,Ni, Cu etc and the other which contract the γ - field and improves the limits of ferrite formation of α-stabilizers which includes Cr, Mo, W, Co, Si etc [4].

Hardenability is termed as the ability of the steel to get transformed into martensite on quenching. Alloying elements which slow down the reactions as well as the austenite grain size and carbon content all contributes to increases in hardenability [5]. M_s and M_f represent the formation of martensite starting and finishing temperature when the austenite is cooled in that range. Martensite is hard, strong and brittle and is having a body centered tetragonal lattice. Fine grain steel tend to promote the formation of pearlite and ferrite and hence decrease in grain size shift the TTT diagram towards left. An increase in carbon content will lower the Ms temperature and will shift the curve towards right [6].

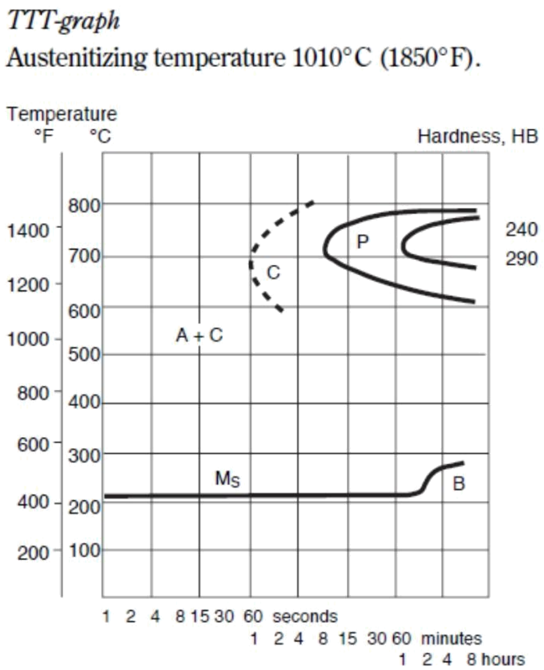

Fig.1 a. TTT diagram for AISI A8 tool steel

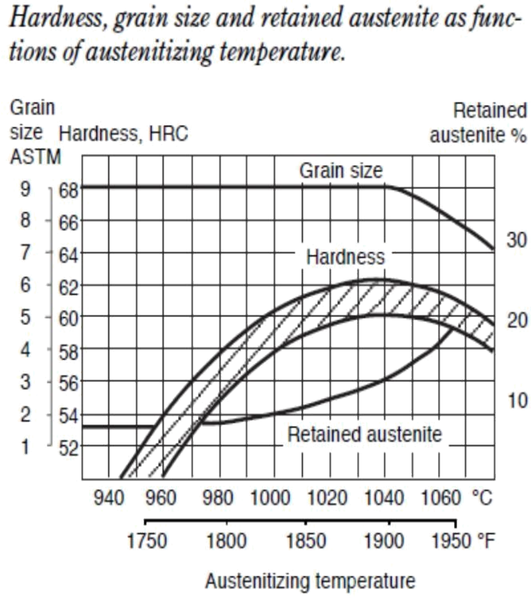

Fig.1. b. Graph showing grain size with relation to austenizing temperature.

3. Methodology

In this paper we are trying to obtain a model with known data of TTT diagrams of a set of cold working tool steel and using the model to predict the TTT curves for varying parameters. This model is developed with the help of Support Vector Machine (SVM) algorithms which is extensively used for generalization properties and automatic image annotations [7-8]. SVMs are reliable classification methods based on machine learning theory. When compared with other methods such as artificial neural networks, Bayesian networks etc, SVMs have higher accuracy, mathematical tractability and direct geometric interpretation. The number of training samples required is also less in comparison to other similar techniques [9]. SVM have the power of non linear machine learning along with the conceptual and computational advantage of the linear systems. Basically SVM creates a hyper plane which acts as a decision plane and that separate data into classes [10].

The methodology is briefed as follows:

1. Collection of TTT curves for cold working tool steel
2. Digitizing TTT curves to extract time, temperature and phase transformation data
3. Determining Time- Temperature coordinate points related to distinct phases
4. Designing Support vector machine (SVM) architecture composition ranges of cold working tool series as inputs and time-temperature coordinates for different phase changes as outputs
5. Training TTT curves data for cold working steel
6. Testing using unknown data and validation
7. Reconstruction of TTT curves using SVM simulation and spline functions

The decision function learned by such a machine has the form,

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$$f(x) = sign(\sum_i \alpha_i y_i k(x_i, x) + b)$$

where xi , yi , k are training points, their labels, and the kernel function, respectively, and x is a generic test point. It is important to note that the problem of constructing the maximal margin hyper plane reduces to a quadratic programming problem [11].

4. Modeling :

The data obtained from the TTT diagrams of the following materials are used for training of model. D2, D3, D6, A2, A8, O1, S7 are the grades of steel as per AISI classification are considered. They are all coming under cold working tool steel category and are also rich in chromium content. From the given TTT diagram the points are selected within the temperature range of transformation based on the logarithmic scale of the time taken.

The following are the steps involved in modeling and testing

Step 1: The TTT curves for A2, A8, D2, D3, D6, O1, S7 and Viking steels are digitized to get 110 points each for the entire temperature and time domain along with the phases. Totally 880 datasets are considered for the analysis. The compositions of the alloys are also given as inputs.

Step 2: The phases are classified as shown in Table 1:

Table 1. Phase classification

Austenite	Class 1
Austenite + carbide	Class 2
Pearlite + carbide	Class 3
Bainite + carbide	Class 4
Martensite	Class 5

Step 3: Out of 880, 770 are considered for training and data related to Viking steel is considered for testing.
Step 4: The data sets for training are used for modelling using support vector machine multi class classification approach. Gaussian non-linear function and quadratic programming are used for the analysis.
Step 5: The classification using training datasets is completed and the model developed is used for simulating the training datasets and TTT curves are regenerated and compared with actual ones. The figure 2 a shows the actual TTT diagram of AISI D2 tool steel and figure 2 b is the regenerated model of the same .

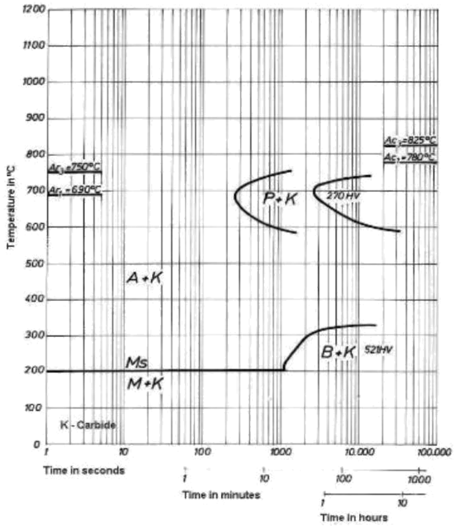

Fig 2 a. TTT diagram of AIS D2 steel

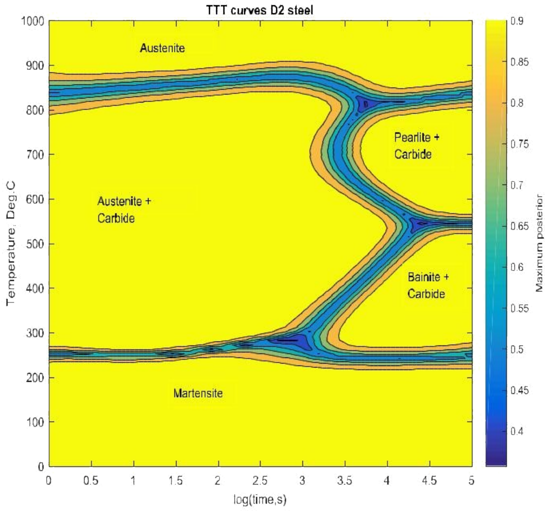

Fig 2 b . D2 model with the trained data

The yellow portion indicates the formed phases and the other colors show the path of transformation. On cooling down the martensite begins to form in a temperature range near to 200^{o}C and bainite is obtained in the region above with a shift towards right. Similarly training cases are made for D3, D6, A2, O1 AND S7. The figure 3 below is the regenerated curves for D3 and O1 respectively. The prediction accuracy for both the trained class in is the range of 98%.

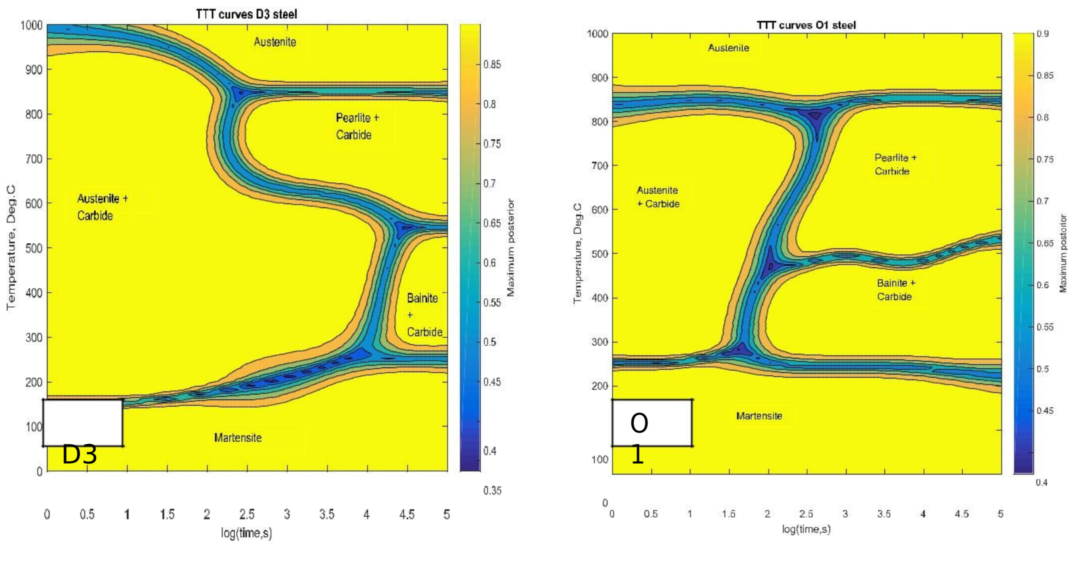

Fig 3 Model developed for training case a. D3 and b. O1

Step 6: Using confusion matrix, the performance of the proposed classification algorithm is tested and found to be close to 99.6%.

Figure 4 is the TTT diagram model generated for Viking classified under AISI A8 steel using SVM and Table 2 is the confusion matrix for the same.

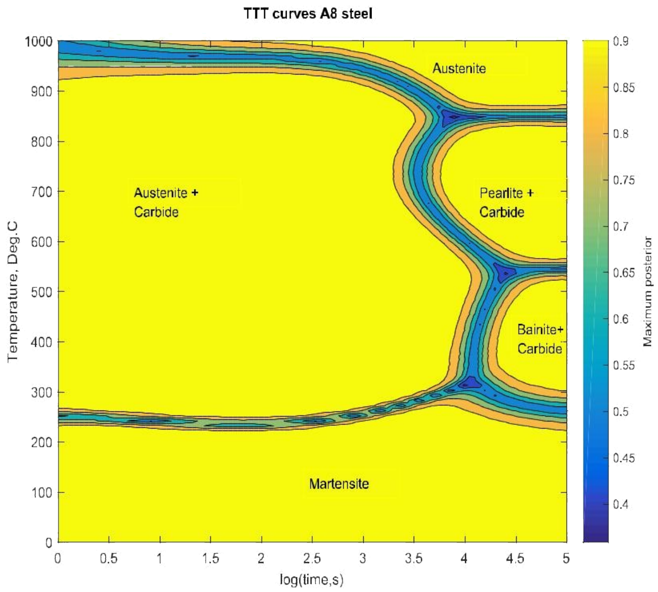

Fig 4. TTT diagram of Viking (A8) training case

Table 2 : Confusion matrix (target class vs true class) training case

PREDICTEDCLAS S	ACTUAL CLASS					
		1	**2**	**3**	**4**	**5**
	1	116	1	0	0	0
	2	0	302	5	5	0
	3	3	3	74	1	0
	4	0	0	0	61	0
	5	0	1	0	4	194

PREDICTION ACCURACY=99.6%

Step 7: The developed model is tested using the Viking steel data (test case). Initially the complete composition of alloy along with time and temperature are given as inputs to predict the phases (classes). The performance was measured using confusion matrix. The accuracy of prediction was around 83.63%.

The figure 5 and Table 3 is respectively the TTT curve model and confusion matrix of A8 with all the constituents in the composition alloy. Other alloying elements than carbon are also included in this case and test model is generated.

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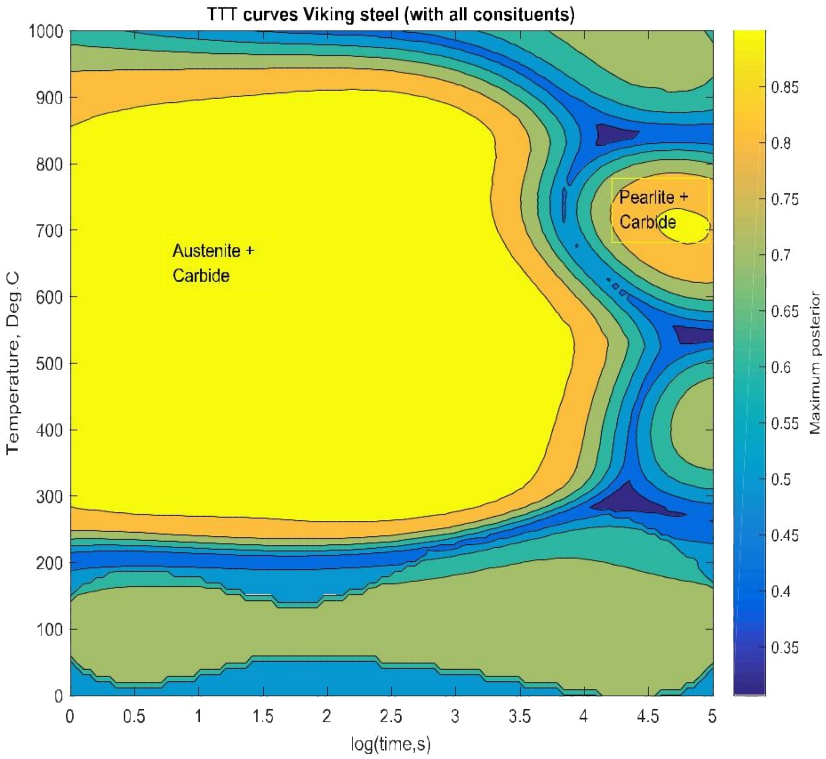

Fig 5. TTT test model for Viking with all constituents.

Table 3: Confusion matirix for test case with all constituents (Viking steel)

		ACTUAL CLASS				
PREDICTEDCLASS		**1**	**2**	**3**	**4**	**5**
	1	10	0	0	0	0
	2	10	40	1	6	0
	3	0	0	8	0	0
	4	0	0	0	5	0
	5	0	0	0	1	29

PREDICTION ACCURACY= 83.63%

Step 8: The developed model with only carbon content along with time and temperature was tested again for the performance for test case and found to be better with 93.6%.

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Table 4 .Confusion matrix (with temp, time & %C as parameters)- Test case

	ACTUAL CLASS					
PREDICTEDCLAS S		**1**	**2**	**3**	**4**	**5**
	1	14	0	0	0	0
	2	6	40	1	1	0
	3	0	0	8	0	0
	4	0	0	0	10	0
	5	0	0	0	1	29

PREDICTION ACCURACY = 93.36%

The confusion matrix to measure the performance in this case is given in table 3 and generated model is plotted in figure 6. As we know carbon is the main driving component in the TTT diagram and the test prediction of our model with carbon alone is more nearer to the regenerated trained model.

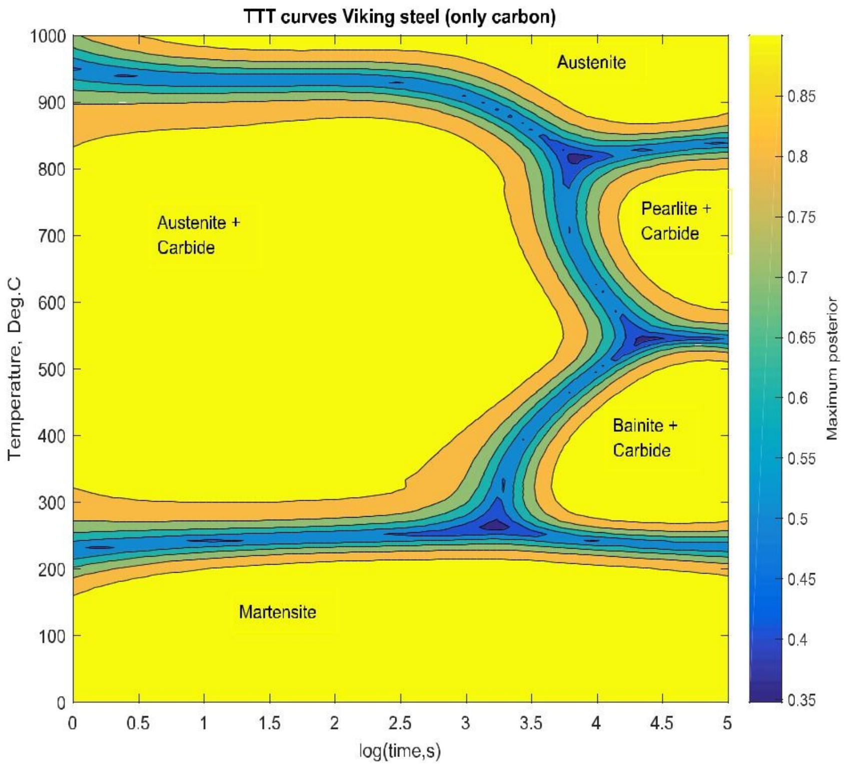

Fig 6 . TTT test model for Viking with only carbon.

5. Conclusion:

The TTT curves for different types of cold working tool steels are used to digitize and train to obtain model to generate TTT diagram for cold working tool steels. Machine learning technique SVM is used for this non linear regression model. The same model is then used to predict the TTT diagrams of other types which is giving a prediction accuracy above 90%. When all constituents are included the accuracy drops because of the constituent variation between the trained data. However when did with carbon alone the accuracy level improved drastically. The percentage of carbon and its influence is mainly dragging the TTT curves with the formation of carbides along with the phase changes.

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