Online mechanical property prediction system for hot rolled IF steel

I. Mohanty*[1], S. Sarkar[2], B. Jha[2], S. Das[1] and R. Kumar[2]

Traditionally, mechanical property estimation is carried out by destructive testing, which is costly and time consuming. Sometimes, the time schedule in the mill is so tight that coils are dispatched, while the samples are still under investigation; thus, knowledge of the strip quality immediately after rolling without mechanical testing can save a lot of time and money. As the rolling process is complex and final mechanical properties of steel depend on many parameters, it is almost impossible to develop an accurate first principle based mathematical model, so an artificial neural network based model to predict the mechanical properties of hot rolled steel strip has been developed. This paper describes the neural network based online system that helps in predicting mechanical properties of interstitial free (IF) steel strip and also elaborates how this models can help in capturing various metallurgical phenomena during rolling.

Keywords: Artificial neural network (ANN), Interstitial free (IF), Mechanical property, Yield strength (YS), Tensile strength (UTS), Elongation (el)

Introduction

Over the past few years, tailoring microstructures with ultrafine grain sizes in bulk materials has attracted significant interest from the scientific community. It has been possible to improve the material strength without compromising toughness by grain size strengthening.[1–3] In the automotive industry, in order to reduce weight, making car bodies from high strength steel sheet with adequate formability is required. Microalloyed, aluminium killed and interstitial free (IF) steel grades are currently available in the market to meet demands of the auto sector, with IF steel the major focus area. IF steels constitute an important class of steels with a carbon content of less than 0·003 wt-% and possess high formability. Microalloying elements such as Ti and/or Nb are used to stabilise the interstitial carbon and nitrogen atoms as carbide and nitride precipitates. Solid solution hardening elements such as Mn, P and Si are used to achieve the desired strength in some grades.[4–6] The reduction in the amount of interstitial and alloying elements in the matrix leads to a measurable difference in texture development and improved deep drawability. In recent years, efforts have been made to improve the strength of this class of steels.[7,8] In Tata Steel India, different IF steels are produced in hot strip mill (HSM) to cater to the needs of different customers, such as IF titanium, IF low draw, IF high draw, IF skin panel and high strength IF.

One of the key determinants of the quality of the hot rolled IF steels are mechanical properties within a stretched tolerance range,[6] but precise control of the mechanical properties for high end applications is very much necessary. Improving and controlling the properties depends on the control of compositional and process parameters. The variation in mechanical properties in different grades of steel is due to the process and steel chemistry variation. Traditionally, mechanical property determination is carried out by destructive testing, which is costly, time consuming and inefficient.

It is very difficult to predict the mechanical properties accurately with a first principles based mathematical model, so an artificial neural network (ANN) based model has been developed due to its capability in solving non-linear problems by understanding the complex relationship in the process. ANN models have been established to predict the mechanical properties of hot rolled C–Mn steels with good learning precision and good generalisation.[10] One of the earliest attempts to predict the mechanical properties of steel using ANN was by Bhadeshia.[11] The models demonstrated the ability of the ANN technique to address non-linear relationships between several input parameters. Kim *et al.*[12] exploited the modelling technique to improve the model performance. In this case, ANN has been successfully used to develop a manufacturing model, which is capable of achieving an accurate calculation of mechanical properties for a hot rolled alloy steel. A good ANN model can be successfully used to control the mill process for achieving target properties with available steel composition and mill constraints and several attempts have already been made in this direction.[13–15]

HSM process

The processing of strip in HSM is mainly divided into three stages:

(i) reheating

[1]Research and Development, Tata Steel Limited, Jamshedpur, Jharkhand 831 001, India
[2]Hot Strip Mill, Tata Steel Limited, Jamshedpur, Jharkhand 831 001, India

*Corresponding author, email iti.mohanty@tatasteel.com

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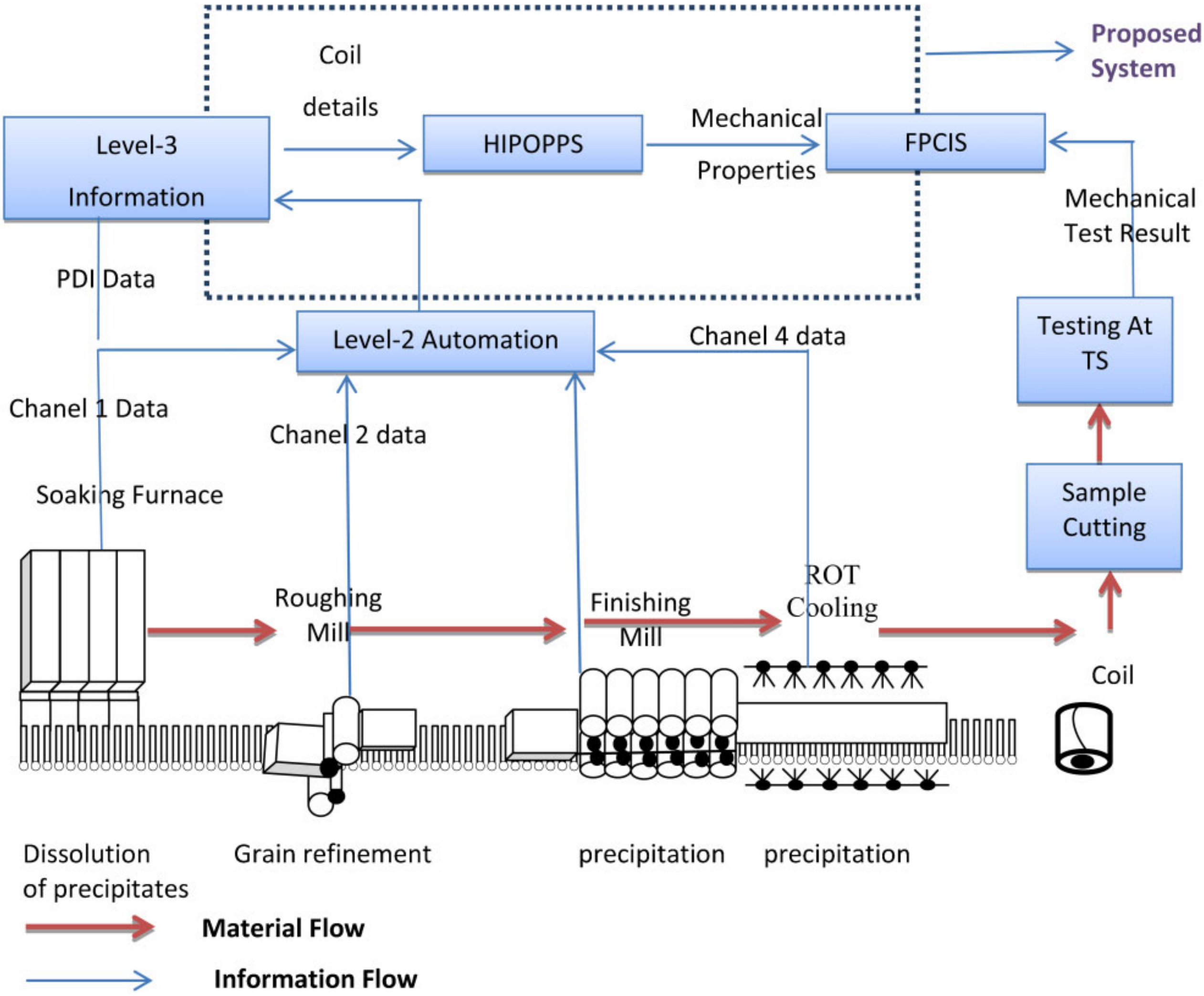


1 Information flow between different automation and IT systems during hot rolling process with metallurgical phenomenon

(ii) rolling
(iii) cooling.

The objective of slab reheating is to maintain a uniform slab temperature to provide a correct and uniform starting austenite grain size. It will also ensure that all the microalloying elements (Ti, Nb and V) are in complete solid solution.

The metallurgical objective of roughing rolling is to achieve the finest possible recrystallised austenite grain size before the finishing stage and it is completed at temperatures above 1000°C. During this stage, most of the plastic deformation takes place and austenite grain refinement through recrystallisation is achieved.[16]

During finish rolling, as the deformation temperature decreases, the progress of recrystallisation become increasingly difficult. The finishing rolling temperatures (FRTs) during hot rolling process influence the ferrite grain size and mechanical properties.[17] Depending upon the chemistry and final mechanical properties, FRT is set.

The cooling of the hot strip is accomplished to attain a temperature of 500–650°C in a controlled manner. After exiting from the last finishing stand, the strip temperature is typically between 800 and 900°C. It travels a distance of 10 m before reaching the first laminar water jet. This controlled cooling is carried out in a 90 m run-out table (ROT) before the cooled strip is coiled. This controlled cooling has major influence on the final properties. The controlled cooling is achieved by several banks of a spray of water jets, termed laminar water cooling. Cooling is carried out by following certain cooling patterns in opening–closing the water heads on top as well as bottom side of ROT.

During cooling, the lower the transformation temperature, the greater is the strengthening effect affecting all the strengthening mechanism. The lower the transformation temperature, the finer the grain sizes of the transformation product and the greater the dislocation density. It is also true that as the transformation temperature is lowered, the finer is the dispersion of any precipitated phases. The tendency to retain solute in supersaturated solution is also increased, thus giving increased solid solution strengthening. For different kinds of products, different cooling strategies are adopted. The cooling rate also affects the precipitate strengthening by altering the transformation temperature. Fast cooling rates can prevent precipitation, intermediate cooling rates cause maximum age hardening, while slow cooling rates give overaging, which produces low strength. If the precipitation can be supressed during cooling, it can be induced during aging.

After ROT cooling, the strip is coiled in a down coiler and transferred to a bay to cool at ambient air. Then sample for each coil is taken for testing of mechanical properties at the stage laboratory of the mill. This process takes a substantial amount of time to complete. This time has been minimised with the help of online property prediction system in the case of IF steel.

The information flow between different automation and IT systems during hot rolling process with metallurgical phenomenon, which occurs during hot rolling, is given in Fig. 1.

Methodology

The final mechanical property of the hot rolled steel is an influence of geometrical parameters, chemical parameters and process parameters.[18,19] A total of 1939 cases consisting of different IF grade steels were collected after removing those with missing values. These cases are analysed to check the range and errors occurred due to bad signal and manual intervention in the level 1 and level 2 automation systems. This process reduced the number of valid records to 1557. This data set was taken as input to the ANN model. The mechanical properties such as yield strength (YS), ultimate tensile strength (UTS) and percentage elongation (%el) are considered as output parameters for this proposed system. The ranges of variables used in the present work are listed in Table 1. The Pearson correlation matrix between parameters is given in Table 2. Each variable is normalised within the range from −1 to 1 for ANN modelling using the equation given in equation (1)[20]

$$X_N = \frac{2(x - x_{min})}{x_{max} - x_{min}} \tag{1}$$

where X_N is the normalised value of a variable x, and x_{max} and x_{min} are the maximum and minimum values of x respectively.

The ANN used in the present case is a supervised multilayered network, which is trained and validated using standard gradient descent backpropagation algorithms.[5] The inputs and outputs are connected through hidden units. The inputs x_i are multiplied by weights w_{ji} for a hidden node h_j; summation of all the $w_{ij}x_i$ is then added to a bias value θ_{ji} and finally operated by a suitable transfer function (f). The operation may therefore be written as

$$h_j = f\left(\sum w_{ji}x_i + \theta_{ji}\right) \tag{2}$$

Similar operations are repeated for varying numbers of hidden units in order to find out suitable network architecture. The transfer function used in this work is tanh. Hidden layers contribute to the output nodes through a linear operation. The output Y can be written as

$$Y = \sum w'_j h_j + \theta' \tag{3}$$

where w'_j and θ' are new sets of weights and bias values.

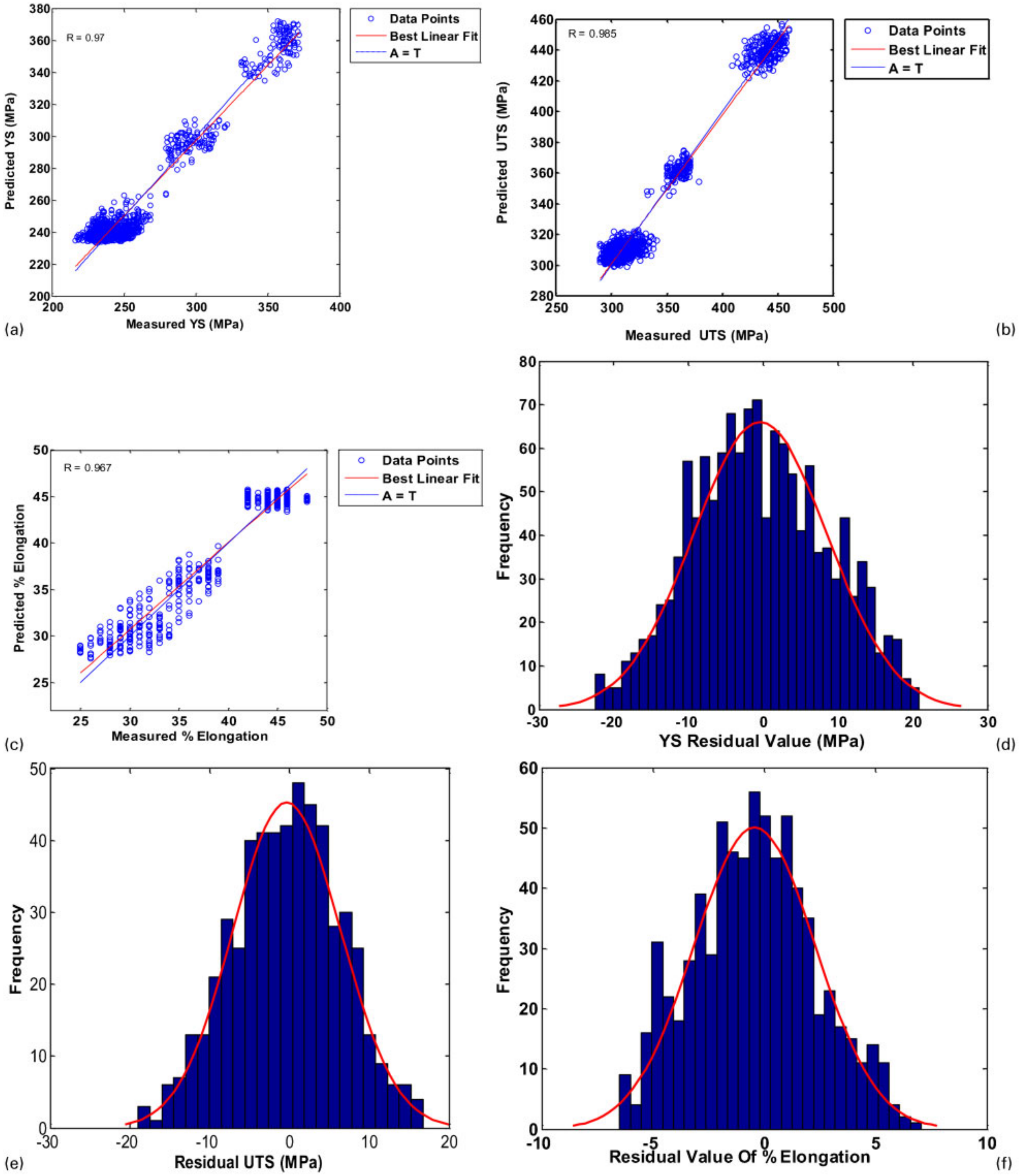
In the process of learning, the error of the calculated or predicted output in relation to the actual output is back propagated to adjust all the weight and bias values. This approach is useful and successful only when the network topology and configuration is chosen correctly. A too small network cannot learn a problem well and on the other hand, an oversized neural network will lead to an over fitting of the training data set and subsequent poor generalisation performance.[21] This is followed by a backward error propagation pass in which weights of neurons are updated using the gradient of a cost function, such as the sum squared error between network outputs and desired target outputs. Several ANN models have been generated separately for UTS, YS and %el with number of hidden units varying from 8 to 40 in a single hidden layer to find the appropriate network to simulate the problem. Among the alternate

Table 1 Maximum, minimum, average value and standard deviation of parameters

Variable name	Min.	Max.	Average	Standard deviation
Input variables				
Thickness/mm	2·5	6·06	3·93	0·48
Carbon (C)/wt-%	0·0013	0·004	0·002	0·0005
Manganese (Mn)/wt-%	0·01	0·62	0·145	0·15
Aluminium (Al)/wt-%	0·017	0·06	0·041	0·005
Phosphorus (P)/wt-%	0·007	0·055	0·016	0·01
Sulphur (S)/wt-%	0·004	0·012	0·006	0·001
Nitrogen (N)/ppm	15	40	23	5
Titanium (Ti)/wt-%	0·001	0·09	0·049	0·014
Chromium (Cr)/wt-%	0·012	0·046	0·02	0·003
Copper (Cu)/wt-%	0·003	0·016	0·004	0·001
Niobium (Nb)/wt-%	0·001	0·025	0·005	0·005
Vanadium (V)/wt-%	0	0·002	0·0009	.0009
Silicon (Si)/wt-%	0·002	0·105	0·009	0·017
Boron (B)/wt-%	0	0·001	0·0001	0·0002
Speed at F6/m s^{-1}	4·97	11·06	8·85	0·80
FRT/°C	887	938	931	6
CT/°C	564	748	707	20
Roughing mill exit Temp. (RMET)/°C	1027	1162	1106	18
Slab drop-out temp. (SDOT)/°C	1022	1274	1207	22
Soak time/min	8	1490	53	189
Slab retention time/min	139	548	215	45
Output variables				
%El	25	50	42	4
UTS/MPa	287	476	326	41
YS/MPa	206	405	256	38

Table 2 Pearson correlation matrix between parameters

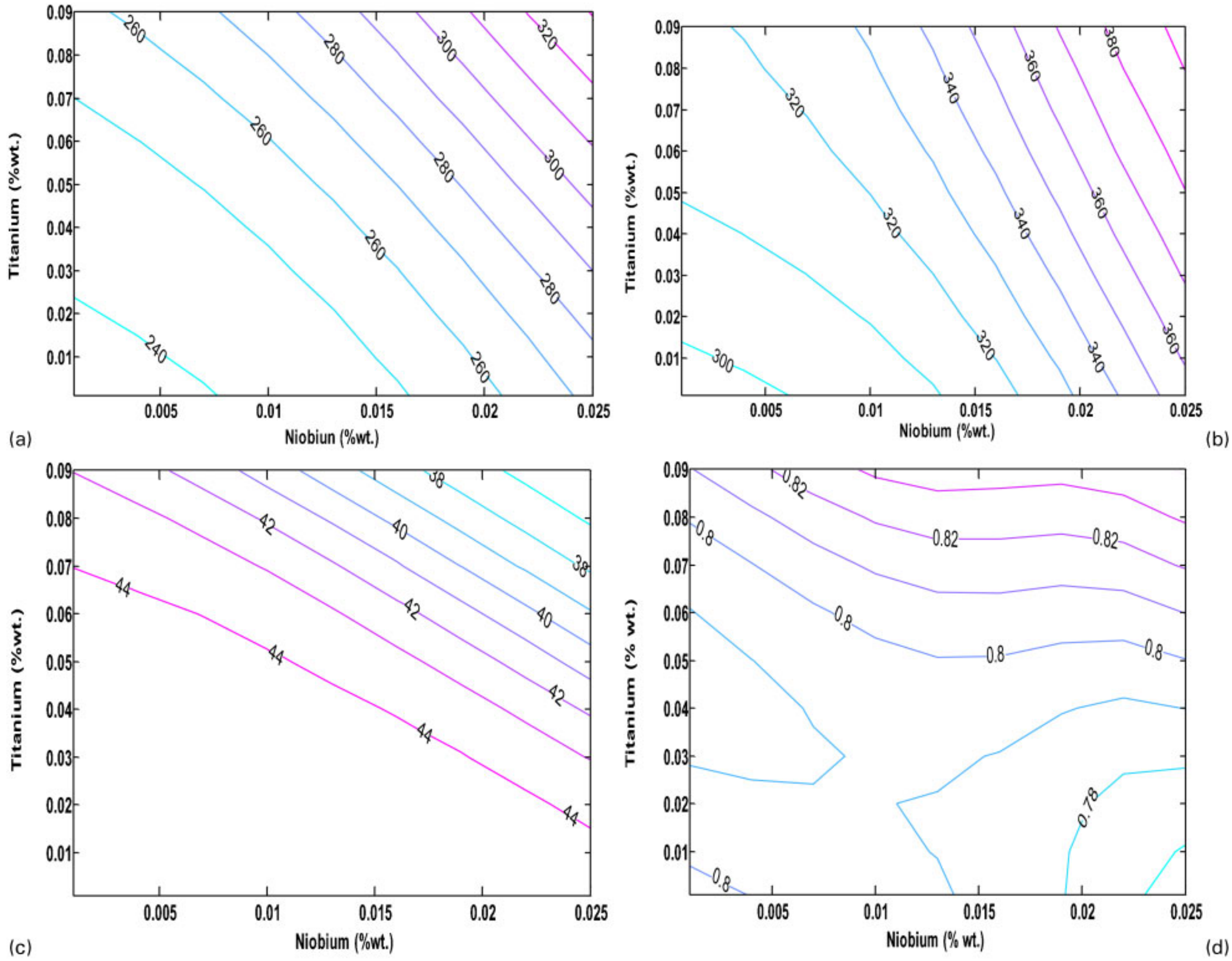
	Tk	C	Mn	Al	P	S	N	Ti	Cr	Cu	Nb	V	Si	B	F6	FRT	CT	RMET	SDOT	Soak time	Ret. time	%El	UTS	YS
Tk	1	−0·146	−0·279	0·0988	−0·274	−0·03	−0·002	0·035	0·0206	0·0223	−0·058	0·015	−0·119	−0·265	−0·33	−0·025	0·244	0·003	0·113	−0·044	0·049	0·219	−0·127	−0·278
C	−0·146	1	0·384	−0·201	0·345	−0·064	0·139	−0·1	0·005	−0·018	0·133	−0·047	0·205	0·379	0·076	0·062	−0·03	−0·184	−0·136	0·008	0·025	−0·339	0·186	0·406
Mn	−0·279	0·384	1	−0·249	0·861	0·0243	0·03	−0·22	0·086	0·022	0·405	0·018	0·414	0·919	0·165	0·0009	−0·03	−0·45	−0·443	0·036	−0·054	−0·808	0·429	0·919
Al	0·099	−0·201	−0·249	1	−0·188	−0·088	−0·117	0·194	0·008	−0·172	−0·149	0·026	−0·199	−0·214	−0·01	−0·017	0·018	0·140	0·165	0·002	−0·054	0·233	−0·149	−0·27
P	−0·274	0·345	0·861	−0·188	1	0·013	−0·019	−0·16	0·130	−0·000	0·019	0·014	0·180	0·871	0·253	0·0329	−0·21	−0·210	−0·283	0·013	−0·043	−0·654	0·335	0·725
S	−0·03	−0·064	0·024	−0·088	0·014	1	−0·023	−0·11	0·094	0·065	0·137	0·010	0·089	0·0133	−0·044	−0·07	0·01	−0·02	0·013	0·003	−0·033	0·008	0·011	0·025
N	−0·002	0·139	0·03	−0·117	−0·019	−0·023	1	0·045	−0·232	0·0236	0·0405	−0·002	0·142	0·012	−0·06	−0·037	−0·03	−0·054	−0·069	0·030	−0·013	−0·06	0·039	0·046
Ti	0·035	−0·095	−0·219	0·194	−0·158	−0·108	0·045	1	0·069	−0·062	−0·637	−0·033	−0·118	−0·107	−0·124	0·004	−0·35	0·135	0·122	−0·000	−0·029	0·039	−0·01	−0·056
Cr	0·021	0·006	0·087	0·008	0·13	0·094	−0·232	0·07	1	0·055	−0·017	0·014	0·010	0·086	0·006	0·0412	0·038	−0·01	0·01	−0·025	−0·008	−0·081	0·089	0·072
Cu	0·022	−0·018	0·022	−0·172	−0·000	0·065	0·024	−0·062	0·055	1	0·036	0·035	0·022	−0·017	0·029	−0·042	−0·01	−0·04	−0·057	0·002	0·014	−0·033	−0·009	0·014
Nb	−0·058	0·134	0·405	−0·149	0·019	0·137	0·041	−0·64	−0·017	0·036	1	0·033	0·434	0·205	−0·06	−0·077	0·475	−0·47	−0·358	0·0378	−0·015	−0·326	0·178	0·403
V	0·015	−0·047	0·018	0·0261	0·014	0·010	−0·002	−0·03	0·014	0·034	0·033	1	0·010	0·011	−0·07	−0·104	−0·01	−0·05	−0·086	−0·022	−0·013	−0·035	0·0094	0·005
Si	−0·119	0·206	0·415	−0·199	0·181	0·0897	0·142	−0·12	0·010	0·022	0·434	0·01	1	0·341	−0·120	−0·055	−0·18	−0·37	−0·275	0·037	−0·046	−0·279	0·225	0·42
B	−0·265	0·379	0·919	−0·214	0·872	0·013	0·012	−0·11	0·086	−0·017	0·205	0·011	0·341	1	0·179	0·0329	−0·06	−0·34	−0·348	0·022	−0·042	−0·731	0·388	0·845
F6	−0·329	0·076	0·165	−0·01	0·253	−0·044	−0·057	−0·124	0·005	0·029	−0·056	−0·068	−0·12	0·178	1	0·2961	0·068	−0·07	−0·072	−0·021	−0·027	−0·081	0·019	0·086
FRT	−0·025	0·063	0·000	−0·017	0·033	−0·07	−0·037	0·004	0·041	−0·042	−0·077	−0·104	−0·055	0·0329	0·296	1	0·084	0·196	0·17	−0·037	−0·058	0·030	−0·027	−0·028
CT	0·244	−0·026	−0·029	0·018	−0·213	0·009	−0·028	−0·35	0·0384	−0·006	0·474	−0·015	−0·18	−0·055	0·068	0·0835	1	−0·19	−0·04	−0·075	0·046	0·03	−0·046	−0·06
RMET	0·003	−0·185	−0·447	0·140	−0·21	−0·015	−0·055	0·135	−0·012	−0·045	−0·474	−0·05	−0·373	−0·337	−0·070	0·1959	−0·19	1	0·529	−0·019	0·079	0·382	−0·22	−0·469
SDOT	0·113	−0·136	−0·443	0·165	−0·283	0·0126	−0·069	0·122	0·010	−0·057	−0·358	−0·086	−0·275	−0·348	−0·072	0·1697	−0·04	0·529	1	−0·028	0·105	0·376	−0·183	−0·439
Soak time	−0·044	0·009	0·036	0·002	0·013	0·003	0·031	−0·000	−0·025	0·002	0·037	−0·022	0·037	0·022	−0·020	−0·037	−0·07	−0·02	−0·028	1	0·015	−0·066	0·019	0·052
Ret. time	0·049	0·025	−0·054	−0·054	−0·043	−0·033	−0·013	−0·03	−0·008	0·013	−0·015	−0·013	−0·046	−0·042	−0·03	−0·058	0·046	0·079	0·105	0·014	1	0·004	−0·023	−0·016
%el	0·219	−0·339	−0·808	0·233	−0·654	0·0084	−0·06	0·04	−0·081	−0·033	−0·326	−0·035	−0·279	−0·731	−0·081	0·0308	0·03	0·383	0·377	−0·066	0·005	1	−0·384	−0·831
UTS	−0·127	0·187	0·429	−0·149	0·336	0·011	0·04	−0·01	0·089	−0·009	0·178	0·009	0·225	0·388	0·019	−0·027	−0·05	−0·22	−0·183	0·019	−0·023	−0·384	1	0·443
YS	−0·278	0·406	0·919	−0·27	0·725	0·024	0·046	−0·06	0·071	0·014	0·402	0·005	0·419	0·844	0·086	−0·028	−0·06	−0·47	−0·439	0·051	−0·016	0·443	0·443	1



2 Performance of models for *a* YS, *b* UTS, *c* % elongation and histograms of residual values of *d* YS, *e* UTS and *f* % elongation

Table 3 Model design parameters

Parameter name	Parameter value	Parameter name	Parameter value
No. of layers	3	Cost function	MSE
Training algorithm	Backpropagation (scaled conjugate gradient)	Error value (goal)	$1{\cdot}0000\times10^{-10}$
Training data size	1557	Sigma	$5{\cdot}0000\times10^{-15}$
Transfer function	Tanh	Lambda	$5{\cdot}0000\times10^{-7}$
No. of input parameters	22	No of output	3



3 Effect of titanium and niobium on *a* YS, *b* UTS, *c* % elongation and *d* YS/UTS ratio

models, the best was chosen for each output variable. Table 3 shows the model design parameters.

Online system design

A computer based online property evaluation system was developed to evaluate mechanical properties of hot rolled coils soon after rolling is completed. To handle the day to day operational activity, the HSM has various levels of automation systems and data warehouses. Based on the rolling schedule given by the planning department, slab related information including chemistry, which is called primary data input (Fig 1), is transferred from level III to HSM level II system.

HSM level 2 automation system has many subsystems, which serve different stages of hot rolling. As, at the same point in time when one slab is in reheating furnace, another slab is in roughing mill and third slab is in finishing area, it is very necessary to coordinate and synchronise the data properly. This synchronisation of data is carried out at level 2 system and all the parameters related to a coil starting from chemistry of liquid steel to coiling temperature (CT) are sent to level III system as soon as the rolling is over. The communication between these systems is given in Fig. 1.

The property prediction system receives all the necessary input parameters such as (1) slab information, (2) chemistry, (3) roughing mill parameters and (4) finishing mill parameters from the level 3 system as soon as the rolling is over. After receiving data, the system calculates the mechanical properties and sends it to Flat Product Complex Information System, which is used by the Technical Services (Fig. 1) for dispatching any coil to the market. The online property prediction system helps in reducing mechanical testing time. Indirectly, it helps in reducing product cycle time and better utilisation of manpower. It is an unmanned system where very little maintenance is required. It has the capacity to store data for 1 month, which can help in further analysis.

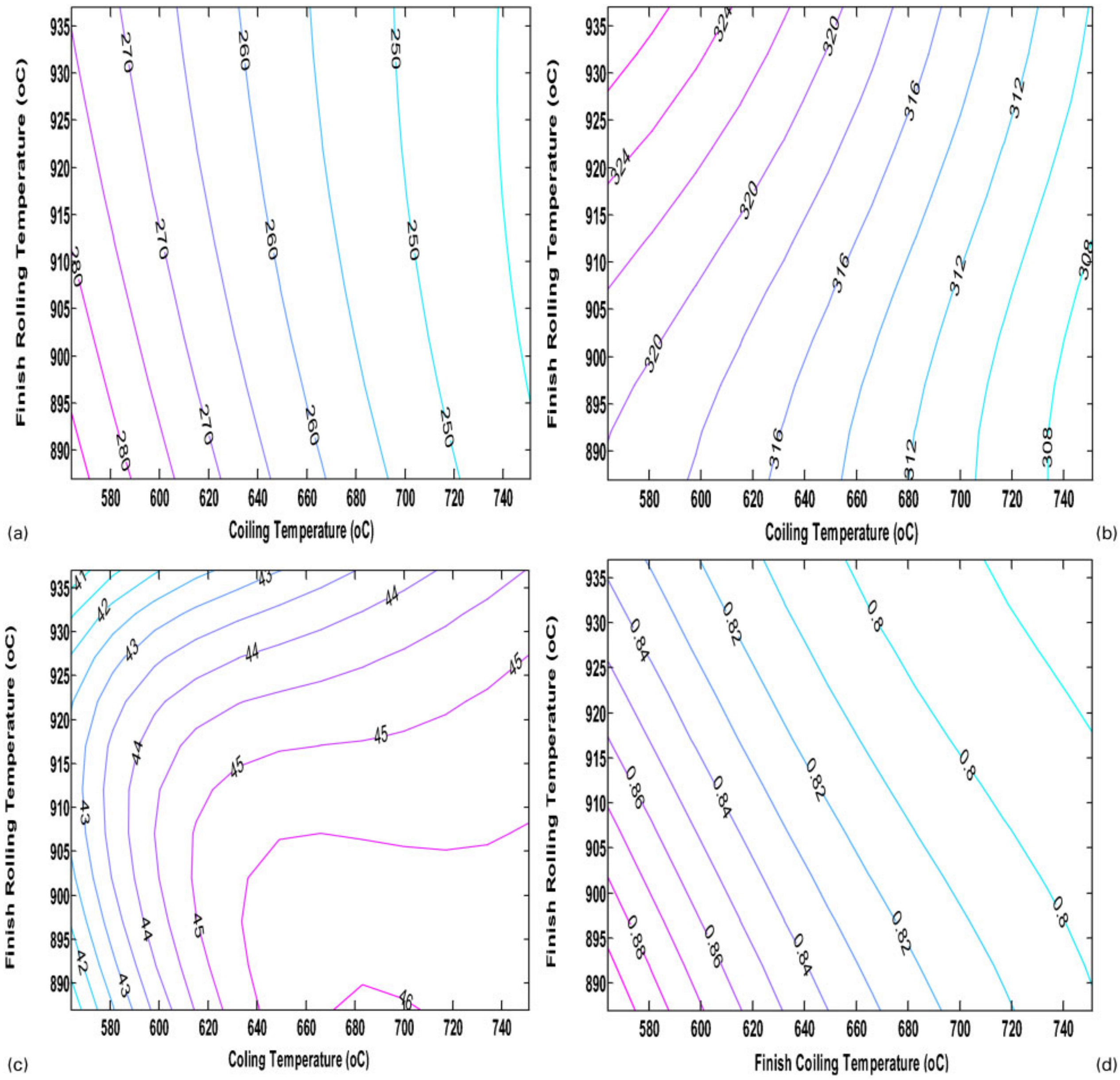
In the present work, the online system developed during the course of this work is based on an off line model. MATLAB 7·0·1 is considered as basic programming software for the design of neural network architecture and development of algorithms. The process which communicates with level III system through 'ftp (file transfer protocol)' is written in 'C' language.

Results and discussion

All the neural network models were tested and validated to avoid any kind of overfitting in the model. Some representative results of these models are described below.

Performance of model

Figure 2 shows the predictive capacity of the model. It can be seen that the property prediction capability is very good and it can serve the plant very well. The

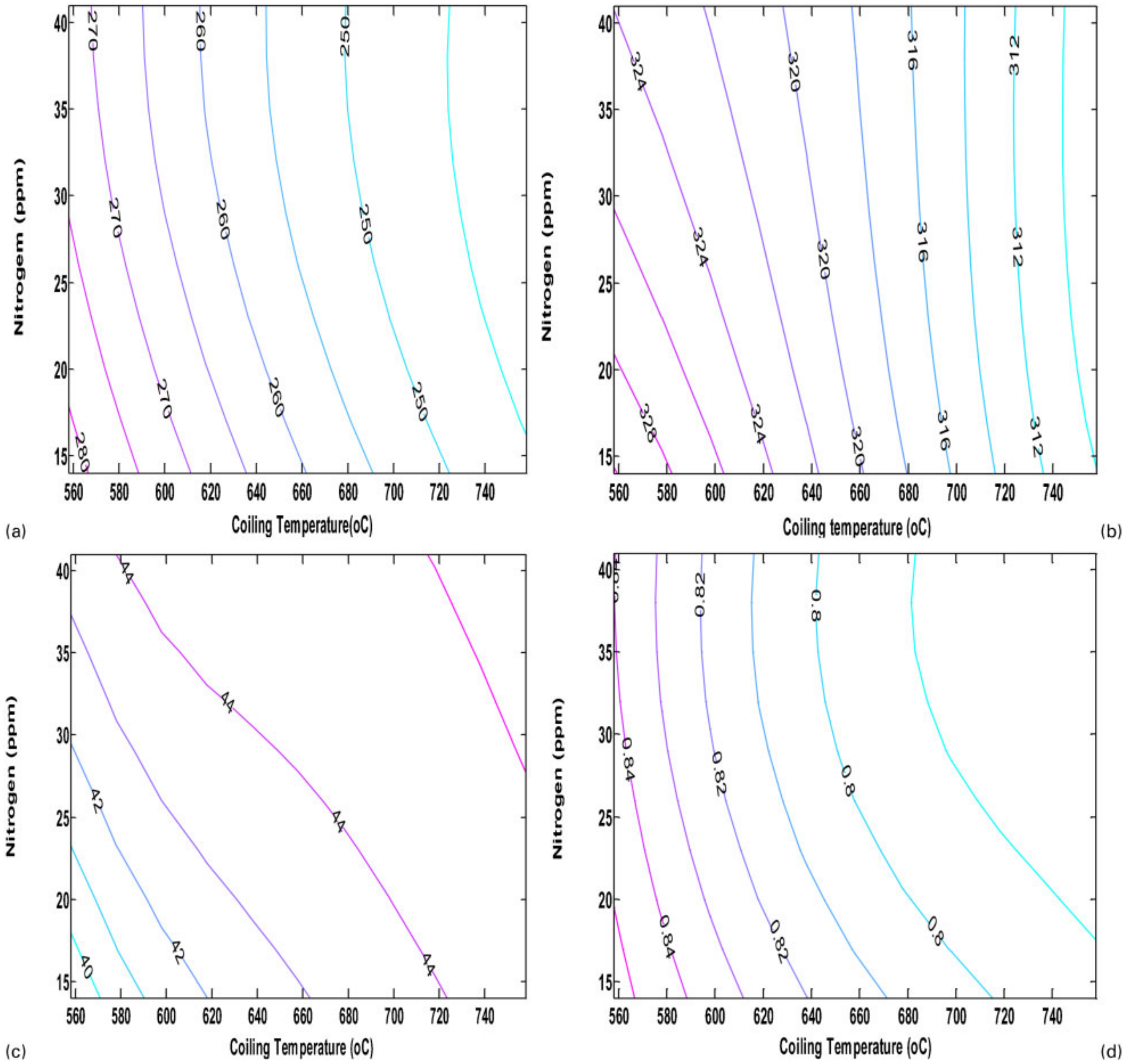


4 Roles of FRT and CT on *a* YS, *b* UTS, *c* % elongation and *d* YS/UTS

predictive accuracy of the neural network model has been evaluated and is 97%, 98% and 96% for YS, UTS and %el respectively. Figure 2 also shows the histograms of the residual values of YS, UTS and %el which are (almost) bell shaped, which supports the assumption of normality of the residuals. However, the ANN model is also used for having better understanding on how chemistry and various processing parameters affects the mechanical properties of hot rolled IF steel.

Effect of chemistry and process parameters on mechanical properties

Simulation studies were conducted on YS, UTS and %el models to see the synergistic effects of some of the variables. For these simulation studies, two variables are varied at the same time, while other variables are kept constant at an average value. The effective utilisation of Nb in strengthening the steel depends on slab drop-out temperature (SDOT). Suitable SDOT helps in putting the Nb in solution which during rolling can effectively retard the recrystallisation of austenite. However, wrong SDOT might lead to partial dissolution of Nb, which will lessen its effectiveness. That is why it is important to examine the combined effect of these two parameters on the mechanical properties of steel. FRT and CT are two most important rolling parameters that can be controlled easily. Both of them have pronounced effect on the mechanical property. However, they are also dependent on each other. It is understood that the difference between FRT and CT indicates the cooling rate on the ROT. It is well known that the cooling rate has high impact on the mechanical property of steel. Owing to this, we need to examine the effect of FRT and CT together. Ti and Nb are the two most important microalloying agents added to steel. The dissolution temperatures of both Ti and Nb could depend on the amounts of N and C in steel. Quite often these two microalloying elements strengthen the steel by same mechanism, i.e. grain size refinement and precipitation hardening. Both these alloying elements also effectively fix C and N and improve the properties of IF steel. However, as these are costly elements, it is important to



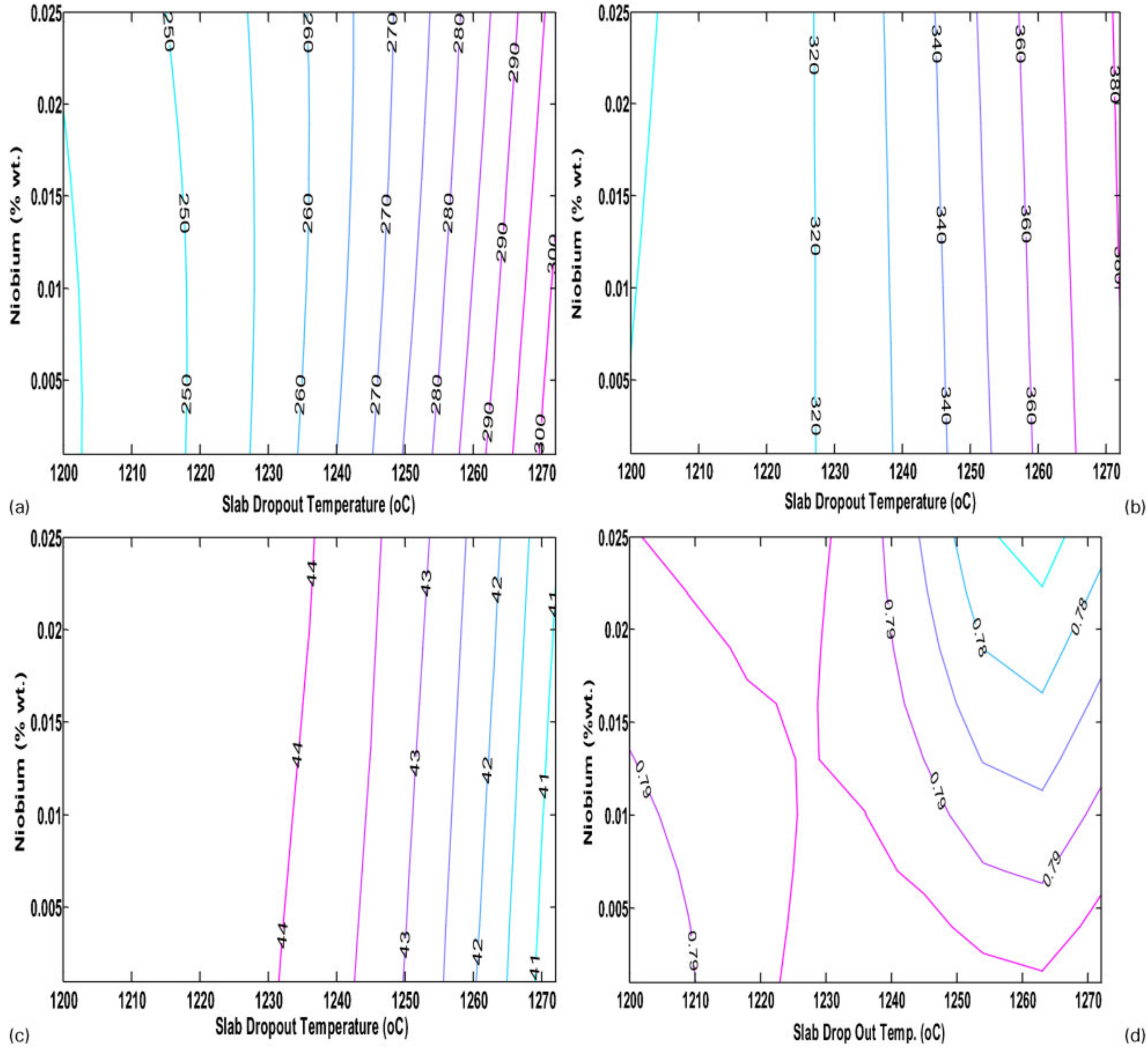
5 Roles of CT and N on *a* YS, *b* UTS, *c* % elongation and *d* YS/UTS

use them in right combination. For this reason, we have studied the combined effect of Ti and Nb on the mechanical properties of steel. The range of variables considered for this study is reported in Table 1. Some interesting results are displayed here.

In Fig. 3, it can be seen that effect of Nb on UTS and YS is much higher in comparison to Ti. With increasing niobium and titanium, strength increases. The reason behind higher strength (YS and UTS) as a result of addition of Nb is described in detail in Refs. 23 and 24. Nb prevents the recrystallisation of austenite and makes the final grain size finer. But the increase in strength due to higher Ti is not always observed. The reason behind this could be due to the fact that some titanium might remain in solution at this level of FRT, which increases the T_{nr}, and as a result, the final microstructure becomes finer and the strength increases. It is also seen in this figure that with increasing microalloying elements, %el decreases.

Among the process variables, the effects of FRT and CT are shown in Fig. 4. It is observed that YS is impacted more by the change in CT than the FRT. UTS is less impacted by the change in CT or FRT. However, both FRT and CT increase the UTS more or less in similar quantity. By lowering the CR through longer periods of accelerated cooling, the yield stress can be increased as lowering of CT makes the structure finer. In turn, slow cooling from the coiling temperature enables beneficial effects, such as precipitation hardening.[16] The lower YS of the hot rolled material coiled above 650°C is due to the larger ferrite grain size. For low CR (approximately $<$620°C), YS is almost independent of finishing temperature, which indicates that to control the strengthening, CT has a larger impact than FRT. %el increases with increasing CT, which is expected due to increase in ferrite grain size; however, it seems any change in FRT does not impact the %el to any appreciable amount.

It is interesting to examine the combined effect of some of the input parameters, which are of different nature, on the final properties of IF steel. In Fig. 5, the combined impact of N and CT is examined on the final properties. It is shown that higher strength is achieved at low CT, but it is also observed that at a particular CT,



6 Roles of SDOT and Nb on *a* YS, *b* UTS, *c* % elongation and *d* YS/UTS ratio

strength increases with decreasing nitrogen. The trend of decreasing strength with increasing N needs further explanation. N in this steel is very low, but it should have shown some hardening as it goes into the interstitial voids of ferrite. However, in this steel, during this analysis, Ti is considered to be constant at an amount of 0·04%. Higher N will help producing more TiN at higher temperatures, which is coarse in nature and does not contribute to strengthening. As a result of this, the free Ti is less available at FRT. Lowering of free Ti in austenite will reduce its capability to increasing the T_{nr} or refining the ferrite grain size. This analysis also proves that in hot rolled IF steel, Ti contributes to strength by refining the microstructure and not by precipitation.

Figure 6 shows the combined effect of SDOT and Nb on mechanical properties. All other chemical and process parameters were kept constant during analysis. For this analysis Ti is kept constant at 0·04 wt-%. It can be seen that with increasing SDOT, strength (YS, UTS) increases. Niobium does not impact the strength, which is varying between 0·001 and 0·025 wt-%. By investigating further with the help of solubility product concept (equations (4)–(6)), it was found that during reheating at 1200°C, all the niobium is in solution[25]

$$\log\,[\mathrm{Nb}]\,[\mathrm{C}+12/14\,\mathrm{N}]=2{\cdot}26-6770/T \tag{4}$$

$$\log\,[\mathrm{Ti}]\,[\mathrm{C}]=2{\cdot}75-7000/T \tag{5}$$

$$\log\,[\mathrm{Ti}]\,[\mathrm{N}]=2{\cdot}0-20790/T \tag{6}$$

With the help of equations (5) and (6), it is also found that the all the Ti (0·04 wt-%) is also in solution at a minimum SDOT of 1200°C. Increase in strength with increasing SDOT can happen if it takes more and more microalloying elements into solution. However, that is not possible here as at the lowest SDOT, all NB and Ti are already in solution. Therefore, the reason behind the increase in strength could be due to segregation of microallying elements in slabs after casting, as a result the weight percentage of microalloy during reheating increases, which is responsible for increase in strength at higher SDOT. It is well know that Ni and Ti segregate during casting[26] and at different places of the slab, amount of microallying elements could be much higher than the average.

Conclusions

A neural network based model has been developed to predict YS, UTS and %el of hot rolled IF steels. This model has been integrated with the level 3 system of the HSM and an online prediction system developed. Online availability of this property prediction system is helping in reducing the expenses incurred by sample taking, yield loss due to sample cutting and by the delay in delivery to downstream processes. It also helps in predicting variation of properties over the length of the strip.

The results of this work indicate that the offline ANN model can be a good tool for studying the role of various processing and composition variables on the final properties of IF steel. Findings from this study can be successfully utilised to design the composition and processing of IF steel with desirable properties. This model can be used as a guideline for further experimentation.

It has been explicitly shown that an ANN model, trained by comprehensive datasets, can even track and simulate the complicated metallurgical phenomena like the effect SDOT, CT and also the impact of microalloying elements in hot rolled steel.

By coupling the explanatory insights of neural network with its powerful predictive capabilities, ANN can be efficiently applied to evaluate, understand and predict the complex metallurgical phenomena. This system can not only predict such metallurgical behaviour, but also can be exploited to identify 'optimal' recipes for an effective metal design.

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