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Comparison of Some Neural Network and Multivariate Regression for Predicting Mechanical Properties of Investment Casting

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Investment casting enables producing complex shapes with good accuracy and surface finish. A key goal for investment castings used in automobile, aerospace, chemical, biomedical and other critical applications is to be free of internal defects and to possess mechanical properties within the desired range. At present, casting quality is ascertained by destructive testing at the end of production cycle, leading to the possibility of scrapping the entire batch. In this work, the mechanical properties of investment castings have been predicted based on process parameters and chemical composition, by employing artificial neural network (ANN) and multivariate regression (MVR). The data of related process parameters (wax making, shell making, dewaxing, melting etc.), chemical composition of the alloy, and the resulting mechanical properties (ultimate tensile strength, yield strength, and percentage elongation) for 800 heats were collected in an industrial investment casting foundry. Three different ANN models: back propagation, momentum and adaptive, and Levenberg-Marquardt, with varying number of neurons in the hidden layer (from 20 to 45 in steps of 5) were trained using a portion of the data and tested with remaining data. A prediction penalty index (PPI) was developed to compare the relative predictive capability of various neural network and MVR models. It is observed that both ANN and MVR could predict the mechanical properties well, though MVR gave slightly better results. For the ANN model, better results were produced when the number of neurons in the hidden layer was equal or slightly higher than the number of input parameters.

Keywords artificial neural network, investment casting, mechanical properties, multivariate regression, prediction penalty index

1. Introduction

Investment casting is one of the oldest manufacturing processes and was mainly used to create jewelry and idols earlier. The modern investment casting plants produce intricate parts with high dimensional accuracy and surface finish, for automotive, aerospace, bio-medical, chemical defense, and other sectors. Major steps and some relevant parameters in investment casting process are illustrated in Fig. 1.

Major quality metrics of investment casting include dimensional fidelity (with the designed part), internal soundness (no shrinkage, gas porosity, or inclusion defects), and the correct range of mechanical properties. The mechanical properties that are of main interest include the ultimate tensile strength (UTS), yield strength (YS), and elongation. These are becoming increasingly important, since they affect the service life of a cast component. Manufacturing defect-free castings with the required mechanical properties are, however, extremely challenging since the properties depend on the process variables, which are difficult to control, and therefore change from one component to another.

At present, the mechanical properties of investment castings are checked using various destructive testing methods. This includes measurement of tensile strength, YS, and elongation using universal testing machine (UTM). These tests are expensive and take a considerable time, especially if required to be carried on all samples of all batches. Testing only a few samples in a batch can lead to scrapping the entire batch if the mechanical properties of the tested samples are found to be out of the specified range, or passing the batch with possible defective castings, if the samples happen to be within the specified range.

The mechanical properties are driven by the chemical composition of metal and the process parameters related to various steps namely, wax pattern making, shell making, shell dewaxing, and metal pouring. There is a need to predict the properties based on the values of the parameters involved. This will help in optimizing the chemical composition and process parameters in advance to achieve the desired mechanical properties, and thereby reduce the level of rejections in the industry. Previous work in this direction is reviewed in the following section.

2. Previous Work

Computer simulation as well as statistical techniques has been employed to predict mechanical properties of castings.

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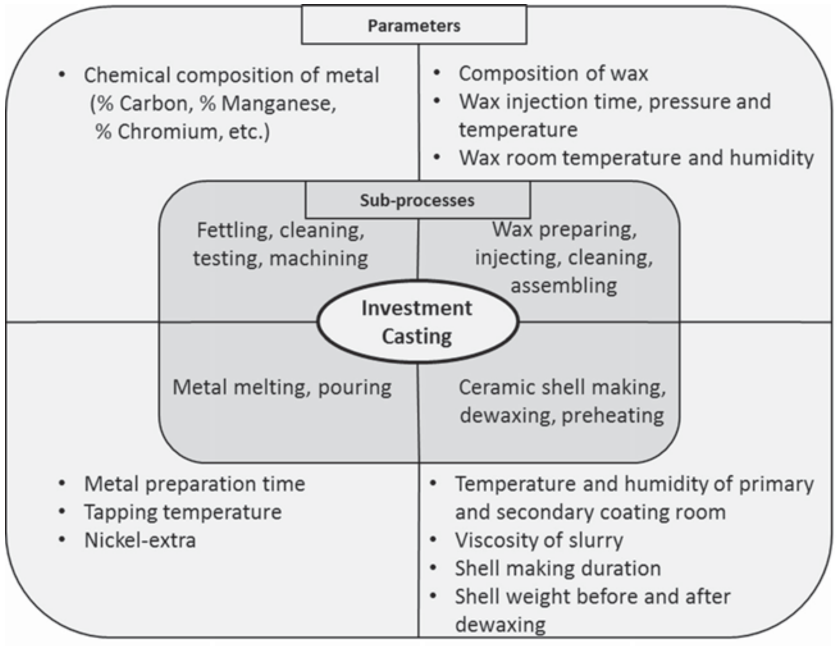

Fig. 1 Major steps and relevant parameters in investment casting process

Casting simulation has been found to be very useful for predicting the relative magnitude of mechanical properties in different regions of casting, mainly driven by micro-structure. This is in turn influenced by the relative cooling rates, which are computed using an appropriate multi-physics mathematical model after discretizing the part and mold geometry, inputting the relevant temperature-dependent physical properties of the materials, and providing the boundary conditions. These software programs are therefore, very complex in nature, and require a high level of domain knowledge as well as computational skill. Their use in optimizing process parameters to achieve the desired range of mechanical properties is at best iterative in nature, consuming a large amount of time and effort. The previous work in this area is summarized in Table 1.

Statistical techniques (curve fitting, simple regression, and multiple regression) have also been employed to develop empirical models for mechanical property prediction. Important input includes the chemical composition, microstructure (grain size, secondary dendrite arm spacing), design parameters (component thickness), and process parameters (pouring temperature, solidification time) of castings, which are correlated with the values of mechanical properties mentioned earlier. The relationships are derived using curve fitting, linear regression, or multiple regression techniques; the least square method is used to fit a line through a number of observations. These techniques are, however, difficult to employ when the datasets are complex, with a large number of input and output parameters. The previous work in this area is summarized in Table 2.

In the last 10 years, few researchers have explored the use of artificial neural networks (ANN) for prediction of mechanical properties. The ANN can be learnt from examples, and has powerful capabilities to classify and recognize (Ref 18). It can establish functional relationships from experimental data even when the correlations are difficult to find or describe scientifically. The application of ANN in this area is summarized in Table 3.

Another relatively new technique called multivariate data analysis was recently introduced in engineering applications for prediction purposes. Noori et al. (Ref 19, 20) used MVR for predicting solid waste generation and river flow. Riad et al. (Ref 21) applied MVR for prediction of initial setting time of the concrete mixer in civil engineering. Applications of MVR in the field of manufacturing, especially prediction of mechanical properties in metal casting, do not appear to have been reported in technical literature.

It has been clearly established that the chemical composition and process parameters are important parameters influencing the mechanical properties of castings (Ref 10, 12). While ANN has been reported for predicting the mechanical properties of sand and die castings, it does not appear to have been employed for investment castings. The selection of appropriate training algorithm and number of neurons in hidden layer is still a challenging task. Another important aspect for ANN as well as MVR is the extreme care needed in collecting the data, since it affects the accuracy of subsequent predictions. Their applications in industrial settings, especially in metal casting domain, need to be proven.

When exploring different techniques for mechanical property prediction of metal castings, it is also important to know their relative predictive capability. One of the most common criteria for comparison of predictive capability is R square (R^2), which is mainly suitable for multiple regression (Ref 22). The Mean Squared Error (MSE) has also been used extensively; its major limitation is that it heavily weights the outliers (Ref 23).

Perzyk and Kochan (Ref 15) proposed prediction quality index (PQI) to compare the results obtained from different ANN networks. This method ranks the methods of prediction based on the average error of the prediction (AE), standard deviation of the error distribution (SD), and fraction of results

Table 1 Mechanical property prediction using computer simulation

Researcher	Year	Software	Alloy	Process	Input parameters	Predicted output	Concluding remarks
Guo and Samonds (Ref 1)	2006	ProCAST	Ti	Investment castings	Volume fraction	YS	Prediction was accurate
Seifeddine (Ref 2)	2008	MAGMA	Al	Sand Casting, GDC, and HPDC	Metallurgical (SDAS), process parameter (cooling rate)	YS and elongation	Predicted results are comparable
Zhou et al. (Ref 3)	2012	InteCAST	Gray CI	Sand casting	Process parameter (cooling rate)	Hardness	Cooling rate can be employed
Seifeddine and Svensson (Ref 4)	2012	MAGMA	SG Iron	Sand casting	Metallurgical (microstructure)	Residual stress	Predicted results show good agreement with actual results
Schneider et al. (Ref 5)	2012	MAGMA	Al	Sand casting	Metallurgical (SDAS), process parameter (grain size)	YS	Simulation can be employed for prediction

(FR) with error below 15% (FE_{15}). The PQI can be found out using Eq. 1

$$PQI = (1 - |AE|)(1 - SD)(1 - FE_{15}). \quad \text{(Eq 1)}$$

The statistical information is collected from the predicted results to calculate the modulus of average of error, standard deviation, and number of observations that fall within 15% of error. Thus, PQI can be employed to determine the relative capability of prediction of different techniques, and has been selected in this work to compare the results obtained from ANN and MVR models.

3. Modeling Using ANN and MVR

In this work, different models based on ANN and Multivariate Regression (MVR) have been explored to predict the mechanical properties of stainless steel investment castings. The modeling of ANN involves selection of controlling parameters for a network; MVR requires determining the coefficients for the empirical model. The relevant details are presented here.

3.1 Artificial Neural Network (ANN)

An ANN involves adjusting the output by iterations during the training period till the error is minimized. Hence, the selection of appropriate training algorithms and the number of neurons in the hidden layer are critical for modeling an ANN for a given purpose. There is a significant amount of technical literature about ANN modelling (Ref 14, 18, 24, 25). Several researchers have predicted multiple outputs from multiple inputs using ANN, showing that it is not necessary to build three independent networks for predicting multiple outputs (Ref 26-28). Therefore single ANN architecture was built to predict mechanical properties.

In this work, three training algorithms namely Back Propagation (BP), Momentum and Adaptive (MA) learning rate, and Levenberg-Marquardt (LM) algorithm have been employed for prediction due to their strong learning ability (Ref 20, 29). The basic architecture of neural network is shown in Fig. 2.

The number of layers was three, including one hidden layer. The number of neurons in the hidden layer was varied from 20 to 45 in steps of 5. The transfer function was kept as a hyperbolic tangent sigmoid for all variations of ANN. The maximum number of epochs is restricted to 10,000, the learning rate was set as 0.25, and the error goal was taken as 1×10^{-5}. Out of the total number of observations, 75% were used for training, and the remaining were used for testing the ANN. The training of ANN was stopped when one of these conditions was met: the maximum number of epochs is reached, or the error goal is achieved.

3.2 Multivariate Regression (MVR)

MVR analysis is also referred as multivariate multiple regression, where multivariate refers to the output variables, and multiple refers to the input variables. MVR defers from multiple regression analysis (MRA). While MRA enables developing an empirical model for a single output, the MVR is capable of multiple outputs for multiple inputs (Ref 30).

The general form of input matrix X and output matrix Y, for modelling the present problem is given in Eq 2 and 3.

Table 2 Statistical techniques for mechanical property prediction

Researcher	Year	Statistical technique	Alloy	Process	Input parameters	Predicted output	Concluding remarks
Morinogo et al. (Ref 6)	1998	Linear regression	Al and Mg	Cold chamber die casting	Metallurgical (orbital energy)	Tensile strength, hardness	Very easy to model
Goulart et al. (Ref 7)	2006	Curve fitting	Al	Gravity die casting	Metallurgical (secondary dendrite arm spacing-SDAS and tip growth rate), Process (heat-transfer coefficient and solidification- time)	Tensile strength, YS	SDAS is most significant parameter
Collini et al. (Ref 8)	2008	Weibull regression	CI	Sand casting	Metallurgical (graphite lamellas morphology and eutectic cell size), Chemical composition (inclusion content)	Tensile strength, fatigue strength	Graphite content is most significant variable
Costa et al. (Ref 9)	2010	Multiple regression	SG Iron	Sand casting	Metallurgical (graphite nodules' size, shape, and microstructure)	Fatigue strength	Predicted with good accuracy
Pucher et al. (Ref 10)	2011	Multiple regression	Al	Gravity die casting	Chemical composition (silicon, copper, magnesium, manganese)	Tensile strength	Can be employed to predict
Shabani and Mazahery (Ref 11)	2011	Curve fitting	Al	Sand casting	Microstructure (SDAS)	Tensile strength, yield stress, elongation	Excellent match with actual results
Shinde et al. (Ref 12)	2012	Multiple regression	SG iron	Sand casting	Chemical composition (copper addition), design parameter (thickness of casting)	Tensile strength, elongation, hardness	Copper content is important parameter
Dong et al. (Ref 13)	2012	Curve fitting	Al	Gravity die casting	Metallurgical (SDAS), process parameter (cooling rate)	Tensile strength, elongation, hardness	Analytical correlation can be used

Table 3 ANN models for mechanical property prediction

Researcher	Year	Training algorithm	Alloy	Process	Input parameters	Predicted output	Concluding remarks
Calcaterra et al. (Ref 14)	2000	Single/multi layer perceptron (SLP and MLP)	SG Iron	Sand casting	Process parameters (cooling rate and inoculation temperature), chemical composition (% C, %Si, %Mn, %S, %P, %Cu, %Sn, %Ni, %Mo, %Mg, and %Cr)	Tensile strength	MLP with one layer gives best results
Perzyk and Kochan (Ref 15)	2001	Back pro-pagation	SG Iron	Sand casting	Process parameters (spheroidisation and pouring temperature), chemical composition (%Al, %Ti, and %Sn)	Tensile strength, elonga-tion, hardness	ANN shows good results
Dobrzanski et al. (Ref 32)	2007	K-Mean learning algorithm	Al-Si-Cu	Gravity die casting	Process parameter (cooling rate), chemical Composition (%Si, %Cu, %Fe, %Mg, and %Mn)	Hardness, micro-hard-ness, elongation, YS	ANN can accurately predict the outputs
Dobrzanski and Krol (Ref 27)	2010	Back pro-pagation	Al-Mg-Zn	Gravity die casting	Process parameter (cooling rate), chemical Composition (%Al, %Zn, %Mn, %Si, %Cu, %Fe, and %Mg)	Hardness, compressive strength, grain size	ANN is showing accurate results
Emadi and Mahfoud (Ref 16)	2011	Not available	Al	Sand casting, gravity die casting	Process parameters (Aging temperature), Chemical Composition (%Si, %Na, %Sn, and %Sb)	Tensile strength, YS	ANN is better than Multiple regression
Krupinski and Tanski (Ref 17)	2012	Not available	Mg	Gravity die casting	Chemical composition (%Al, %Zn, %Mn, %Zr)	Hardness, tensile strength	ANN can be employed

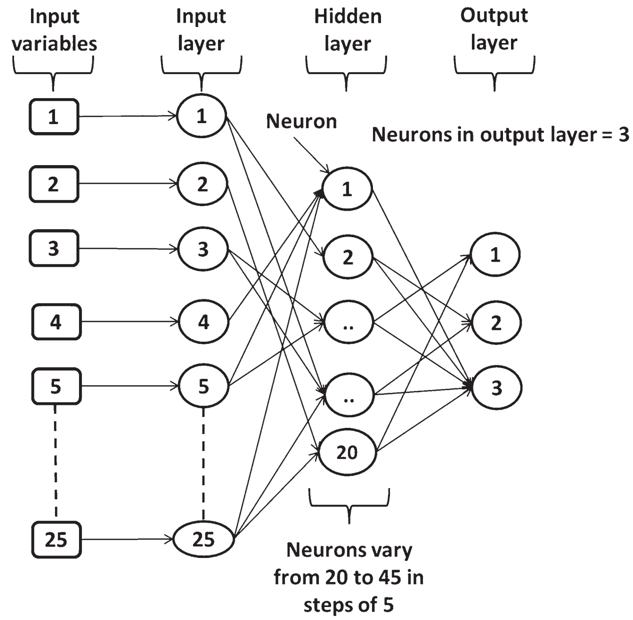

Fig. 2 Architecture of Neural Network

$$X = \begin{pmatrix} X_{11} & X_{12} & X_{1q} \\ X_{21} & X_{22} & X_{2q} \\ \vdots & \vdots & \vdots \\ X_{n1} & X_{n2} & X_{nq} \end{pmatrix}, \quad \text{(Eq 2)}$$

$$Y = \begin{pmatrix} Y_{11} & Y_{12} & Y_{1p} \\ Y_{21} & Y_{22} & Y_{2p} \\ \vdots & \vdots & \vdots \\ Y_{n1} & Y_{n2} & Y_{np} \end{pmatrix}, \quad \text{(Eq 3)}$$

where Y the mechanical properties; $Y1$ the tensile strength, $Y2$ the yield strength, and $Y3$ the elongation; p the number of output variables = 3 (in this case); n the total number of observations; X the process parameters and chemical composition; q the number of input variables = 25 (in this case).

The co-efficients (β_1, β_2, …, β_p) were calculated from experimental data in a such way that it minimized the error (ε) between output (Y) and input variables (X). These co-efficients were used to develop the empirical model, which was tested for prediction with the help of inputs using Eq 4.

$$Y = \beta X + \varepsilon. \quad \text{(Eq 4)}$$

The detailed inputs and results are presented next.

4. Data Collection and Property Prediction

Shop floor data were collected from an investment casting foundry situated near Rajkot (India), which supplies cast components to automobile, chemical, and aerospace industries. The main alloy is ASTM A351 (stainless steel). In this work, data of about 800 heats were acquired along with the values of process parameters related to wax making, shell making, dewaxing, and pouring, as well as the chemical composition of the alloy (charge composition). The actual data represented 1580 observations, since two batches of shells were used for each heat. The foundry measured the mechanical properties (UTS, YS, and percentage elongation) for each batch, by casting sample bars along with the castings in each batch, and testing each sample bar on an UTM as per ASTM A370 (Ref 31) (Fig. 3). The total dataset comprises 25 input parameters and three output parameters. Their range of values of input parameters is given in Table 4, along with the average and standard deviation of each one.

Out of the 1580 observations, data corresponding to 1185 observations (75% of data) were used for training the ANN and MVR models. The remaining 395 observations (25% of data) were used for testing the models. The data is initially normalized (between −1 and 1) using Eq 5 to avoid dimensionality conflict amongst input and output. The normalized dataset is fed into the ANN and MVR for training. The output data are reconverted into the original form after testing. The predicted results from the models are compared with the actual results. The code for ANN and MVR was written and executed in MATLAB environment.

$$X_n = 2 \times \left[\frac{(X - X_{\text{min.}})}{(X_{\text{max.}} - X_{\text{min.}})}\right] - 1, \quad \text{(Eq 5)}$$

where $X_{\text{max.}}$ and $X_{\text{min.}}$ are the maximum and minimum values of a particular input variable X in the dataset; X_n is the normalized value of parameter X.

5. Comparative Evaluation of ANN and MVR Models

A total of 19 models were developed and compared for their prediction ability. This included three different types of ANN (BP, MA, and LM), which were varied in terms of the number of neurons in the hidden layer: six variations (20-45 neurons in steps of 5), giving a total of 18 models. Results of one ANN model (BP with 25 neurons in the hidden layer) shown in Fig. 4; others are not shown here for paucity of space. The MVR model was also developed and tested on the same set of data (as for the ANN), and its results are shown in Fig. 5.

The error for each model was calculated from the predicted and actual results, and the AE was determined. The standard deviation of the error and the number of observations falling within it were estimated to calculate the performance quality index (PQI). These results are given in Table 5, where σ_{Error} indicates standard deviation of error, N_σ is the number of predicted results that are within the standard deviation of error. The FR is the ratio of N_σ to the total number of observations, and is represented in percentage. If a large number of predicted results fall within the range of σ_{Error}, then the prediction is considered to be acceptable. For prediction of elongation, the maximum value of FR was found to be 65%, and σ_{Error} is very low. In the case of ANN model, it was observed that the number of results falling within σ_{Error} is more when the number of neurons in the hidden layer is equal or more than the number of inputs. The MVR model also produced a large number of results within standard deviation of σ_{Error}. The above observations are supported by the PQI calculated using Eq 1.

A new metric called prediction penalty index (PPI) is proposed here for comparing the accuracy of ANNs and MVR models. This was inspired from the practical application of true Bayesian estimate (used in movie rating). The PPI is calculated using Eq 6, and compared with PQI.

$$\mathrm{PPI} = \frac{(N_\sigma) \times (|\mathrm{AE}|)}{(N_\sigma + N_{\min})} + \frac{(N_{\min}) \times (|\mathrm{Median}|)}{(N_\sigma + N_{\min})}, \quad \text{(Eq 6)}$$

where N_σ the number of observations falling within the standard deviation of error, |AE| the positive value of the average error, |Median| the positive value of the median error, and $N_{\min}$ minimum number of observations assumed to be within standard deviation of error (~40).

The |AE| and |median| were calculated from the predicted results for MVR, and shown in Table 6. The value of $N_{\min}$ was taken as 40 (about 10% of 395 tested results), while N_σ was taken from Table 5. The PQI and PPI were calculated using Eq 1 and 6, and shown in Table 7. The accuracy of prediction is considered to be acceptable if the value of PQI and PPI is low.

The metric of PQI and PPI was scaled (between 0 and 1) using Eq 7 for all models, and represented in Fig. 6, 7, and 8. The three ANN models (BP, MA, and LM) and their variations (number of neurons in the hidden layer) are indicated on the horizontal axis while the normalized prediction scale is shown on the vertical axis. A model is considered acceptable in terms of prediction ability when the value of S_n is close to 1. The values of S_n for MVR are equal to one in all cases; showing that MVR is the most accurate model for prediction of mechanical properties.

$$S_n = 1 - 2 \times \left[\frac{(I_n - I_{\min.})}{(I_{\max.} - I_{\min.})}\right], \quad \text{(Eq 7)}$$

where S_n the prediction scale of model, I_n the value of PQI (or PPI), $I_{\max.}$ the maximum value from PQI (or PPI) for UTS, YS, or elongation, $I_{\min.}$ the minimum value from PQI (or PPI) for UTS, YS, or Elongation.

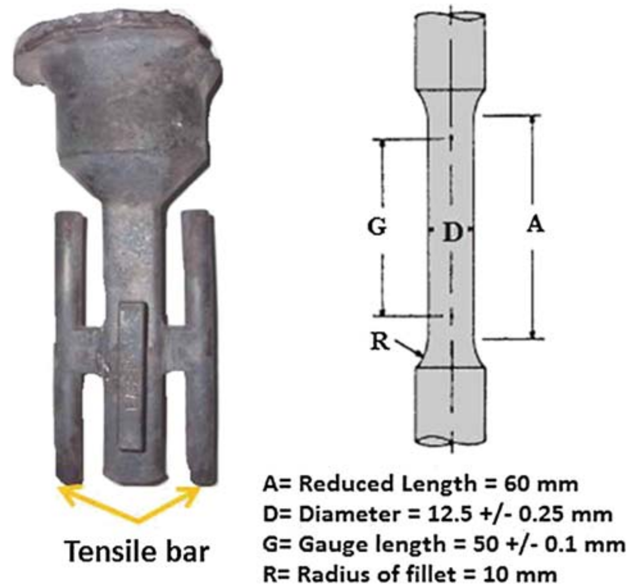

Fig. 3 Tensile bar and test specimen as per ASTM A370 guidelines

6. Discussion and Conclusion

This work showed that it is possible to predict the mechanical properties of stainless steel investment castings used in automotive industries using an appropriate ANN or

Table 4 Range of input parameters

No.	Parameters	Minimum	Maximum	Average	SD
1	Time taken for injection (s)	0.69	10.42	8.92	1.61
2	Press room temperature (°C)	14.85	21.67	18.86	1.27
3	Press room humidity (%)	56.00	90.00	72.22	8.38
4	Viscosity—primary slurry (s)	18.63	26.59	21.62	1.15
5	pH—primary slurry	9.00	9.65	9.40	0.14
6	Temperature of primary coating room (°C)	18.75	24.33	21.26	1.30
7	Humidity of primary coating room (%)	9.50	82.00	71.65	8.63
8	Viscosity—secondary slurry (s)	9.43	11.50	10.51	0.31
9	pH—secondary slurry	9.25	9.50	9.50	0.02
10	Process duration (days)	2.00	9.00	4.32	1.01
11	Temperature of secondary coating room (°C)	19.67	26.44	23.20	1.46
12	Humidity of secondary coating room (%)	54.50	90.00	73.40	7.53
13	Shell weight before dewaxing (kg)	5.55	11.90	6.67	1.02
14	Shell weight after dewaxing (kg)	3.93	9.16	5.15	0.83
15	Metal preparation (min)	22.00	317.00	74.21	18.35
16	Tapping temperature (°C)	1548.00	1580.00	1559.96	5.61
17	Nickel-extra (%)	0.00	0.69	0.09	0.06
18	Carbon (%)	0.04	0.08	0.05	0.01
19	Manganese (%)	0.56	1.43	0.96	0.08
20	Silicon (%)	1.01	1.51	1.25	0.06
21	Sulphur (%)	0.00	0.03	0.01	0.01
22	Phosphorous (%)	0.03	0.04	0.04	0.01
23	Chromium (%)	18.00	18.54	18.25	0.10
24	Nickel (%)	8.00	8.85	8.17	0.09
25	Molybdenum (%)	0.11	0.42	0.24	0.03

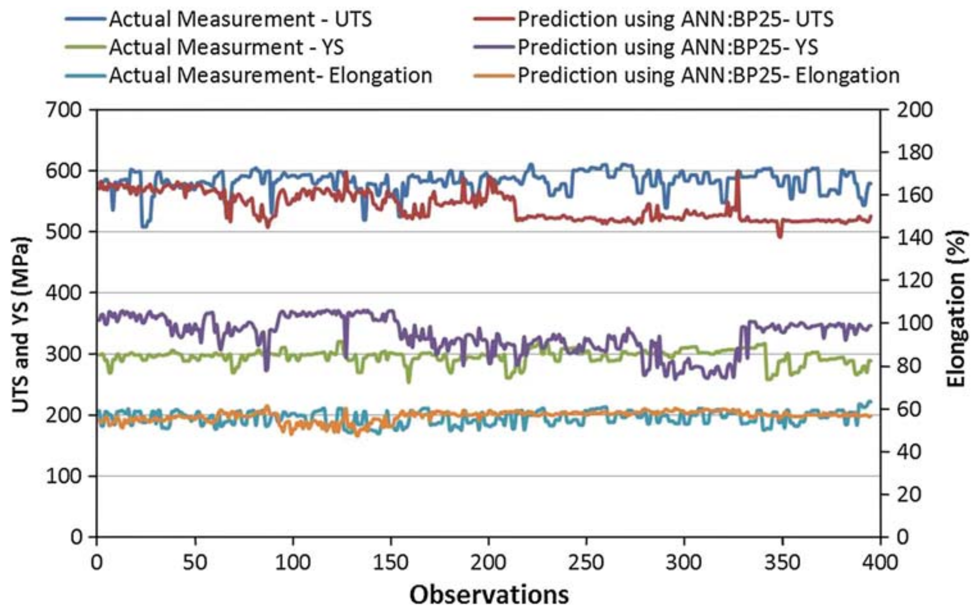

Fig. 4 Comparison of predicted and actual results from ANN: BP25

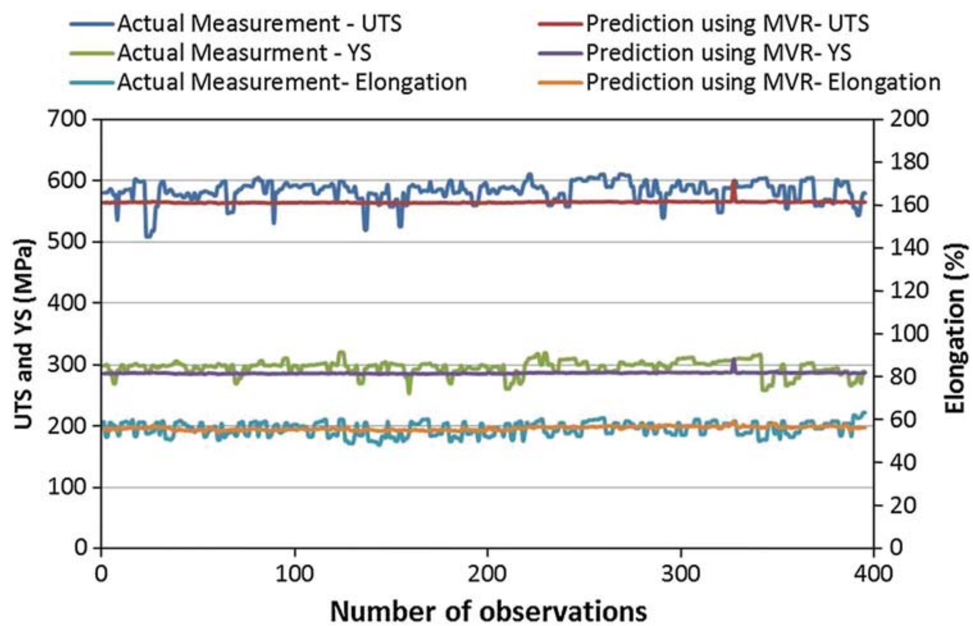

Fig. 5 Comparison of predicted and actual results from MVR

MVR model. Nineteen different models, including three training algorithms of ANN with different number of neurons in the hidden layer, and one MVR model were employed. It was observed that both ANN and MVR can be employed for the above purpose, though MVR gave better results than any ANN model. The ANN gave better results when the number of neurons in the hidden layer was equal or slightly more than the number of input parameters. The performance quality index proved to be useful for comparing the relative capability of ANNs and MVR in the above predictions. The prediction performance index, proposed in this work based on true Bayesian estimate, was found to be a better metric for comparison, since it is linear in nature and minimizes the inaccuracies that may be caused in the estimation of AE and standard deviation. The performance of ANNs can be further improved by tuning the transfer function, momentum rate, learning rate, or error goal. The number of input parameters can be reduced using Principal Component Analysis (PCA) or Factor Analysis (FA) to reduce computation complexity along with a possibility of better prediction ability.

In summary, ANN and MVR models are useful for predicting the mechanical properties of investment castings and thereby avoid expensive and time-consuming destructive tests used at present. These models can be used easily on the

Table 5 Comparison of accuracy of different models

Prediction method	UTS, MPa			YS, MPa			Elongation (%)		
	σ_{Error}	N_σ	FR (%)	σ_{Error}	N_σ	FR (%)	σ_{Error}	N_σ	FR (%)
MVR	17.54	149	38	11.48	138	35	3.1	256.0	65
ANN with BP									
20	23.62	16	4	23.54	116	29	3.6	5.0	1
25	25.71	76	19	12.57	143	36	3.8	223.0	56
30	22.45	200	51	21.67	100	25	5.0	160.0	41
35	32.12	0	0	26.13	42	11	3.2	0.0	0
40	30.44	24	6	28.24	0	0	4.5	21.0	5
45	44.4	0	0	33	32	8	6.2	105.0	27
ANN with MA									
20	23.29	27	7	21.36	73	18	3.6	1.0	0
25	23.64	166	42	36.6	130	33	3.5	97.0	25
30	29.06	140	35	13.83	134	34	6.7	123.0	31
35	31.26	0	0	27.26	5	1	3.2	0.0	0
40	33.51	13	3	34	1	0	3.5	0.0	0
45	52.33	2	1	24.89	37	9	6.7	71.0	18
ANN with LM									
20	39.19	77	19	27.34	60	15	5.4	39.0	10
25	42.32	178	45	35.38	104	26	8.7	40.0	10
30	34.28	203	51	31.86	92	23	10.1	62.0	16
35	35.3	99	25	33.66	104	26	13.5	6.0	2
40	140.79	0	0	22.94	0	0	8.7	2.0	1
45	34.12	54	14	24.28	18	5	4.9	48.0	12

Table 6 N_σ, AE, median and N_{min} values for prediction using MVR

Method	Total number of observations	UTS			YS			Elong.		
		AE	Median	N_{min}	AE	Median	N_{min}	AE	Median	N_{min}
MVR	395	18.18	21.16	40	9.26	12.6	40	0.25	0.04	40

Table 7 PQI and PPI for comparison of ANN and MVR models

Approach of prediction	UTS		YS		Percentage elongation (Elong.)	
	PQI	PPI	PQI	PPI	PQI	PPI
MVR	29	3	27	1	−1	0
ANN with BP						
20	1131	55	170	12	28	12
25	965	44	163	10	0	1
30	963	42	390	20	4	3
35	3800	124	859	39	38	18
40	33	47	994	74	33	12
45	6721	158	881	49	16	5
ANN with MA						
20	1082	57	437	27	38	16
25	386	22	56	10	11	5
30	177	19	29	2	9	3
35	7443	178	973	76	38	18
40	1402	66	401	17	37	15
45	5334	145	1002	50	17	6
ANN with LM						
20	1152	38	619	31	25	7
25	31	4	224	10	21	3
30	563	24	1806	69	66	11
35	186	13	253	12	73	13
40	39,686	336	1838	82	111	17
45	1068	40	381	23	19	7

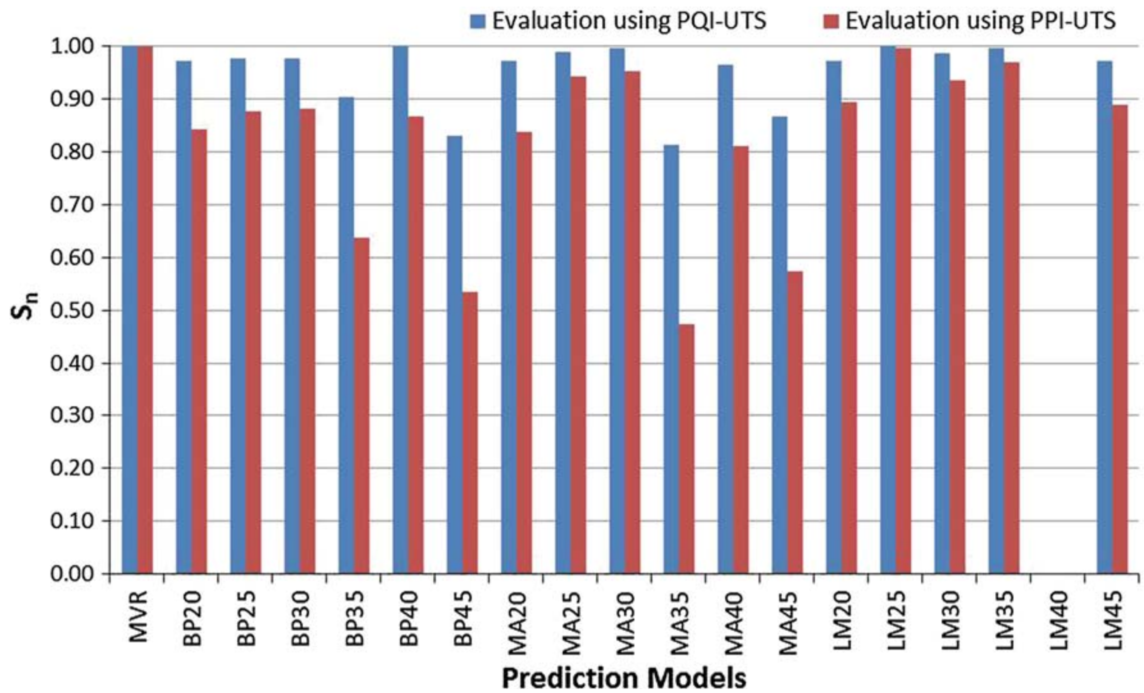

Fig. 6 Comparative evaluation of ANN and MVR models—UTS

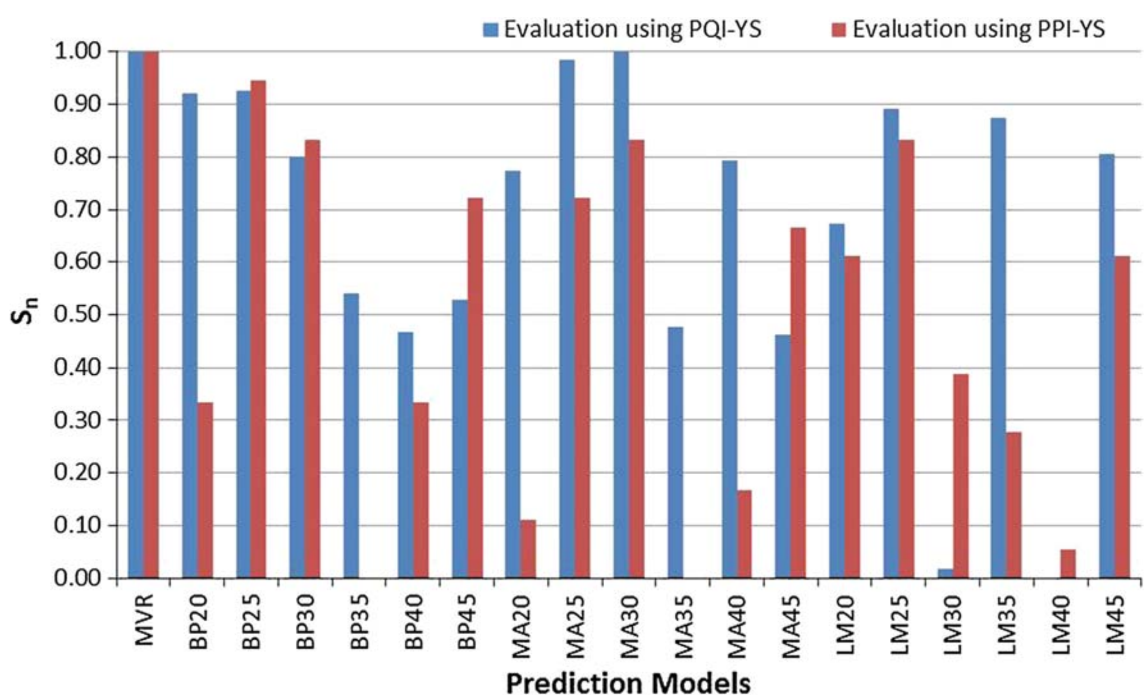

Fig. 7 Comparative evaluation of ANN and MVR models—YS

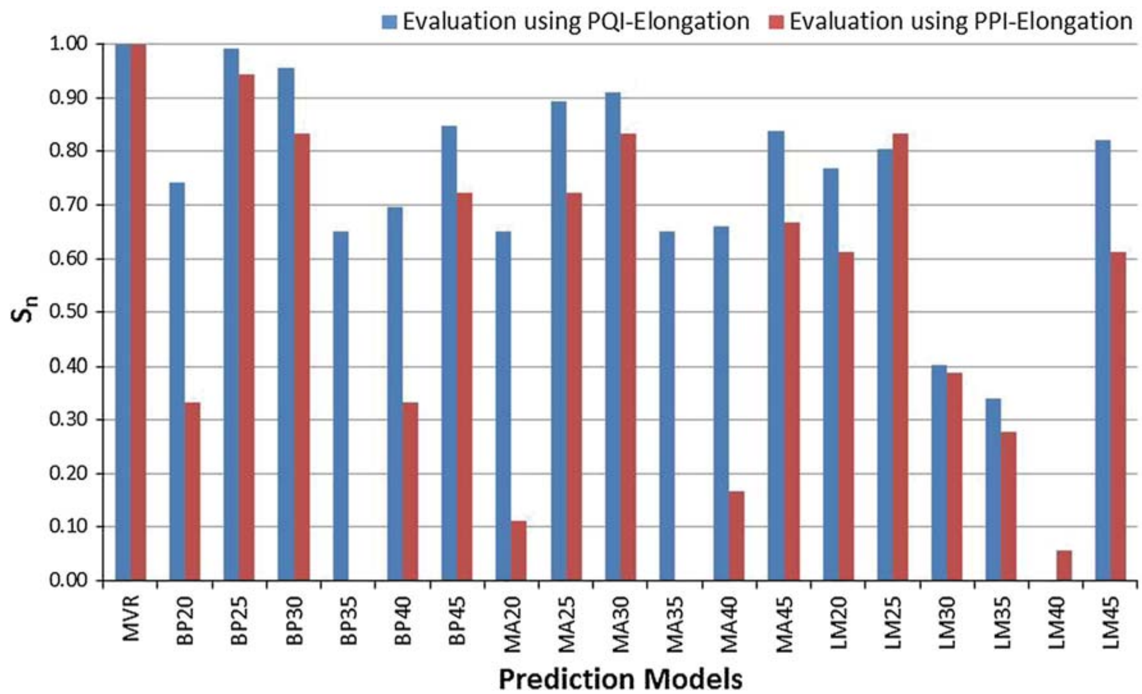

Fig. 8 Comparative evaluation of ANN and MVR models—elongation

shop-floor and do not need high level of computation tools or knowledge characteristic of simulation programs.

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