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Prediction of critical fraction of solid in low-pressure die casting of aluminum alloys using artificial neural network

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Abstract. Casting simulation programs are computer programs that digitally model the casting of an alloy in the sand, shell, or permanent mold and, then, the cooling and solidification processes. However, obtaining consistent results out of casting modeling depends on the incorporation of many accurate parameters and boundary conditions. Critical Fraction of Solid (CFS), which is one of the most important of these parameters, is defined as the point where solid dendrites do not allow any flow of the liquid metal in the mushy zone. Since the CFS value varies based on many factors, inconsistent results can be experienced in the modeling applications. In this study, the CFS value obtained during the solidification of various commercial aluminum alloys' casting process, carried out using low-pressure die casting method, is predicted by using Artificial Neural Network (ANN) method based on alloy type, grain refiner and modifier additions, initial mold temperature, and pressure level parameters. In the scope of the study, 162 experiments are conducted. The results obtained from the low-pressure die casting experiments using a special model designed for the study are validated by using SOLIDCast casting simulation. The CFS values are obtained in this validation range of 33% to 61%. These CFS values are used in the development of ANN models. Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Square Error (MSE) are used to assess the prediction accuracy of the ANN models. Calculated values of MAE, MAPE, and MSE are 0.0188, 7.06%, and 0.0006, respectively. The results show that the proposed ANN model predicts a CFS value with high accuracy.

1. Introduction

One of the most important issues in the casting process is that liquid metal and its alloys fill the mold cavity properly, and casting without any void is obtained during solidification. The success in this issue is directly related to the runner and the riser in the casting process. The design of the casting parts integrated with the runners and the risers is defined as the molding design. The production of quality casting parts by using the minimum metal is aimed at the molding design, especially in today's market competitive conditions [1,2]. The advancement in computer technology has enabled the use of casting simulation software for molding design in the casting industry. It is possible

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to produce strong casting in one attempt by designing and modeling using casting simulation programs in the computer environment. However, the actual boundary conditions of casting in the foundry environment need to be provided accurately in the computer program to obtain a successful result. The computer program carries out calculations based on boundary conditions, and the material properties are defined by the user. Therefore, it is not possible to obtain correct results by providing wrong data [1-5]. Some of the boundary conditions that are effective in the casting simulation program and need to be added correctly include the solidification rate, the temperature gradient, the interfacial heat transfer coefficient for the casting-mold interface, the thermal properties of the mold material, the casting temperature, the alloy shrinkage rate, the mold filling time of the liquid metal, and the Critical Fraction of Solid (CFS) value for continuing feeding in the mushy zone. The CFS value is one of the important factors for feeding during the solidification of the castings [3-6].

The solidification of the aluminum alloys occurs in a solidification temperature range between the liquidus temperature and the solidus temperature, in which the liquid and solid phases coexist [7]. The viscosity of the liquid alloy increases due to the dendritic branches growing along with the progress of the solidification, and the liquid flow becomes difficult in this semi-solid region; however, the feeding still goes on. With the progress of the solidification, dendritic networks are established and dendrites become stronger by holding together [8]. The resistance to fluid flow from the interfaces between the dendrites begins to form. With further solidification, the feed stops and no more liquid flow is allowed when the solid ratio of the semi-solid region reaches the level that will resist the liquid flow. The point at which no more fluid flow is allowed by the growing dendrites along with the progress of solidification is defined as CFS. Figure 1 shows the CFS on the cooling curve of an exemplary alloy. The shrinkage of the piece can be provided by the riser until it reaches the CFS value. In this case, there will be no shrinkage on the part as the feed path will be open. However, the feed path is clogged below the CFS value, and since the flow of liquid is interrupted, unfed regions are seen in the casting part, even though there is enough liquid metal to feed the part in the riser. Thus, the product has to be discarded. Therefore, the determination of the CFS value in the critical sections for each piece is very important for the effective use of casting simulation programs and for the production of faultless parts [6,9].

The CFS value is not a constant value, which varies only based on the alloy. The change in the CFS value is affected by the cooling and solidification conditions of the alloy. Since the size of the dendrites to be formed during solidification will be shorter, the CFS values are expected to increase for the alloys with a narrower solidification temperature range. This means that it is possible to feed the part without being subject to a longer dendritic blockage. Similarly, since there is enough time for the formation and growth of dendrites in the alloys in a wider solidification temperature range, the liquid flow will be difficult at the lower solidity levels and the feed will stop [9].

There are a limited number of studies on the CFS, which is important for the casting process. The results of a study on determining the CFS values by a thermocouple method for A319 and A356 alloys have been found to be consistent with the values determined by other thermal methods [10]. However, some studies report that the thermal analysis method has been affected by the solubility rate of the elements in the alloy, thus showing inconsistent results [11]. In another study, the issue of modeling the CFS in the die casting of the aluminum alloys has been studied using modeling techniques experimentally by a specially developed permanent mold. Initial mold temperature and grain refiner addition have been taken into account in modeling the CFS [12]. In a similar study, the effect of grain

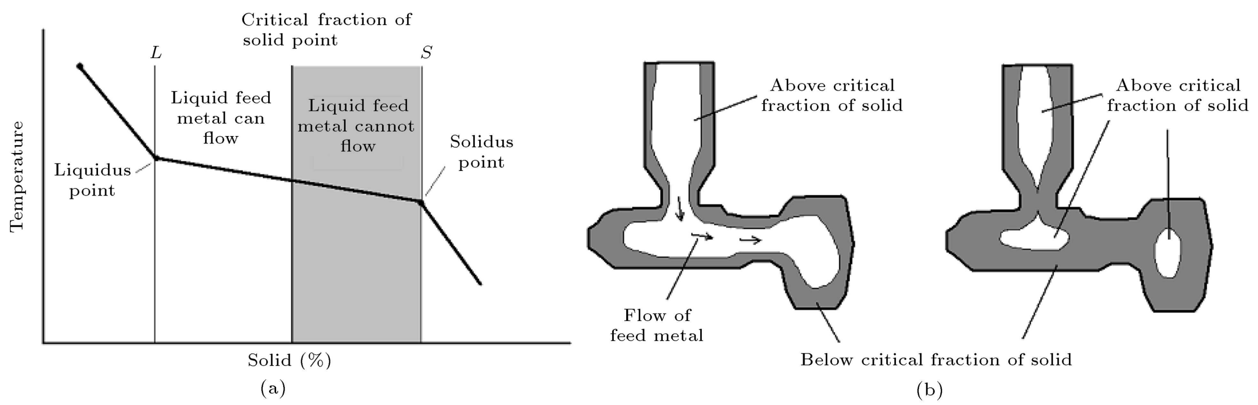

Figure 1. (a) CFS point on the cooling curve of a given alloy. (b) Stopping the feed of the metal reaching the CFS value [9].

refiner addition on CFS value has been experimentally investigated in sand casting [8].

The Artificial Neural Network (ANN) is an artificial intelligence technology developed by the inspiration of the ways neurons operate in the human brain. It is generally used for prediction, classification, and pattern recognition. The main characteristics of ANN are modeling of non-linear problems, fast data processing, and the ability to manage the unreliable or imprecise data [13]. These characteristics make it possible to use ANN in many fields such as manufacturing, production planning, finance, and medicine. Studies about manufacturing field show that ANN has been used for predicting experimental results, analyzing the effects of process parameters, and predicting mechanical properties in manufacturing such as casting and welding processes [14-18]. Considering the studies carried out in the field of production planning, it is seen that ANN has been used to solve the production back allocation problem, lot-sizing problem, and workforce scheduling problem [19-21]. Considering the studies done in the field of medicine, it is seen that ANN has been used for the purposes such as disease diagnosis, prediction of bone loss rate, and stiffness estimation [22-26]. Some examples of the objectives of using the ANN in the field of finance are bankruptcy prediction, credit scoring, resource allocation, portfolio selection, inflation forecasting, and revenue management [27-30].

The aim of this study is to predict the CFS value in low-pressure die casting of aluminum alloys. For this purpose, ANN is used because effects of different values of the experiment parameters can be analyzed efficiently. Moreover, this study is the first research attempt to predict the CFS value in low-pressure die casting of aluminum alloys by the ANN method.

2. Materials and methods

2.1. Material

The determination of aluminum alloys for the experiments is based on chemical composition. The differences in chemical composition directly affect solidification. For this reason, attempts have been made to make sufficient and proper alloy selection in order to gather information about all aluminum casting alloys commonly used in the casting industry. Thus, this study aims to obtain results that will represent not only alloys used in the experiments but also all aluminum casting alloys. Alloys selected for use in the experiments are given in Table 1.

2.2. Experimental study

The low-pressure die casting experiments was carried out using a model with a specially designed geometry. The model was designed to have a measurable shrinkage void in the casting part of the inner section during solidification. Therefore, there should be a cross-section to form a bottleneck on the model. With the early solidification of this section, the feed path of the casting part was clogged and shrinkage voids formed at the internal parts due to inadequate feed. The CFS value can be quantitatively examined considering the proportion of these shrinkage voids. The designed geometry was used to have a geometry to form distinctive porosity under different casting conditions (pressure, initial mold temperature, etc.), different alloys, and the different CFS values. The suitability of the design was verified using SOLIDCast casting simulation software during the stage of model design. For this purpose, modeling studies were carried out under different casting conditions and with different CFS values by using the cast alloys planned to be used in the experiments. The formation of porosity in various sizes was expected to be in accordance with the results, and the conformity of the design was tested accordingly. Figure 2 shows the model geometry used in the experiments, measurements, and the module values obtained from the SOLIDCast casting simulation program.

Considering the current market conditions, the parameters with the greatest effect on the CFS and the formation of the porosity were taken into account for determining the parameters of the low-pressure die casting experiment. Three different temperature and pressure values were determined based on the size of the part to examine the effect of the initial mold temperature and pressure. Al5Ti1B master alloy was

Table 1. Chemical composition of the alloys used in the experiments (Al balance), wt.% [31].

Alloy	Fe	Si	Cu	Mn	Mg	Zn	Ti	Sn
A319	0.70	4.00-6.00	2.00-4.00	0.20- 0.60	0.15	0.20	0.20	0.05
A413	0.60	11.50-13.50	0.10	0.40	0.10	0.10	0.15	0.05
A380	1.00	7.50-9.00	3.00-4.00	0.50	0.30	1.00	0.20	0.10
A360	0.50	9.00-10.00	0.10	0.40-0.60	0.30-0.45	0.10	0.15	0.05
A356	0.20	6.60-7.40	0.02	0.03	0.30-0.45	0.04	0.08-0.14	0.05
$AlCu_4Si$	0.30	0.35	4.00-5.00	0.10	0.10	0.10	0.05	0.05

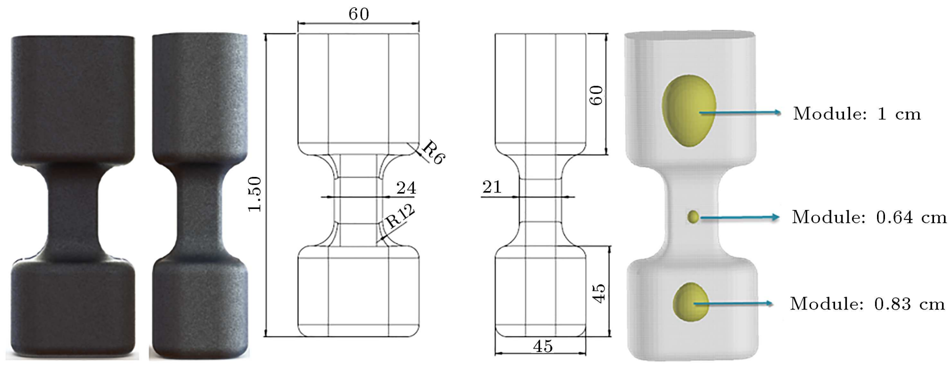

Figure 2. The final model design and geometry used in the casting experiments.

Table 2. The experiment parameters.

Parameters	Levels					
	I	II	III	IV	V	VI
Alloy type	A319	A413	A380	A360	A356	AlCu4Si
Grain refiner addition	No addition	TiB	—	—	—	—
Modifier addition	No addition	Sr	—	—	—	—
Initial mold temperature (°C)	200	300	400	—	—	—
Pressure level (mbar)	250	500	1000	—	—	—

used as a grain refiner to have an effect of 0.2% Ti. Al10Sr master alloy was used as a modifier to have an effect of 0.1% Sr. The experimental parameters are given in Table 2.

The produced mold was connected to a hydraulic opening-closing press. This system was used to fill the mold with the liquid metal under the specified pressure and to open the molds after solidification. The surfaces of the molds were cleaned with dry ice before casting and painted with the wash. The ceramic runner was added to the low-pressure die casting mold runner box, and the liquid metal was heated to prevent solidification in the runner before casting. After slagging and degassing by nitrogen, the liquid metal prepared in accordance with the experiment parameters were taken from the furnace and poured into the sprue by means of a hand casting ladle using primary ingot for each alloy. With the applied pressure, the liquid metal in the sprue filled the mold and, thus, the casting was carried out. Upon the solidification after applying pressure for 5 minutes, the mold opened and the samples were taken using ejector pins. The low-pressure die casting method is schematically shown in Figure 3.

In the experimental study, 162 experiments were conducted. Results obtained from these experiments are used in the development of the ANN models. A small experimental set is given in Table 3.

2.3. Artificial neural network models

In this study, ANN models were constructed to predict CFS value in low-pressure die casting of aluminum

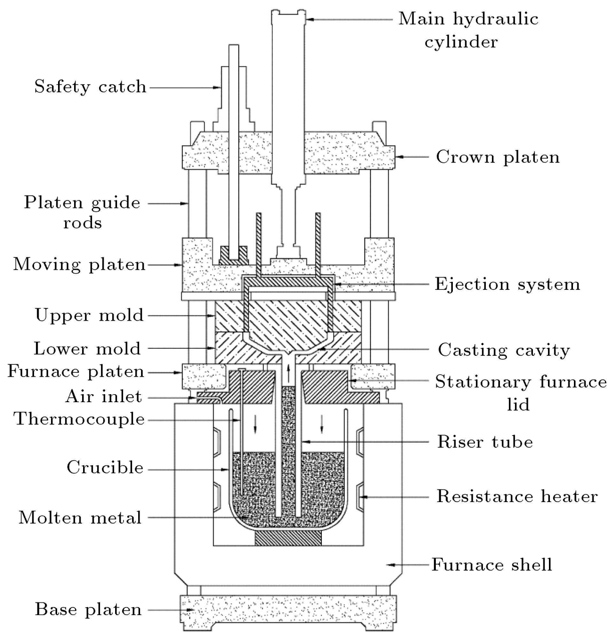

Figure 3. Schematic of low pressure die casting method [32].

Table 3. A small experimental set.

Data no.	Alloy type	Grain refiner addition	Modifier addition	Initial mold temperature (°C)	Pressure level (mbar)	CFS (%)
1	A319	0	0	200	250	39
2	A319	0	0	200	500	39
28	A413	0	0	200	250	34
29	A413	0	0	200	500	36
66	A380	0	0	300	1000	40
67	A380	1	0	300	250	53
87	A360	1	0	200	1000	54
95	A360	1	0	300	500	54
117	A356	1	1	200	1000	57
118	A356	0	0	300	250	35
...	...	...	...	...	...	...
161	AlCu4Si	1	1	400	500	57
162	AlCu4Si	1	1	400	1000	59

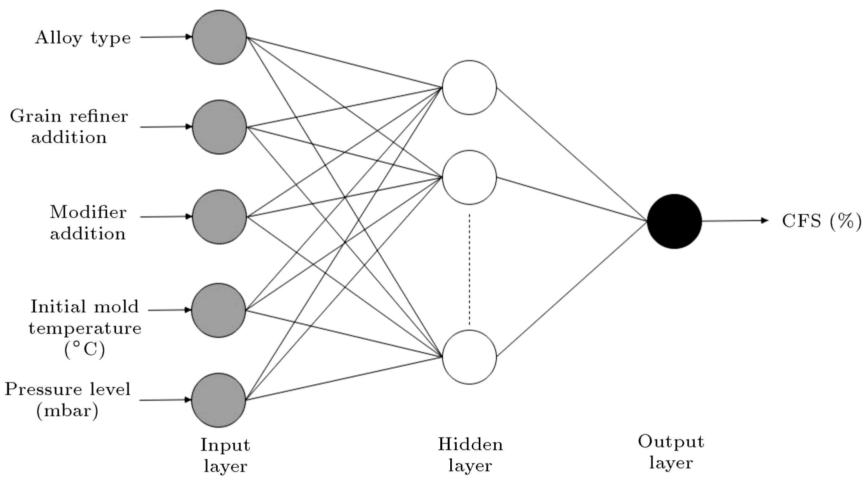

Figure 4. The basic architecture of the developed ANN models.

alloys. The feed forward back propagation algorithm is preferred because it is often used as an approximator [33]. The developed ANN models consist of three layers. These are input layer, hidden layer, and output layer. The alloy type, grain refiner addition, modifier addition, initial mold temperature, and pressure level parameters affecting CFS value in low-pressure die casting were defined as input variables in the ANN models. The CFS value was defined as the output variable in the ANN models. There is no precise and specific rule in determining the number of neurons in hidden layer. It is usually determined by applying a trial-and-error method. The small number of neurons in hidden layer may cause the ANN to be too inadequate to solve the problem. On the other hand, the high number of neurons in hidden layer may cause overfitting and a decrease in network generalization capacity. Thus, the optimal number of neurons in hidden layer is determined by comparing the predictive performance of ANN models with different neuron numbers in hidden layer [34]. The basic architecture of the developed ANN models is shown in Figure 4.

In ANN models, all data processed in the network must be numerical [22]. Therefore, alloy type, grain refiner addition, and modifier addition parameters are converted to numerical values. For example, if the grain refiner addition is available, value 1 is assigned; otherwise, value 0 is assigned. The data used in the ANN model are either normalized or used with real values. It is known that normalizing the data affects the learning performance of ANN models positively [33]. The following equation is used for data normalization:

$$X = \frac{(X_i - X_{\min})}{(X_{\max} - X_{\min})}, \tag{1}$$

where X is the normalized data, X_i is the actual data,

Table 4. A small normalized experimental set.

Data no.	Alloy type	Grain refiner addition	Modifier addition	Initial mold temperature (°C)	Pressure level (mbar)	CFS (%)
1	0	0	0	0	0	0.214286
2	0	0	0	0	0.333333	0.214286
28	0.2	0	0	0	0	0.035714
29	0.2	0	0	0	0.333333	0.107143
66	0.4	0	0	0.5	1	0.25000
67	0.4	1	0	0.5	0	0.714286
87	0.6	1	0	0	1	0.75000
95	0.6	1	0	0.5	0.333333	0.75000
117	0.8	1	1	0	1	0.857143
118	0.8	0	0	0.5	0	0.071429
...	...	...	...	...	...	...
161	1	1	1	1	0.333333	0.857143
162	1	1	1	1	1	0.928571

$X_{\min}$ is the minimum value of actual data, and $X_{\max}$ is the maximum value of actual data. The data are normalized between 0 and 1. Some of the normalized data are given in Table 4.

In the developed ANN models, the Levenberg-Marquardt training algorithm is used. Furthermore, Gradient Descent with Momentum (GDM) was used as a learning algorithm. The logsig (log-sigmoid) function was used as a transfer function. Logsig function is given by:

$$a = \text{logsig}(n) = \frac{1}{1+e^{-n}}. \tag{2}$$

3. Results and discussion

Simulations based on the developed ANN models were conducted through the MATLAB® 7.10 (R2010a) mathematical software. Then, 162 experimental data were used as dataset to feed the ANN model. The number of neurons in hidden layer of the network was determined as 10 for the test and analysis. The test and analysis were carried out in two stages to determine the optimal topology of the network. In the first stage, 3 different training and test sets were randomly generated using the existing data set (70% training set −30% test set, 80% training set −20% test set, 90% training set −10% test set). The network was trained separately with these 3 datasets. While the network was being trained, learning of the network reached the desired level after 300 iterations. Therefore, the number of iterations in network training is set to 300. After completing the training, the ANN outputs were compared to the actual values obtained from the experiments. Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Square Error (MSE) as error types were selected to measure the predictive performance of the ANN. MAE, MAPE, and MSE are defined as follows:

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} |A_t - F_t|, \tag{3}$$

$$\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n} \left|\frac{A_t - F_t}{A_t}\right|, \tag{4}$$

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n} (A_t - F_t)^2, \tag{5}$$

where A_t is the actual data, F_t is the forecast at time t, and n is the number of samples.

According to the results in Table 5, it is seen that when the size of the training data set increases, the error rate of the ANN model decreases. When 90% of current dataset is used for training, the ANN model gives the best performance for prediction.

In the second stage, the number of neurons in the hidden layer that will provide the best prediction

Table 5. MAE, MAPE, and MSE values of the developed ANN models.

	Ratio of the training set		
	70%	**80%**	**90%**
MAE	0.061124	0.044159	0.029762
MAPE (%)	14.599454	13.996248	8.545339
MSE	0.009970	0.003136	0.001212

performance is determined when 90% of the current dataset is used for training. For this reason, ANN models with different neurons (3-4-5-6-7-8-9-10-15-20) in the hidden layer were formed. These ANN models were trained with a current training set. After completing the training, the outputs of the networks were compared to test set including the actual values obtained from the experiments. MAE, MAPE, and MSE were selected to measure the predictive performance of the networks. Results of the ANN models are shown in Figures 5 to 7.

Results show that the number of neurons in the hidden layer to maximize the prediction performance is 7. Therefore, the optimal topology of the network is 5 neurons in the input layer, 7 neurons in the hidden layer, and 1 neuron in the output layer. When considering MAE, MAPE, and MSE, the proposed ANN model predicts CFS values with 98.12%, 92.94%, and 99.94% performances, respectively.

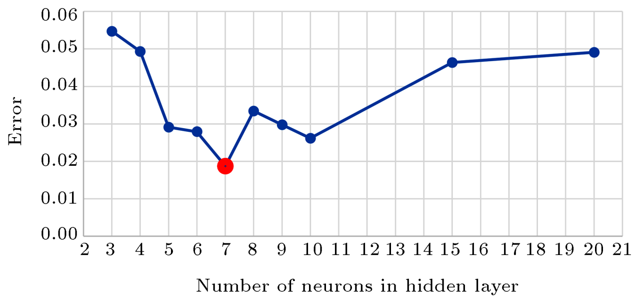

Figure 5. MAE values of the developed ANN models consisting of different number of neurons in the hidden layer.

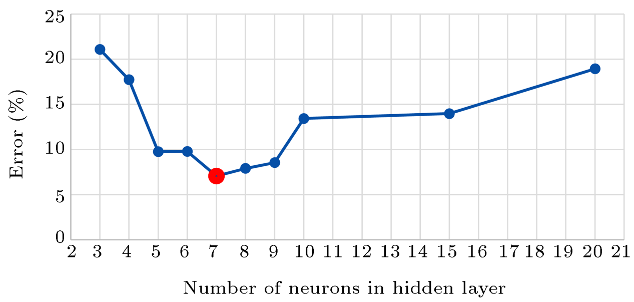

Figure 6. MAPE values of the developed ANN models consisting of different number of neurons in the hidden layer.

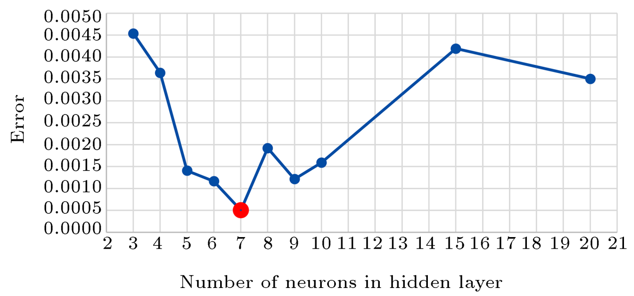

Figure 7. MSE values of the developed ANN models consisting of different number of neurons in the hidden layer.

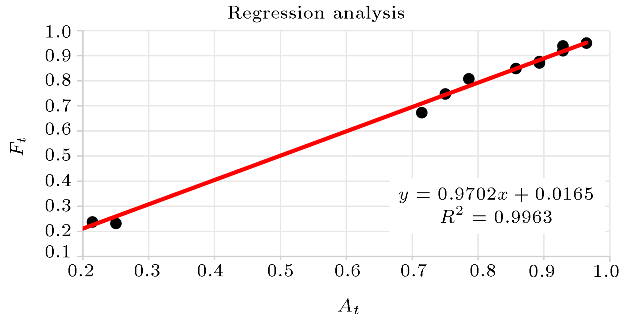

Figure 8. Correlation between experimental and predicted values for the CFS.

Figure 8 shows regression analysis of the ANN model consisting of 7 neurons in the hidden layer. Regression equation and correlation coefficient values (R^2) of the proposed ANN model are given in the related figure.

Regression analysis clearly shows that the ANN model including 7 neurons in the hidden layer and using training set consisting of 90% of current dataset produces the most realistic results ($R^2 = 0.9963$).

When comparing this study with similar studies about CFS in the literature, a number of differences can be detected among them. Akar et al. conducted a study for determining the CFS value of Al-4.3% Cu alloy in the die-casting process. The initial mold temperature and grain refiner addition parameters were used while determining the CFS value. When initial mold temperature was 155°C and grain refiner addition was available, CFS value was found as 52% [12]. Kayıkcı and Çolak carried out a study for determining the CFS value of A380 alloy in the sand-casting process. Grain refiner addition parameter was taken into account in modeling CFS. CFS value was determined as 50% when grain refiner addition was available [8]. In this study, the ANN model based on alloy type, grain refiner addition, modifier addition, initial mold temperature, and pressure level parameters was developed for predicting the CFS value in the low-pressure die casting process. The CFS value was obtained as 54% when the alloy type was A380, grain refiner was used, initial mold temperature was 400°C, and the pressure was 250 mbar. In addition, the CFS value was obtained as 57% when the alloy type was A356, grain refiner was used, modifier was used, initial mold temperature was 200°C, and the pressure was 500 mbar.

4. Conclusions

In this study, the difficulty of determining the CFS in low-pressure die casting of aluminum alloys was discussed. The ANN model with the best performance was investigated by developing multiple prediction models to calculate this factor. The data obtained from the experimental study were verified by using SOLIDCast casting simulation, and the results of this verification were used in the ANN models. Various ANN models were developed by changing both the training set ratio (70%-80%-90%) and the neuron numbers in the hidden layer (3-4-5-6-7-8-9-10-15-20), and the changes in the performances of these models were analyzed. The aim here is to determine the optimum ANN architecture that provides the best prediction performance. MAE, MAPE, and MSE defined as standard statistical error measures were used to calculate the performance of ANN. All of the error measures calculated showed that the best prediction performance was obtained from the ANN model with a 90% training set ratio and 7 neurons in the hidden layer. Moreover, the correlation coefficient value ($R^2 = 0.9963$) also verifies this performance.

It will be possible to analyze how the variation of different input parameters affects the CFS by using the developed ANN model. Therefore, the researchers are able to obtain a CFS value very close to the real one. The study is expected to be a guide for modeling the parameters required to be predicted in the experimental studies of various casting methods by using ANN model.

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