JP&M Engineering
Journal of Petroleum and Mining Engineering
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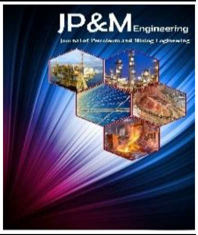

Artificial Neural Network Prediction of Silicon and Nickel recovery in Al-Si-Ni alloy Manufactured by Stir Casting

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Abstract

Artificial neural network (ANN) is a non-linear statistical technique that being used to describe the behaviour of the materials. Al-Si-Ni alloy was prepared by the stir casting method using different optimum parameters as reaction time, temperature, Ni2O3/Al weight ratio, and Na_2SiF_6/Al wt. ratio. The artificial neural network is used in predicting the silicon and nickel recovery of these prepared alloys. The obtained experimental results are used to train the artificial neural network (ANN) and the temperature, Ni_2O_3/Al wt. ratio, and Na_2SiF_6 / Al wt. ratio are used as ANN's inputs. The used ANN consists of three layers; Input layer that includes 4 neurons and the hidden layer include 9 neurons, while the output layer contains 2 neurons. The Levenberg-Marquardt (LM) is used as the training function. Optimal mean square errors (MSE) for the ANN during predicting and estimating silicon and nickel recovery equal 0.0358, 0.0034, respectively, when reaction time is the variable and other parameters are kept constant, MSE equal 1.4007e-04, 1.3478e-04 when temperature is variable and other parameters are kept constant, MSE equal 1.3839e-04, 9.9891e-05 when Ni_2O_3/Al wt. ratio was the variable and other parameters are kept constant and finally MSE equal 0.0287, 0.0263 when Na_2SiF_6/Al wt. ratio is variable and other parameters are kept constant.

Keywords

Artificial Neural Network; MSE; stir casting, Levenberg-Marquardt; aluminum matrix

Introduction

Artificial Neural Network is considered a promising research area in the experimental prediction and recently has become prevalent research field [1,2]. ANN is a category of parametric models which contain various nonlinear relationships between a group of predictions and a targeted variable. Neural network is a perfect modelling scheme and its design is based on studying different variables, which aimed at replacing the obvious conventional constitutive equations that utilized in describe the behaviour of materials [3]. Usually, ANN quickly enables to solve issues, in comparison to other techniques, and with an extra ability to benefit from little empirical data. A trained neural network gives quicker response for any particular input. There are advantages for the neural network as; generalization, adoption, learning, easy-implementation and self-organization [4, 5, 6]. The artificial neural network is a non-linear statistical technique that is used for processing data when it is very difficult or impossible to apply a statistical method [7]. It has the ability to discover the non-linear and unobserved parameters; also it can treat successfully the random or odd inputs [2]. Recently, artificial neural networks have attracted more interest as a predicting system in different research fields as; automotive, electronics, robotics, chemistry, medical diagnosis. The artificial neural networks work through two steps; gaining the data by a learning process and connection the power points (synaptic weights) between interneurons which utilized to save the data [8]. Many researchers studied the production of alloy and composite materials by neural networks with different variables as the weight per cent, particles size and the type of reinforcement material; the neural networks have been successfully used [9, 10]. The properties of aluminium composites synthesized by the stir casting method were predicted by applying Artificial Neural Network modelling and the resulted prediction was effective [9, 10]. Most researches that used neural network applied the multi-layered neural network (MLP) [11]. Neural networks are not programmed; they are trained, which means that it takes long time to train them before being used. The training of neural networks is being performed by updating weight coefficients in order to get an output closer to the given value next time. During the training, the user assigns the input and desired output values, and the program attempts to obtain the corresponding output value [7, 12]. In the present work, the ANN is used to predict the recovery per cent of silicon and nickel in an obtained Al-Si-Ni alloys and hence reducing the number of experiments, time, and consequently the costs. The neural network was modelled in the Matlab software. The training data set (variables) were obtained from the experimental results of a previous work for the authors [13].

Methodology of Using Artificial Neural Networks (ANNS)

Al-Si-Ni alloy was synthesized by using the stir casting method and different parameters were studied which affected in the synthesis process. The application of ANN in this work is divided into four groups. First group: using the reaction time (5, 10, 15, 20 and 25 minutes) as the main variable, while the other parameters are constants such as the temperature, Ni_2O_3/Al wt. ratio and Na_2SiF_6/Al wt. ratio. Second group: using the temperature (800, 850, 900, 950 and 1000 °C) as the main variable, while the other parameters are constants such as the reaction time, the Ni_2O_3/Al wt. ratio and the Na_2SiF_6/Al wt. ratio. In the third group: the Ni_2O_3/Al wt. ratio is the main variable (0.05534, 0.06556, 0.08226, 0.10871 and 0.12172%), while the others parameters are constants. ratio. The fourth group: the Na_2SiF_6/Al wt. ratio is the main variable (0.25, 0.5, 0.75, 1 and 1.25 %), and the others parameters are constants. A back-propagation algorithm is applied for predicting and modelling the obtained data with artificial neural networks. In the applied process of modelling, the optimum parameters such as the reaction time, temperature, Ni_2O_3/Al wt. ratio and Na_2SiF_6/Al wt. ratio are used as inputs. Silicon and nickel recovery are kept as the outputs in ANNs design. Then, by using the prepared set of training, the neural network is trained. Finally, in the training process, the accuracy check of the system was carried out using the test data. Multi-layered neural network architecture and parameters of training are shown in table 1. And the used ANNs architecture is shown in figure 1.

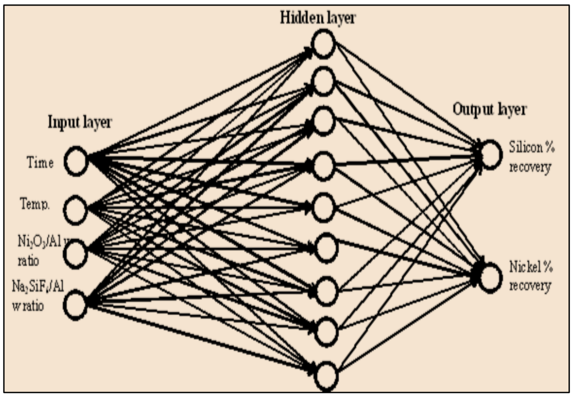

Figure 1 ANNs block diagram.

In the present paper, many training functions that based on the back-propagation approach are used such as Levenberg-Marquardt (LM), trainlm, RProp (trainrp), Conjugate Gradient Back propagation with Fletcher-Reves Restart (traincgf), Conjugate Gradient with polake Ribiere Restart (traincgp), Conjugate Gradien with Beale-Powell Restartst (traincgb), Scaled Conjugate Gradient (trainscg). At the learning process end, the results of Levenberg–Marquardt showed the best training functions, it was fast and efficient in comparison to the others, [14] So Levenberg–Marquardt function was applied in the present work. According to the most minimum error (in terms of MSE) values which are obtained at the end of learning process, mean square error (MSE) is a good scale to have data about the performance of learning. The experimental results and ANN's predictions are compared and mean square error (MSE) is computed using equations (1) and (2) [12].

$$e_k(n) = d_k(n) - y_k(n), \qquad (1)$$

$$\varepsilon_{av} = \frac{1}{2N}\sum_{n=1}^{N}\sum_{k\in c} e_k^2(n) \qquad (2)$$

Where,

N is the total number of samples, and

C is all the neurons in the output layer.

The learning process is repeated till the error is satisfied. The used method was applied for all the information in the training data. Finally, the method used the test data to confirm the non-linear relationship between the sets of inputs and outputs [12]

Table 1 - MLP structure and learning parameters

Num. of neurons in input layer	**4**
Num. of neurons in hidden layer	**9**
Num. of neurons in output layer	**2**
Training algorithms	**Levenberg-Marquardt (LM)**
The initial weights and biases	**Set Randomly by Mat Lab in range [−1, 1]**
Activation functions for hidden layer	**Logsigmoid**
Activation functions for output layer	**Pure line**
Num. of epochs	**1000**
Error goal	**1e-7**

Results and Discussion

ANN prediction of Si and Ni recovery

The results are discussed by using the ANN network (Figure 1) and table 2 to predict the recovery of important elements of the prepared alloys, under the influence of various factors. The performance of the trained NN was reached by MSE criteria. ANN is applied to predict the recovery per cent of silicon and nickel in the Al-Si-Ni alloys. The effect of processing parameters on Si and Ni recovery of the Al-Si-Ni ternary alloy was studied; the studied parameters are reaction time, temperature, Ni_2O_3/Al wt. ratio and Na_2SiF_6/Al wt. ratio. All experimental results, silicon and nickel recovery and the related predictions are shown in table 2.

Table 2 Experimental and prediction recoveries of Silicon and Nickel recovery results

Sample	Experiment's parameters				Experimental	Prediction	Experimental	Prediction
variable	Time	Temp.	Ni_2O_3 /Al wt. ratio	Na_2SiF_6 /Al wt. ratio	Si% recovery	Si% recovery	Ni% recovery	Ni % recovery
Time, (Group A)	**5**	900	0.08226	1	7.3	7.6106	2.653	2.5907
	10	900	0.08226	1	7.44	7.4337	2.655	2.6494
	15	900	0.08226	1	8.03	8.0266	2.75	2.7169
	20	900	0.08226	1	8.4	8.3928	2.755	2.7511
	25	900	0.08226	1	8.69	8.4028	2.863	2.753
Temp., (Group B)	25	**800**	0.08226	1	6.66	6.6644	2.304	2.2882
	25	**850**	0.08226	1	7.2	7.2138	2.308	2.2895
	25	**900**	0.08226	1	7.43	7.4469	2.574	2.5752
	25	**950**	0.08226	1	8.4	8.4028	2.755	2.753
	25	**1000**	0.08226	1	8.41	8.3959	2.757	2.7657
Ni_2O_3/Al wt. ratio, (Group C)	25	900	**0.05534**	1	7.59	7.6038	1.85	1.849
	25	900	**0.06886**	1	8.25	8.612	2.33	2.5032
	25	900	**0.08226**	1	8.4	8.3884	2.755	2.7552
	25	900	**0.10871**	1	6.46	6.5666	3.315	2.9988
	25	900	**0.12172**	1	6.53	6.504	3.46	3.4248
Na_2SiF_6/Al wt. ratio, (Group D)	25	900	0.08226	**0.25**	1.37	1.3449	0.857	0.842
	25	900	0.08226	**0.5**	4.79	4.7849	2.405	2.391
	25	900	0.08226	**0.75**	6.28	6.2847	2.692	2.6834
	25	900	0.08226	**1**	8.4	8.4028	2.755	2.753
	25	900	0.08226	**1.25**	9.31	9.3122	2.756	2.7574

Time reaction parameter

Figure 2 displays the predicted values of Si and Ni recovery in comparison to the experimental results. It is obvious that the per cent of Si increases, slightly, by increasing the reaction time, while the Ni content remains constant. This behaviour of Si and Ni can be attributed to the decomposition of Na_2SiF_6 as a source of Si and Ni_2O_3 as a source of Ni. From Fig. 2, it could be seen, clearly that experimental and predicted values obtained from ANNs for Si and Ni recovery are very close to each other. The superior performance of the trained NN can be indicated by MSE criteria agree with [15, 16] where MSE = 0.0358 for Si recovery and MSE = 0.0034 for Ni recovery values.

DOI: 10.21608/jpme.2019.13519.1003

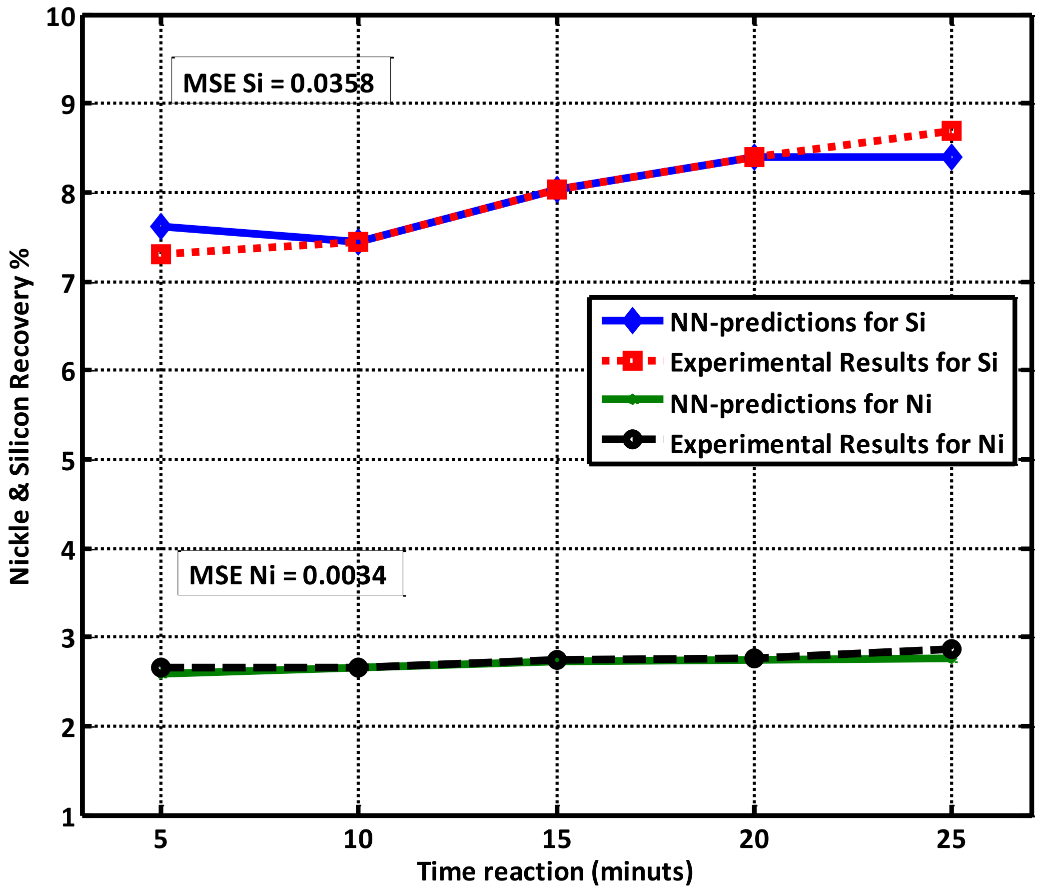

Figure 2 Comparison between experimental results and NN predictions of Si and Ni recovery versus time reaction

Temperature parameter

Figure 3 shows a noticed linearly increasing in silicon and nickel contents in the studied alloys with temperature increase, the silicon percentage reached the highest values at 950 and 1000°C. Moreover, a linear increasing of Ni, nearly at the same rate, until the Ni contents in the produced alloy reached to the highest value at 950°C. The increasing of Si and Ni contents of the alloy, as temperature rises, is attributed to the formation of AlF3 and NaF in the reaction bath due to increasing of fluidity of bath and reduction of SiF_4 and Ni_2O_3 with Al. These results are in agreement with that obtained by others [17,18]. As well as from Fig. 3, it is clear that the NN predictions exactly identical with the experimental results. This outstanding performance of the trained NN can be measured using MSE criteria, where MSE = 1.4007e-04 for Si recovery and MSE = 1.3478e-04 for Ni recovery values.

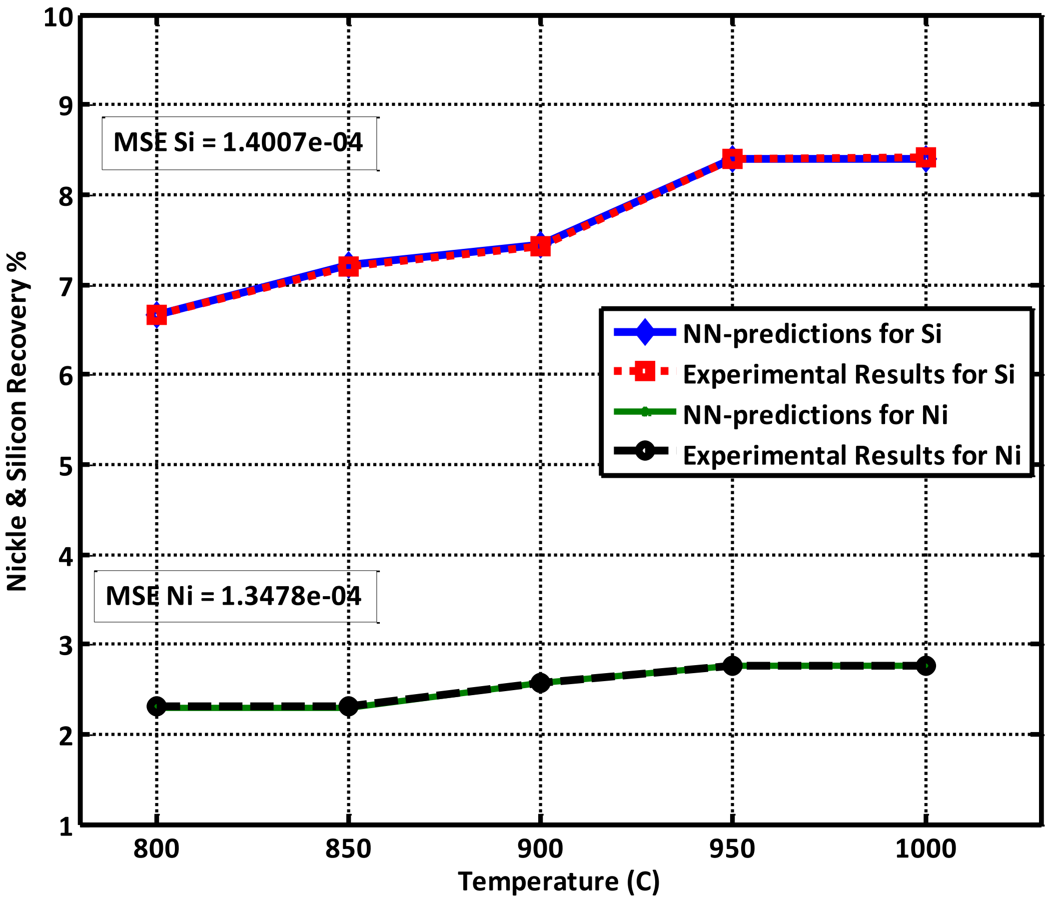

Figure 3 Comparison between experimental results and NN predictions of Si and Ni recovery versus temperature

Ni_2O_3 / Al wt. ratio parameter

As shown in figure 4, it could be illustrated that the silicon dissolution rate under the experimental conditions is almost constant as the nickel oxide ratio increases; it reaches 8.4 % Si when nickel oxide ratio equals to 0.082. Then the Si% in the produced alloys decreased as the nickel oxide ratio increased. It could be attributed to the increasing of nickel quantity in the added material that leads to form more slag in the bath which hinders the formation the silicon and its dissolution in liquid aluminum. On the other hand, the Ni contents increased sharply as the nickel oxide ratio increased. Increasing Ni contents in the produced alloy is attributed to the quantity increase of Ni_2O_3 in the added material which leads to producing more Ni which dissolves in liquid aluminum. Also Fig. 5 shows the predicted values of Si and Ni recovery in comparison to the experimental results. From Fig. 4, it could be noticed, clearly, that the experimental and predicted values obtained from ANNs for Si and Ni recovery are close to each other. The good performance of the trained NN can be indicated by MSE criteria, where MSE = 0.0287 for Si recovery and MSE = 0.0263 for Ni recovery values.

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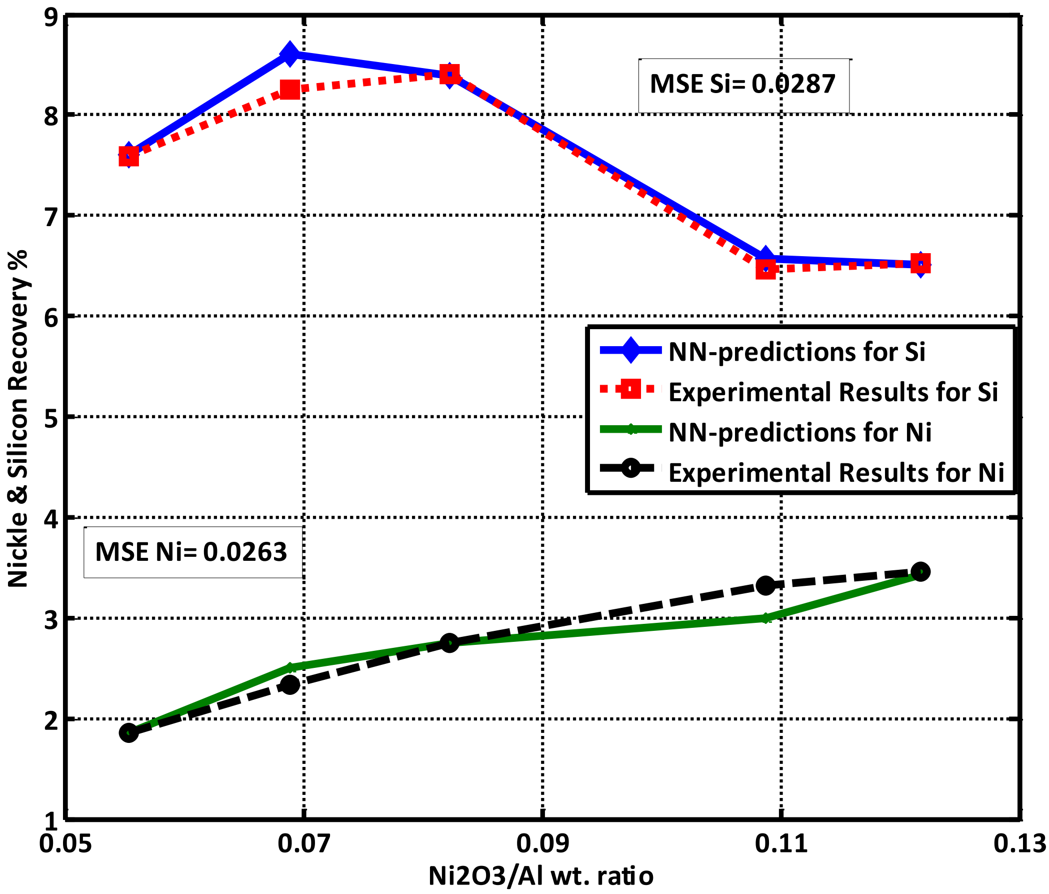

Figure 4 Comparison between experimental results and NN predictions of Si and Ni recovery versus Ni_2O_3/Al wt. ratio

Na_2SiF_6 / Al wt. ratio parameter

The obtained results demonstrated in figure 5. Illustrate that the silicon dissolution rate under the experimental conditions increases linearly by increasing the Na_2SiF_6/Al wt. ratio. The increasing of silicon dissolution could attribute to the increasing of silicon quantity which leads to producing more Si that dissolves in liquid aluminum. On the other hand, the Ni content increased sharply on increasing the Na_2SiF_6/Al wt. ratio. The increasing of Ni content in the produced alloys is attributed to the increasing of fluorine salts in the reaction bath that leads to push the reaction towards the direction of producing more Ni which dissolves in liquid aluminum. According to Fig. 5, it is clear that the NN predictions exactly identical with the experimental results. This outstanding performance of the trained NN can be measured using MSE criteria, where MSE = 1.3839e-04 for Si recovery and MSE = 9.9891e-05 for Ni recovery values.

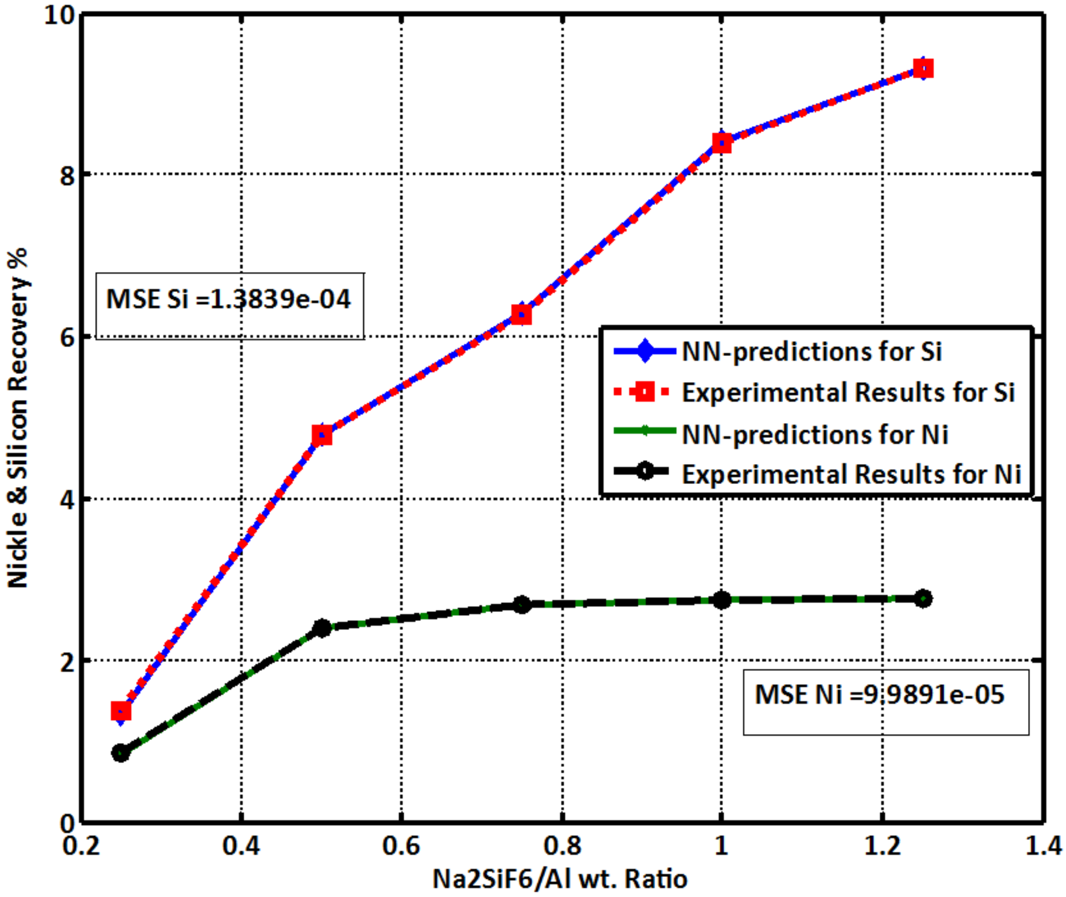

Figure 5 Comparison between experimental results and NN predictions of Si and Ni recovery versus Na_2SiF_6/Al wt. ratio

Conclusions

At variance of the experimental process which is considered time consuming, the use of ANN and MATLAB method are able to simplify the complicated relationships and give simple and approximate results. Data gained from the model predictions and simulations can be employed as guidelines during the design and of adjusting and optimization the synthesis processes. So, the time and costs can be reduced which on the other hand cannot be applied by the experimental methods. In the present work, the predictions of Si and Ni recovery under different processing factors are studied and the following conclusions are obtained:

1- Artificial Neural Network (ANN) can be applied as an effective tool in predicting Si and Ni recovery.

2- Under the studied conditions and utilized materials, predicted recovery values of Si and Ni can be used by designers and process engineers to save costs, efforts, time, materials and items of the experiment.

3- The predicted results of ANN model have shown a uniformity and good agreement with experimental Si and Ni recovery.

4- The designed ANN model achieved Si recovery with mean square error (MSE), from first group to fourth group were 0.0358, 1.4007e-04, 1.3839e-04, and 0.0287, respectively.

5- The designed ANN model achieved Ni recovery with mean square error (MSE) from first group to fourth group were 0.0034, 1.3478e-04, 9.9891e-05, and 0.0263, respectively.

Acknowledgements

The author acknowledges his co-authors (Eng. Mohammed Farag, Prof. A. A. Atlam, and Prof. A. M. Omran), for their approval to use our laboratory data for the Artificial Neural Network modeling.

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