CHAPTER 4

EXPERIMENTAL RESULT and DISCUSION

4.1 Performance of Neural network

Results of testing model are shown in Table 4.1. The model number 2, architecture [11.4.1] (these digits in brackets correspond to the neurons in input, hidden and output layer) gives minimum mean absolute error of 7.46°C. The model for predicting the temperature change in converter process during tapping and adding addition has one hidden layer, four neurons in hidden layer. This architecture will be used for studying the effect of learning rate and momentum on learning behavior of the network. The predicted temperature change of the best network is shown in Figure 4.1. Figure 4.2 shows the distribution of error from this model. It illustrates the relation between the actual temperature change and the predicted temperature change. Good correlation between actual and predicted temperature change is obtained in the range between 40°C to 100°C. Slope of trend line between actual and predicted temperature change is 0.9904. The standard deviation and variance of error from [11.4.1] architecture is only 6.32 and 40.05 respectively. It should be noted that this error is made up of four other errors are:

1) error in process measurement
2) error from reading values from the equipment
3) error from the accuracy of measuring equipment
4) error from neural network

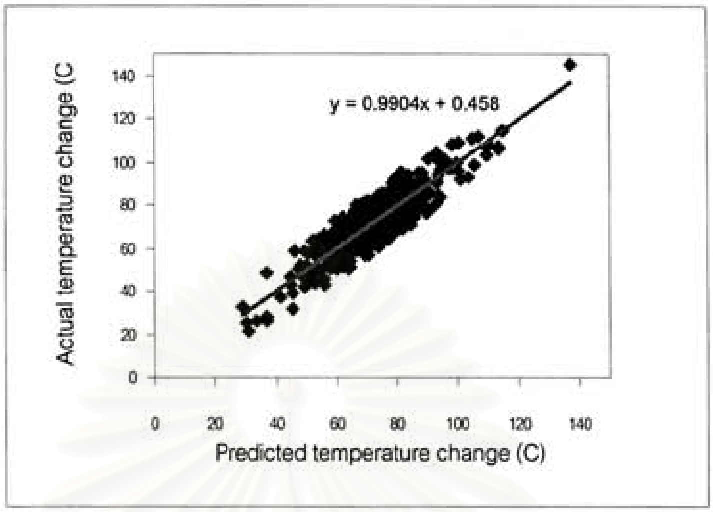

Figure 4.1 Predicted and actual temperature change from the best model

Table 4.1 Error of the different network

Model Number	MAE	MSE	RMSE	MAPE
1	7.682	103.745	10.186	12.437
2	7.457	97.577	9.878	13.280
3	7.516	98.872	9.943	13.409
4	7.824	105.373	10.235	14.421
5	8.937	129.065	11.361	13.135
6	7.671	103.989	10.198	12.357
7	7.508	99.239	9.962	13.197
8	9.026	132.640	11.517	15.619
9	7.480	98.321	9.916	13.001
10	7.956	111.634	10.566	12.85
11	9.393	149.212	12.215	14.172
12	7.593	97.433	9.871	12.947

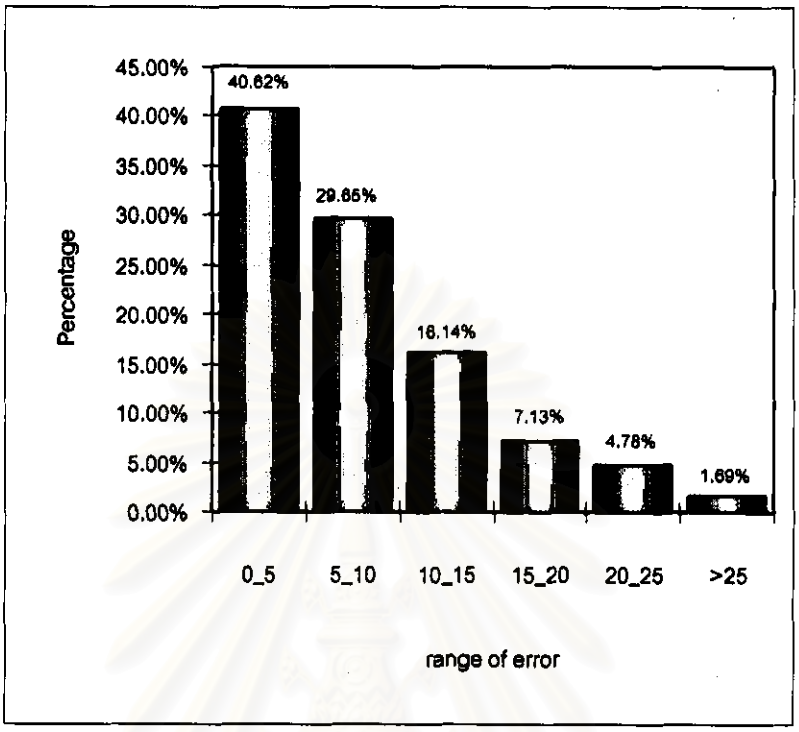

Figure 4.2 The histogram of error

4.2 Parameter in Network

4.2.1 Effects of number of hidden neurons

Figure 4.3 shows error of model with the number of epochs for three layers network with different number of hidden neurons. Network with fewer hidden neurons gives a higher error. The network with more hidden neurons also gives higher error and shows perturbation in learning curve.

Searching of best architecture of network can be done only by trial and error. In this investigation, many trials and errors had been performed until the best architecture [11,4,1], with error of 7.46°C was received. It was found that network has too few hidden units can not learn the training set well. On other hand, networks with too many hidden units tend to memorize the training set but cannot perform well.

This work also makes trial and error with two hidden layers. Even though the two hidden layers can give error of the same magnitude [11,4,1] but it was not chosen as the model to predict the temperature change. Because increasing the hidden layer will increase the complexity and need more time for convergence of the network. Most applications of neural network with backpropagation use only one hidden layer to solve problem. The major reason for this is that intermediate unit not directly connected to output cells will have very small weight changes and will learn very slowly.

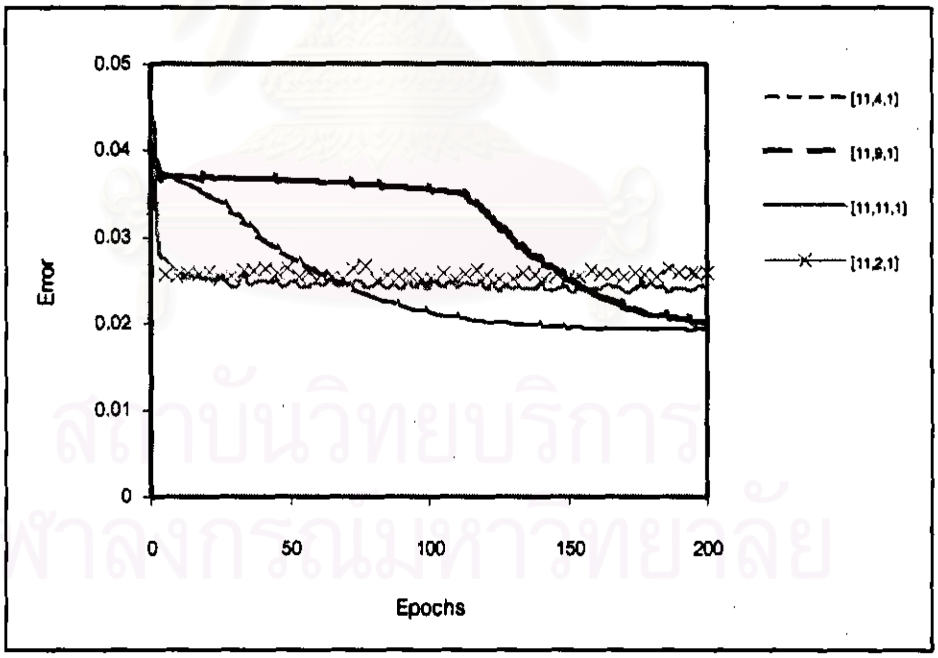

Figure 4.3 Effects of hidden neurons in the learning curve

4.2.2 Effect of learning rate

After getting the network architecture, the suitable learning should be chosen. The effect of learning rate on the learning behavior of network is shown in Figure 4.4. It can be seen that the high learning rate will affect the convergence of the network. The high learning rate leads to fluctuation of the learning curve while the use of a lower learning rate leads to a faster convergence of the curve.

The learning rate coefficient determines the size of the weight adjustment at each iteration and influences the rate of convergence. The different values of learning rates result in different rates of convergence. A large value of learning rate gives bigger step sizes and faster convergence, but only at a point. When learning rate is chosen too large, the error may become unstable, overshooting and fail to converge at all. On the other hand, if learning rate is chosen too small, the convergence will progress in very small step and significantly increase the total time to convergence. The learning rate is probably best to keep it no larger than 0.1 [13] but the appropriate choice of learning rate is problem specific.

4.2.3 Effects of momentum

Figure 4.5 shows effects of changing the momentum on the learning curve. It shows that the best momentum for the prediction temperature change is 0.5. Even though three values show the same convergence error but the network with momentum 0.5 converged more rapidly.

Adding a momentum term is another possible way to improve the rate of convergence. This can be accomplished by adding a fraction of the previous weight change to the current weight change. The addition of momentum term can help smooth out the descent path by preventing extreme changes. The momentum term will filter out higher-frequency oscillations in the weights change.

The value of momentum should be positive and less than 1. Typical value is in the range [0.5-0.9], but for some problems a value of momentum 0 was shown to be the best [14].

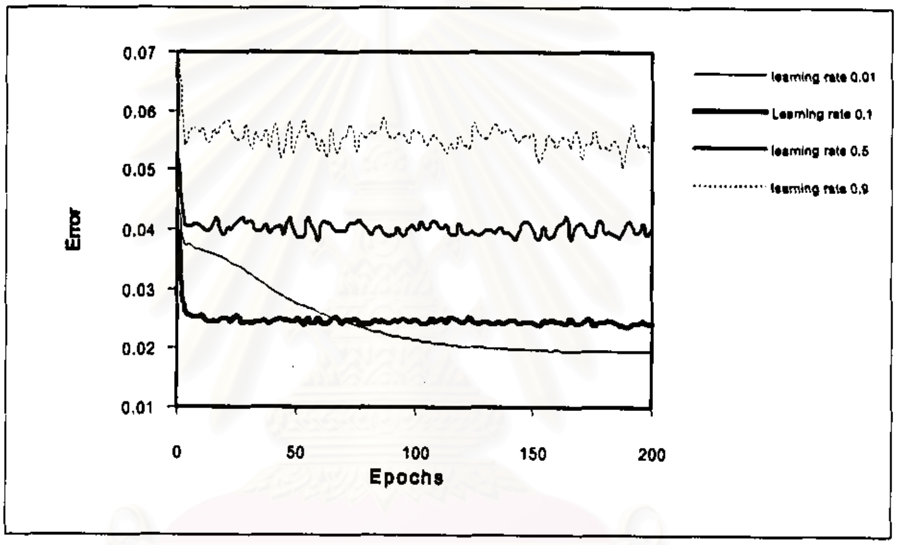

Figure 4.4 Effects of learning rate on learning behavior of the network

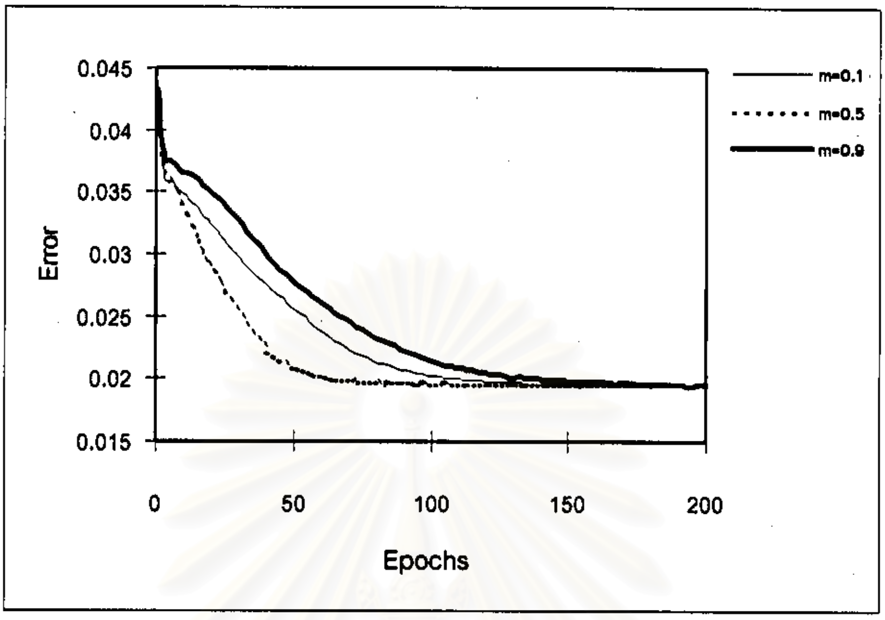

Figure 4.5 Effects of momentum on learning behavior of the network.

4.3 Testing of input-output dependence

There were seven variables which had been tested for its effect on temperature change. These seven variables were variables that have strong relative relevance after pruning the network in training phase.

4.3.1 Effects of tapping time and steel weight

The tapping time and steel weights are variables which influence the temperature drop of the liquid steel. Figures 4.6 and 4.7 show the effects of tapping time and steel weight on the temperature drop respectively. It demonstrates that increasing the tapping time and steel weight will increase the temperature drop. Figure 4.7 shows that the steel weight influences the temperature drop only slightly. The result of temperature drop from steel weight bases on the temperature drop of 140 ton steel weight. In practice, most of tapping time is approximately 5-8 minutes which gives temperature drop of 25°C. Predicted temperature drop from the neural network in this range of tapping time is about 20°C-30°C which corresponds to values in practice. From Figure 4.6, it can be seen that the tapping time is the largest effect on the temperature change. During tapping, the liquid steel is poured from BOF to ladle. The heat can easily transfer from liquid steel to environment due to the liquid steel is flowed and contact with atmosphere and no cover to prevent the heat loss. The heat energy can easily loss to environment by radiation.

Generally, the thermal energy in the liquid steel system should increase as the steel weight is increased. So the temperature drop should be lower when the steel weight is increased. But the network predicts the effect of steel weight contrary that is the temperature drop is increased when the steel weight is increased. The main reason for this point is that in practice when steel weights increase, the tapping time will be also increased and the effect of tapping time is more than the effect of steel weight. However effects of steel weight on the predicted temperature drop is only little.

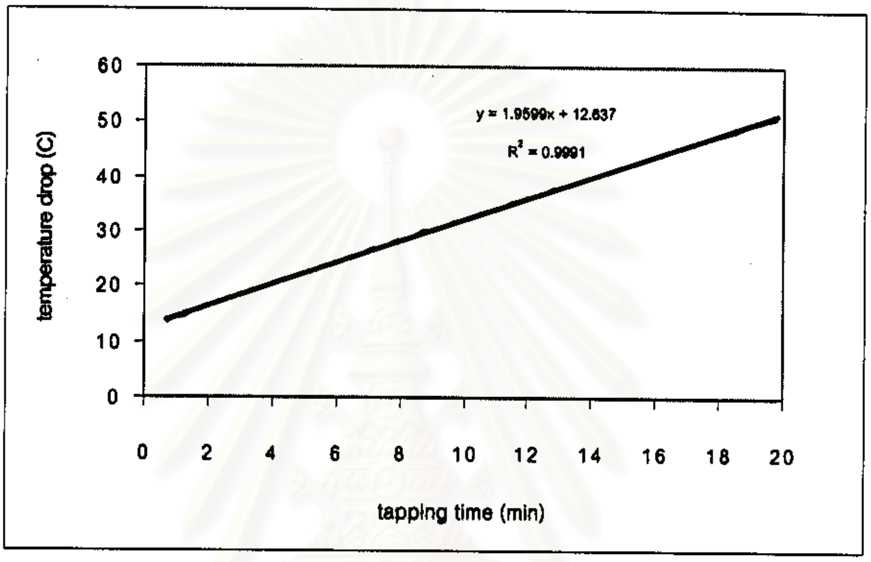

Figure 4.6 Effects of tapping time on temperature drop

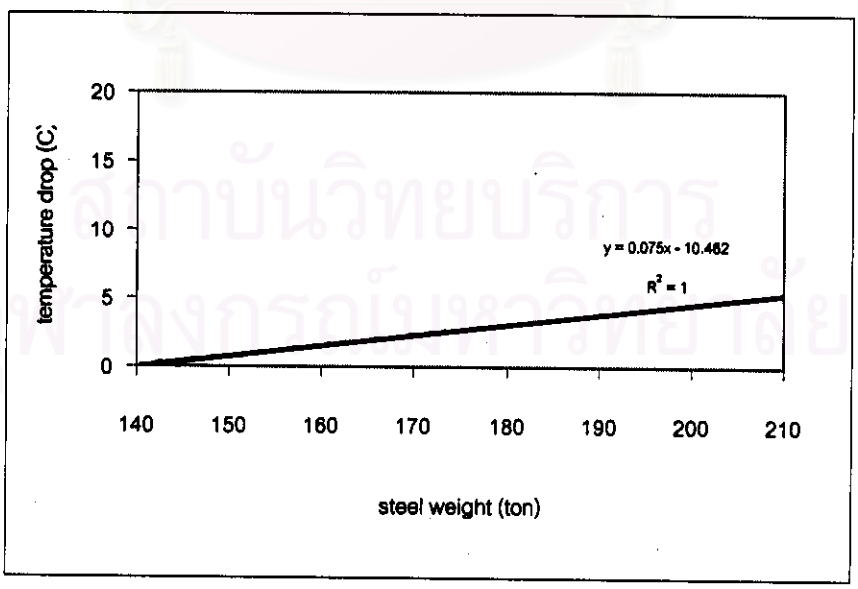

Figure 4.7 Effects of steel weight on temperature drop

4.3.2 Effect of flux and additive

Additives and fluxes are added during the process of secondary metallurgy to improve the quality and properties of steel. All of these additives and fluxes affect temperature change of the liquid steel in the process. Different additives affect on the temperature change of the liquid steel differently. Some additives affect the temperature change in the same way. For example calcium oxide (CaO) absorbs the heat from liquid steel and lower the temperature of the liquid steel. However, aluminium (Al) reacts with oxygen and gives heat to system results in increase of the temperature of the liquid steel. Various effects of additives and flux can now be illustrated in Figure 4.8-4.12.

The optimized neural network, architecture [11,4,1] is able to learn the influence of flux and additive parameters on the temperature change of the liquid steel. It can be seen that additions except aluminium will decrease the temperature of the liquid steel. These result conform to data from thermodynamic calculation. Aluminium react with oxygen (for deoxidation in liquid steel). This reaction is exothermic reaction ($2[Al] + 3\underline{O} = (2Al_2O_3)$) should increase temperature of the liquid steel.

Clearly, the neural network predicts a linear relationship between temperature change and the amount of addition. The relationship from thermodynamic is also linear. From equation 4.1 and 4.2, the temperature change varies linearly with the amount of additions. The difference between calculation line and network line of CaO (in Figure 4.8) is in the boundary of average error (7.46°C). This relationship shows that the network can predict the effects of CaO very well. Adding of other materials occur only in some heats and to a much smallerextent. We can not consider all range of addition in the prediction of other variables. We should consider on the range that takes in the network. Manganese should not be considered in range less than 300 kg and aluminium more than 500 kg. Because there is no data on such range.

One problem about data of this investigation is some variables are discrete data. The network can learn only in range of existed data. The testing of input-output dependence varies such data from minimum to maximum while some range of data can not be found for training in network. For the better performance of network, the real data from minimum to maximum are required. It is difficult to find such data in practice because some additive is added follow the steel grade that can not vary from minimum to maximum.

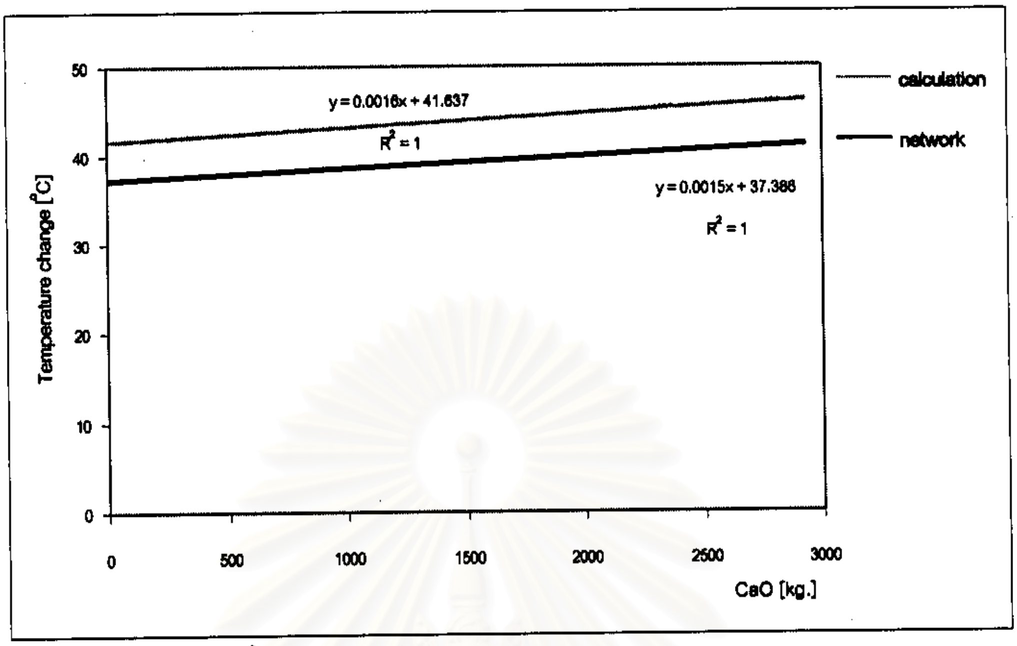

Figure 4.8 The effect of CaO on the temperature change of liquid steel

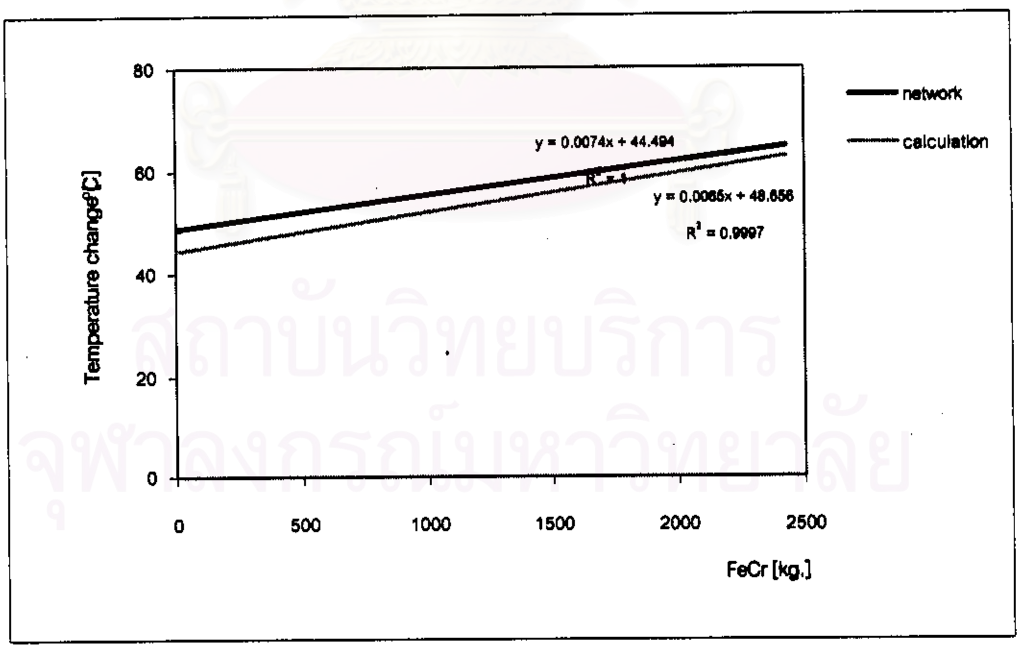

Figure 4.9 The effect of FeCr on the temperature change of liquid steel

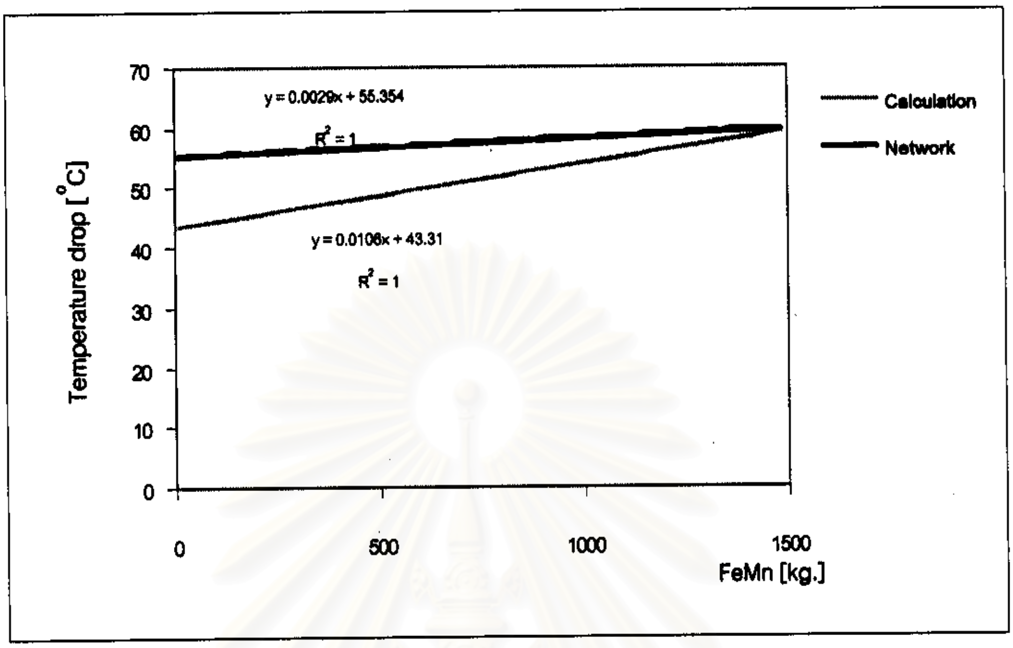

Figure 4.10 The effect of Mn on the temperature change of liquid steel

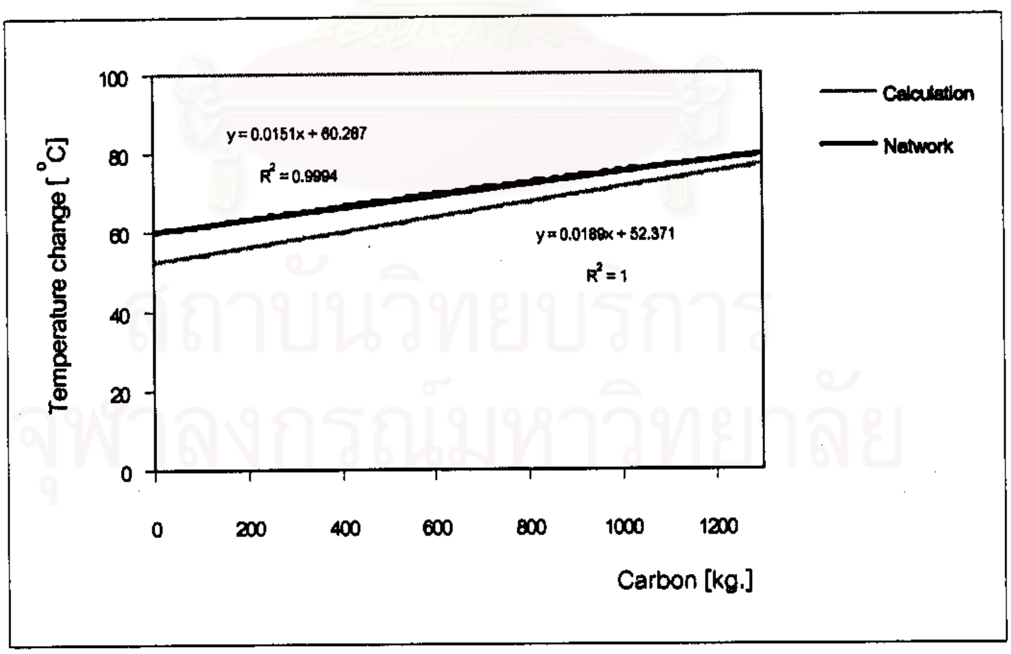

Figure 4.11 The effect of Carbon on the temperature change of liquid steel

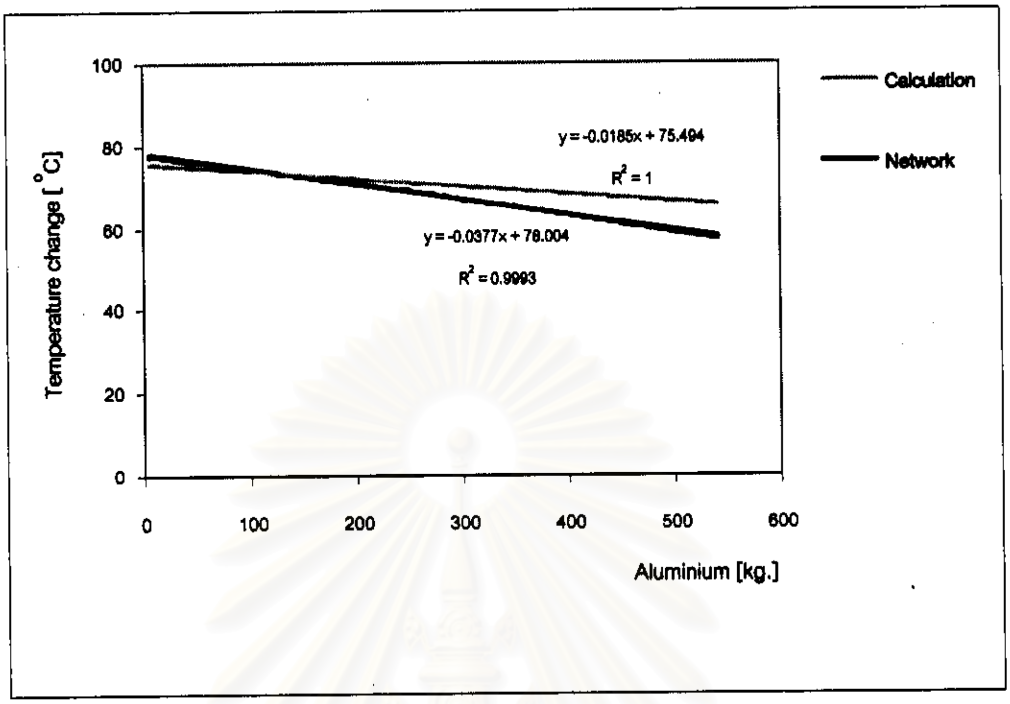

Figure 4.12 The effect of Al on the temperature change of liquid steel