Neural network models for predicting the type of ice accretion

S. Maralbashi, H. Ezzaidi and M. Farzaneh
NSERC / Hydro-Quebec / UQAC Industrial Chair on Atmospheric Icing of Power Network Equipment (CIGELE) and Canada Research Chair on Engineering of Power Network Atmospheric Icing (INGIVRE)
Université du Québec à Chicoutimi, Chicoutimi, Québec, Canada, G7H 2B1
Phone: (418) 545-5044; Fax: (418) 545-5032; Web site: http://cigele.ca

***Abstract*— In this paper, two model based on neural networks are proposed for predicting accreted ice type using temperature, wind speed and droplet size as parameters. The data sets for training the models were created using functions determined from experimental ones recommended in pertinent literature for distinguishing between different ice types. These functions were used as discriminate functions in the models, their combination being used to create the target variable corresponding to the ice types in the training data set. The neural network architecture known as Multi Layer Perceptron was used with two input nodes representing temperature and wind speed in the first model and three input nodes representing temperature, wind speed, and droplet size in the second model. The models contain two output neurons encoding four binary coded ice types, namely wet snow, hard rime, soft rime, and glaze. The number of hidden layer neurons during the experiments was varied to determine the optimum model. Performances of the models were measured by two criteria including: mean square error and learning rate percentage. The optimum models led to a learning rate of more than 99% with both the training and test data sets. The obtained results are promising and show that neural network models can be a good alternative for predicting the type of ice accretion provided that the functions used for creating training data sets are accurate enough.**

I. NOMENCLATURE

Neural networks, accreted ice type, atmospheric icing

II. INTRODUCTION

THE term ice accretion is employed to describe the process of ice growth on a surface exposed to atmospheric icing. The ice growth rate on a surface depends on the impact rate of the ice particles, airflow characteristics, and local thermal conditions of the surface [1]. In general, it is recognized that there are four types of ice accretion: *hard rime*, *soft rime*, *glaze*, and *wet snow*. Usually, the type of accreted ice is determined by assessing the physical properties of the ice including its density, adhesion, color, shape, and cohesion. These physical properties of atmospheric ice may vary within rather wide limits. There are also some meteorological parameters affecting ice accretion which can be used to determine the accreted ice type without having to evaluate its physical properties. Those parameters include: air temperature, mean wind speed, droplet size and liquid water content. The idea of developing a neural network model for predicting accreted ice type was inspired from a figure on experimental functions recommended by IEC (International Electrical Commission) [2] for switching between soft rime, hard rime, and glaze for in-cloud icing.

III. NEURAL NETWORKS

Neural networks, also known as Artificial Neural Networks (ANN), are computational models that consist of a number of simple processing elements that communicate by sending signals to each other over a large number of weighted connections. The ANNs represent an attempt on a very basic level to reproduce the type of nonlinear training which occurs in the neural networks that we find in the nature. In fact, the relationship between ANNs and brain functioning lies in the idea of performing computations by using parallel interaction of a very large number of non linear processing elements [4]. The neuron, i.e. the processing element, is the building block of neural networks. Each neuron is composed of a set of inputs, a body where the processing takes place and an output. It receives inputs from other neurons in the network, or from the outside world, and calculates an output based on these inputs. Each connection (also called a synapse) between the neurons is given a weight which represents the relative importance of a specific input. A neural network "learns" by adjusting its weight sets. Fig. 1depicts a neuron with n inputs.

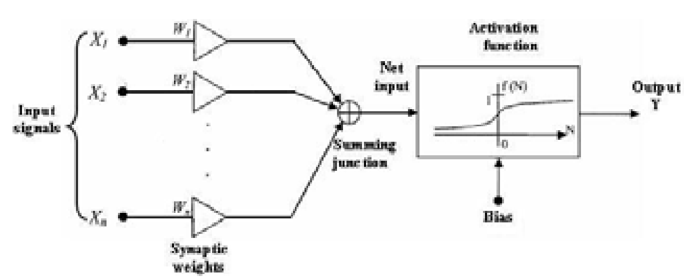

Fig. 1: A single neuron

The input signals X_i are transferred into the neuron after being multiplied by synaptic weights W_i. The neuron then computes the sum of the weighted input signals, called net input, and then passes this value through an activation (transfer) function to produce an output value. The neuron also includes an externally applied bias b. This bias has the effect of increasing or lowering the net input of the activation function, depending on whether it is positive or negative, respectively [3]. In mathematical terms, the following equations give a concise description of the neuron:

$$N = \sum_{i=1}^{n} X_i W_i + b \tag{1}$$

and

$$y = f(N) \tag{2}$$

where $X_1, X_2, \ldots, X_n$ are the input signals; $W_1, W_2, \ldots W_n$ are the synaptic weights of neuron; b is the bias term; N is the net input and f(.) is the activation function.

The combination of two or more of these neurons builds a layer and these layers then connect to one another to construct a neural network. The neurons are connected to other neurons by receiving input from and /or providing output to the other units. The neurons which only have output connections are considered “input” neurons, while those which have only input connections are called “output” neurons. In addition, a neural network may have one or more “hidden” neurons which neither receive input nor produce output for the network, but rather assist the network in learning to solve a given problem. The connectivity of neurons within a neural network is very critical in its ability of processing data. Based on the connectivity pattern between the layers of a neural network, there are different architectures. More information on neural networks field, can be found in the book by Hakin [3].

IV. A TWO-INPUT NEURAL NETWORK MODEL TO DETERMINE ICE TYPE

There are some typical steps in developing a neural network model including analysis of the problem and collection of the related data, choice of the neural network type which is able to solve the problem, and training the neural network and monitoring its performance on test data. The details of these steps have been elaborated in the following sections.

A. Data Collection

The first step in developing any neural network model is collecting the data related to the problem. The first thing to do when planning data collection is to decide what data we will need to solve the problem and from where the data will be obtained. In the context of our problem, we need a data base which attributes the proper ice type to input patterns which are meteorological parameters. Since in the available icing data bases, there is no information related to ice type, the pertinent literature was used as a source for creating the needed training data base. Fig. 2 which is recommended in IEC [2], was our main source for creating the needed training data.

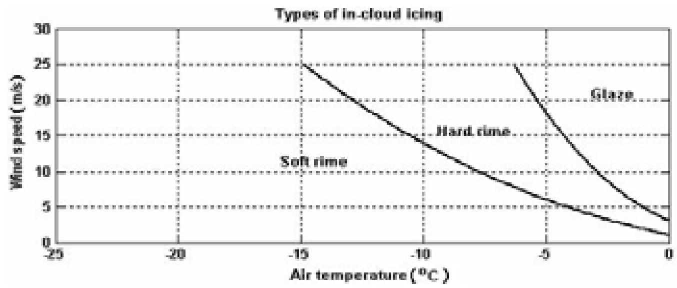

Fig. 2: Accreted in-cloud ice type as a function of wind and temperature[2]

The strategy for obtaining the needed data base was to estimate the equations plotted on the above figure and use them as discriminate functions. It is important to notice that the functions represented in that figure have been accepted as international standards by experts in atmospheric icing for determining ice type. So using polynomial curve fitting, these equations were obtained and were used as discriminate functions. The discriminate function of the first curve, distinguishing glaze ice from hard rime, is represented by (3):

$$G_1(W,T) = W + 0.001T^3 - 0.045T^2 + 0.746T - 1.085 = 0 \tag{3}$$

whereas the discriminate function of the second curve, separating hard rime and soft rime, is given by (4).

$$G_2(W,T) = W + 0.007T^3 - 0.269T^2 + 1.495T - 3.134 = 0 \tag{4}$$

where W is wind speed in m/s and T is temperature in ^{o}C.

A discriminate function is used for dividing a set of data points into two different classes [5]. Each data point is substituted in the discriminate function and if the result is greater than zero the data point is in the right hand of the discriminate or boundary function and if it is less than zero it is in the left hand of it. In summary, each discriminate function divides a given data set into two sections depending on the sign of it. So, using these two discriminate functions, three ice types, glaze, hard rime and soft rime can be classified. The third discriminate function G_3 was obtained from information found in the same reference, as to if temperature is greater than zero, regardless of wind speed, the accreted ice type is wet snow.

In order to create the needed data base, values of temperature and wind speed typical of icing events were considered as input points. These include the range of -25 to 5 for temperature and a range of 0 to 30 for wind velocity. Then, by using the combination of discriminate functions shown in Listing 1 , for each input pair its corresponding ice type was determined and saved as target variable in the data set. Each type of ice was given a specific binary code. Fig. 3 shows the distribution of the created data points.

.

```
If G3>0
ice_type= wet snow coded by [0 0]
else if G1>0
ice_type=glaze coded by [0 1]
else if G1<0 & G2>0
ice_type=hard rime coded by [1 0]
else
ice_type=soft rime coded by [1 1]
```

Listing 1: Pseudo-code for combination of discriminate functions for determining ice type based on temperature and wind speed

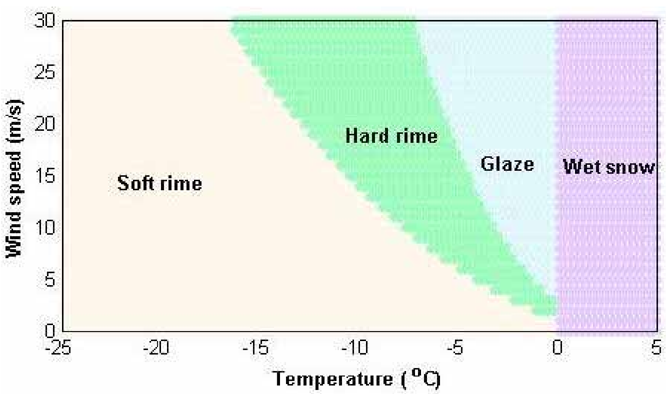

Fig. 3: Distribution of the points in the created data set for the two-input neural network

B. Experimented Neural Network Architecture

The learning task to be dealt with here is a pattern classification problem, which Multi Layer Perceptron architecture (MLP) is the best candidate for solving. The complexity level of the problem is such that only one-hidden layer MLP is sufficient for efficiently reaching a solution. The number of input and output neurons is defined by the problem. Fig. 4 shows the schematic of the chosen architecture.

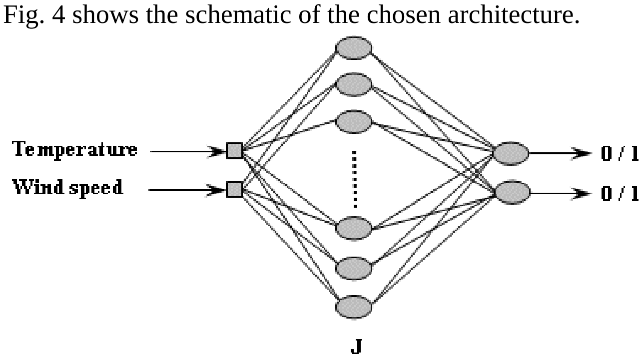

Fig. 4: Schematic of the architecture of the two-input neural network model for determining accreted ice type

In the input layer there are two neurons: one for temperature and the other one for wind speed. The output layer contains two neurons for representing the binary value of the four possible ice types. The number of neurons in the hidden layer is indicated by j which implies that during the experiments there was variable number of neurons in the hidden layer. We began with four neurons in the hidden layer, and with each successive test the number of neurons was increased in order to raise the learning rate of the network. Because of the range of the output, logistic functions were selected as transfer functions for both the hidden and output layers. To perform the training, the Levenberg-Marquardt algorithm, one of the fast algorithms of backpropagation training [3], was used.

C. Performance criteria

Two criteria have been considered to measure the performance of the model. The first one is the classic mean square error (MSE), which computes the average squared error between the network outputs and the observed outputs. The most efficient model has the least MSE. In mathematical terms, MSE is defined as:

$$MSE = \frac{\sum_{i=1}^{N} (Y_i - \hat{Y}_i)^2}{N} \tag{5}$$

where Y_i is the actual output , $\hat{Y}_i$ is the output of the network, and N is the number of the training patterns.

The other performance criterion which is the most important criterion for pattern classification problems is the learning rate percentage for each type of ice. Learning rate percentage is defined as the the number of the correctly classified input patterns for a specific ice type divided by the total number of the patterns for that specific ice type, multiplied by 100.

$$Learning\ Rate\ Percentage = \frac{Number\ of\ correctly\ classified\ patterns}{Total\ number\ of\ patterns} * 100 \tag{6}$$

D. Results of experiments

Fig. 5 shows the results of experiments based on MSE with varying the hidden layer's neurons. The number of epochs for the tests was set to 10,000. Six different structures were tested. –In order to avoid the networks to be trapped in a local minimum, twenty different tests with a new initiation of weight and bias matrices were carried out for each structure. From Fig. 5, it can be concluded that augmenting the number of neurons up to ten in the hidden layer decreases the MSE value, thus improving the efficiency of the network. However, the behavior of the network stays almost the same and the error becomes almost zero, after a number of neurons larger than 10.

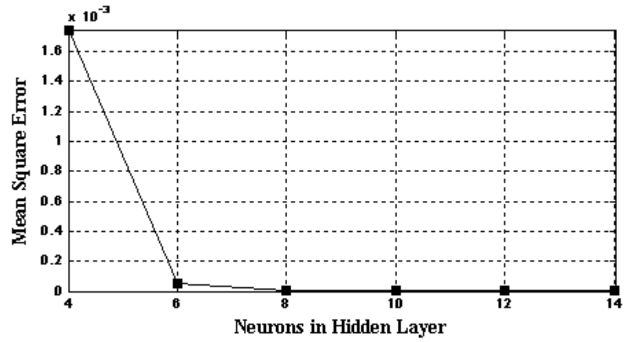

Fig. 5: Results of experiments for the two-input neural model as a function of MSE versus number of neurons in hidden layer (epochs=10000)

In order to quantify the results of classification for each type of ice, the performance of each structure was tested by running the training data and calculating the resulting learning rate percentage. The results are shown in the Table 1. It is important to mention that in the simulation stage, the output of the network was rounded to the nearest integer. This is why some learning rate percentages reach 100% in spite of the existence of small errors in Fig. 5.

Table 1: Results of experiments for the two-input neural model based on learning rate percentage versus number of neurons in hidden layer

NEURONS IN HIDDEN LAYER	LEARNING RATE (%)			
	Wet snow	Glaze	Hard rime	Soft rime
4	94.21	79.51	83.12	95.11
6	98.14	91.36	94.97	98.46
8	99.08	100	98.31	99.05
10	100	100	100	100
12	100	100	100	100
14	100	100	100	100

Based on the obtained results, the number of neurons in the hidden layer was set at 10. -

E. Validation of the proposed model

In order to validate a neural network model, it is applied to a test data set that has not been used during training process. For that purpose, the model was applied to icing data from the Mont Bélair icing site, 25 km northwest of Quebec City. Hourly data records were obtained from measurements during 57 consecutive icing events (1739 hours) during the 1998-2000 winters. First, ice type for the Mont Bélair data set was determined using the functions proposed by IEC [2] as the reference for comparison purposes. Then, using the proposed neural network model the ice type of this icing data set was determined. The results of model performance for this data set are summarized in Table 2. It is obvious that for the majority of the data points, ice type have been correctly determined by the model. It can be concluded that this model is able to perform an ice type determination on new test data with the same accuracy as with the training data set.

Table 2: Learning rate of proposed model for each class of ice type for Mont Bélair data set

LEARNING RATE (%)			
Wet snow	Glaze	Hard rime	Soft rime
99.95	99.59	100	99.58

The results of model performance for the Mont Bélair data set are visually depicted in Fig. 6.

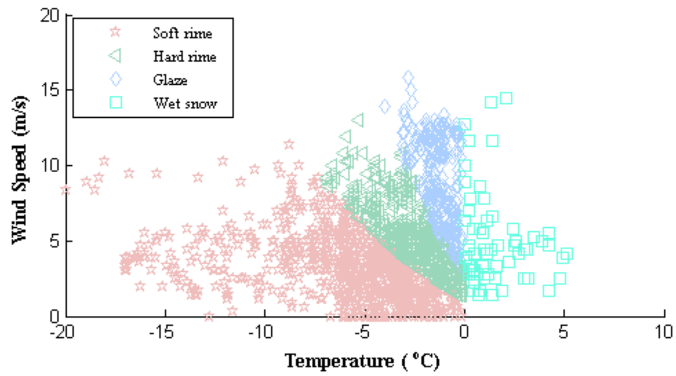

Fig. 6: Visualized results of proposed model's performance on test data

V. A Three-input Neural Network model to determine ice type

In spite of the very good results obtained with the developed model, temperature and wind speed parameters are not sufficient for the determination of a certain ice type. This is why a second model was developed by incorporating an additional parameter, droplet size.

A. Data Collection

Figures 7 and 8, taken from [5] were our main sources for creating the needed data set for the second model.

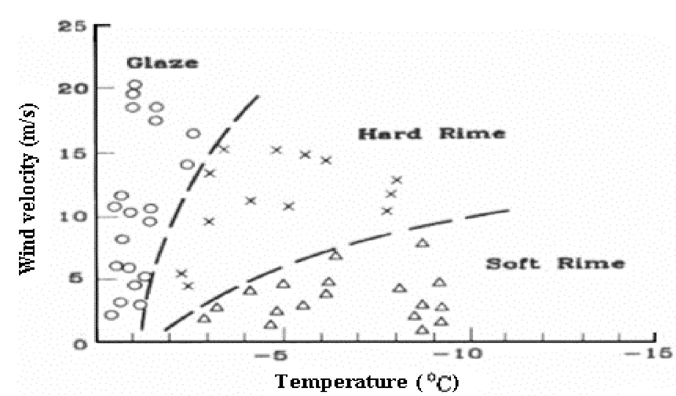

Fig. 7: Accreted ice type as a function of wind speed and temperature [5]

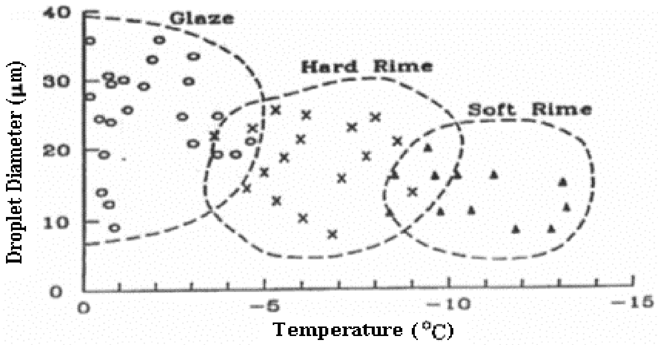

Fig. 8: Accreted ice type as a function of droplet diameter and temperature [5]

Similarly with the development of the two-input model, the equations were estimated from these figures, which was the first step in creating the training data set. Using curve fitting section of Maple software, the following equations were obtained for each of the curves of Fig. 7. The discriminate function of the first curve separating glaze ice from hard rime is represented by (7) whereas the discriminate function of the second curve separating hard rime and soft rime is expressed by (8).

$$y_1(W,T) = W + 0.001T^3 - 0.045T^2 + 0.746T - 1.085 = 0 \quad (7)$$

$$y_2(W,T) = W + 0.007T^3 - 0.269T^2 + 1.495T - 3.134 = 0 \quad (8)$$

where W is wind speed in m/s and T is temperature in ^{o}C.

From Fig. 8, the simplified equations for three regions were obtained with considering all these regions as ellipses. So, the discriminate functions of the regions related to glaze, hard rime and soft rime, are respectively represented by equations (9), (10) and (11).

$$y_3(T,D) = 1.616T^2 + 0.155D^2 - 7.193D + 42.621 = 0 \quad (9)$$

$$y_4(T,D) = 1.849T^2 + 0.135D^2 + 25.097T - 4.788D + 105.486 = 0 \quad (10)$$

$$y_5(T,D) = 1.724T^2 + 0.145D^2 + 38.562T - 4.261D + 232.319 = 0 \quad (11)$$

The combination of these discriminate functions as shown in Listing 2 was used for creating the target variable corresponding to the ice types in the training data set. As it can be seen from this pseudo-code, only three ice types can be determined by the combination of these discriminate functions. This is because it proved impossible to find any information regarding wet snow as a function of temperature, wind speed, and droplet size. Glaze, hard rime, and soft rime are referred to as in-cloud icing in the literature. So, this second model will be used only for predicting in-cloud icing types. Fig. 9 shows the 3D distribution of the created data points. Also, in order to have a better idea of the created data points, Fig. 10 and Fig. 11 show the projection of these points in 2 dimensions.

```
If y2>0 & y3<0 & y4>0
ice_type= glaze coded by [0 0]
elseif y1>0 & y2<0 & y4<0 & y3>0 & y5>0
ice_type=hard rime coded by [0 1]
elseif y1<0 & y5<0 & y4>0
ice_type=soft rime coded by [1 0]
else ice type= undecided coded by [1 1]
```

Listing 2: Pseudo-code for combination of discriminate functions for determining ice type based on temperature, wind speed and droplet size

The white areas in these figures are the regions for which an ice type cannot be determined by the discriminate functions. As it can be observed, the uncertainty region (white area) is much larger than the regions for which an ice type was attributed. However, the available sources in the literature provide only that much information.

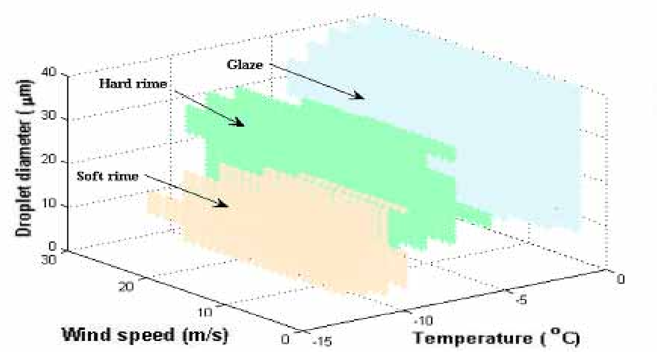

Fig. 9: Distribution of the points in created data set for three-input neural network

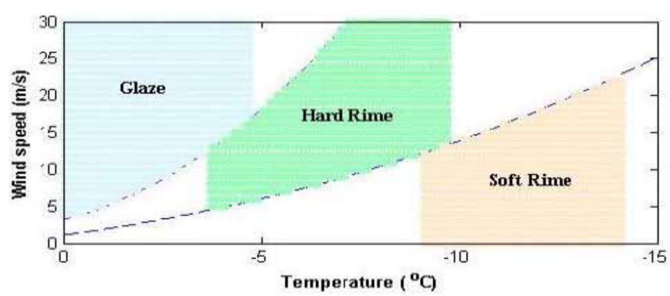

Fig. 10: The view of created data points for three-input neural network in 2-dimensions (temperature and wind speed)

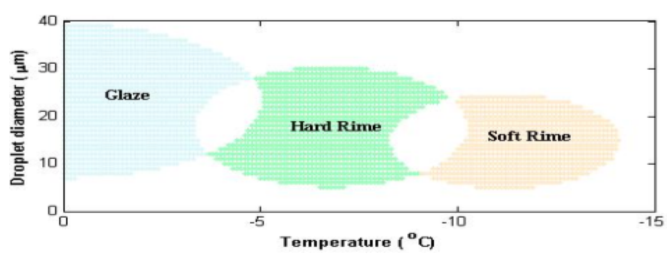

Fig. 11: The view of created data points for three-input neural network in 2-dimensions (temperature and droplet diameter)

B. Experimented Neural Network Architecture

As was the case for previous model, a one-hidden-layer MLP with a varying number of neurons in the hidden layer was the experimented architecture. However, there are three input parameters including temperature, wind speed and droplet size, and the number of inputs neurons is three. In the output layer there are again two neurons with binary value, their combination representing three ice types including soft rime, hard rime, and glaze. The binary coding of [1 1] means that the neural network is not capable of determining the ice type. The number of hidden layer neurons was varied in order to find the optimum structure for the model. Other characteristics of the network including transfer function and the learning algorithm were set as with the two-input model. Fig. 12 shows the schematic of the chosen architecture for the second model.

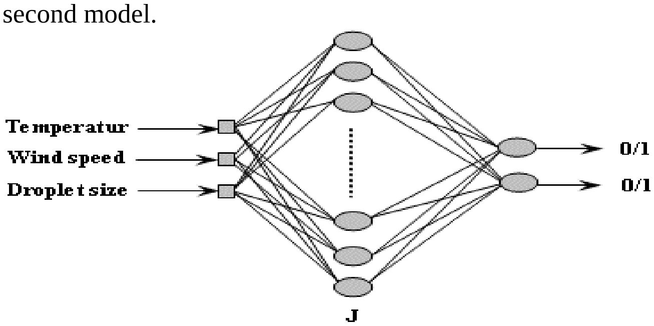

Fig. 12: Schematic of the experimented architecture for the three-input neural network model for determining accreted ice type

C. Results of experiments based on MSE and learning rate percentage

Fig. 13 shows the results of experiments based on MSE for the three-input model. The conditions during the tests were exactly the same as for the previous model. From Fig. 13, it can be concluded that the behavior of the network stays almost the same after a number of neurons larger than 14.

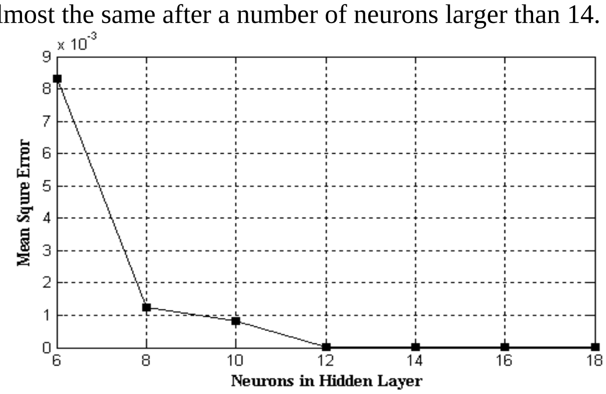

Fig. 13 Results of experiments for three-input neural network as a function of MSE versus number of neurons in hidden layer (epochs=10,000)

The quantified results of classification for each type of ice are shown in Table 3 . They were obtained by testing the performance of each structure by running it with training data and calculating the resulting learning rate percentages. Based on these results, the number of neurons in the hidden layer was set at 14. Because of the lack of droplet size variables in available icing data bases, the model was not validated, which will be the subject of a future study.

Table 3: Results of experiments based on learning rate percentage versus number of neurons in hidden layer

NEURONS IN HIDDEN LAYER	LEARNING RATE (%)			
	Glaze	Hard rime	Soft rime	Uncertain
6	95.37	78.22	85.06	96.24
8	98.56	91.21	84.98	98.47
10	99.09	95.93	95.31	99.05
12	100	99.16	98.49	99.95
14	100	100	100	100
16	100	100	100	100
18	100	100	100	100

VI. Conclusions

In this paper, two models based on neural networks are proposed to predict accreted ice type using meteorological parameters. The first one is a two-input neural network model which makes use of temperature and wind speed as the input parameters for determining four ice types, soft rime, hard rime, glaze, and wet snow. This model was found to have a predictive performance of more than 99% with both the training and test data sets. The second one is a three-input neural network model which utilizes temperature, wind speed, and droplet size as input parameters in order to determine in-cloud ice types. The model has a performance of 100% with the training data set. However, because of the lack of the droplet size parameter in the available icing data, it was impossible to validate this model. It should be noticed that in spite of good results reported, the accuracy of the models is dependent on the accuracy of the references used for creating the training data sets. So, such models are valid and reliable as long as the references used for creating training data set also are.

VII. Acknowledgment

This work was carried out within the framework of the SERC/Hydro-Quebec/UQAC Industrial Chair on Atmospheric Icing of Power Network Equipment (CIGELE) and the Canada Research Chair on Engineering of Power Network Atmospheric Icing (INGIVRE) at Université du Québec à Chicoutimi. The authors would like to thank the CIGELE partners (Hydro-Québec, Hydro One, Électricité de France, Alcan Cable, K-Line Insulators, CQRDA and FUQAC) whose financial support made this research possible.

VIII. References

[1] G.Poots, "Ice and Snow Accretion on Structures" Research Studies Press LTD, 1996,p.2
[2] IEC (CEI) 60826. "Design Criteria of Overhead Transmission Lines", 2003, p.173.
[3] Haykin, S. "Neural Networks-A Comprehensive Foundation", Prentice-Hall, New York, 1999.
[4] Chester, M., "Neural Networks, A Tutorial", Prentice Hall, Englewood Cliffs, NJ, 1993
[5] Duda, Richard O., Stork, David G., Hart, Peter E., "Pattern classification", New York, Toronto: Wiley, c2001.

[6] Electric Power Research Institute. Transmission line reference book: Wind-induced conductor motion, EPRI Research Project 792, Palo Alto, CA, USA, 1979.