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Impedance Identification of Integrated Power System Components Using Recurrent Neural Networks.

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***Abstract*—Impedance characteristics of shipboard power systems provide important information for studies on system stability and integration. Existing injection based impedance measurement techniques require multiple tests on the system to obtain characteristics over wide frequency ranges. In this paper, Recurrent Neural Networks (RNNs) are used to model the small signal dynamics of power electronic systems based on a single test in which randomized signals are injected into the system. The trained RNN is then used to extract the small-signal impedances/admittances of the system. A number of tests have been carried out in simulation to verify the effectiveness of the proposed method.**

***Index Terms*—impedance measurement, recurrent neural networks, power electronics, stability**

I. Introduction

In modern naval shipboard power systems, high power density semiconductor devices and compact high power drives have enabled the use of Integrated Power System (IPS) architecture which can provide high system reliability, increased survivability, and sufficient redundancy. The developments in power electronic devices and their integration at all levels in the power system not only provide exceptional performance gain and enormous operational flexibility, they also pose great challenges. With multiple loads connected to the dc link in a dc zonal distribution system, the design and analysis of the power system has become a major issue due to increased dynamics and probable instability. The constant power operation capability of most power electronic converters often leads to negative impedance characteristic, which is a common cause for system instability [1].

For small-signal stability analysis, most research focuses on the impedance/admittance method that involves examining the Nyquist contour of the product of the source impedance and load admittance in a dc system [2]. In recent years, based on the impedance/admittance method, a variety of stability criteria and design approaches for both dc and three-phase ac systems have been proposed [3-4].

In the design, analysis and integration of these systems, it is often necessary to obtain the frequency-dependent impedances/admittances of a subsystem by experimentation. Several impedance extraction techniques for dc and ac systems have been proposed in recent years. To get the frequency-dependent characteristics by experimentation, periodic voltage or current perturbations are usually injected to the system while it is under operational power. Measurements of the perturbed system are then taken and processed to determine the impedance at a specific frequency. Several methods have been proposed for impedance measurement in high-power ac systems, including utilization of three-phase bridge converters, wound-rotor induction machines and three-phase chopper circuit [5-6]. An impedance measurement technique utilizing a line-to-line current injection chopper circuit was recently proposed [7], which has a simple structure and is much easier to implement compared with other methods. With the injection of either voltage or current perturbations, these techniques can determine the small-signal impedance/admittance of the subsystem at a certain operating point for a specific frequency. Some ac impedance measurement techniques require multiple injections at each frequency. The impedance measurement process is often very time-consuming, and requires that the system is in operation at a fixed operating point for a long period of time. The main disadvantages of this impedance measurement procedure include:

1. It takes a considerable amount of time to complete the injections for all the frequencies and take the measurements.
2. The operating point of the system may vary during the prolonged test procedure, which can lead to inconsistency in the measured system impedance characteristics.
3. The procedure only gives impedance information at the injection frequencies.

To solve these problems, the key point is to minimize the on-line injection time. In this paper, a novel impedance identification method is proposed. Instead of injecting perturbation signals to the system one frequency at a time, a randomized injection signal is employed, thus only one set of the voltage and current measurements is required. The captured signals are then used to train a Recurrent Neural Network in an off-line mode. Once the RNN is trained, it approximates the dynamic behavior of the system in the time domain, and can also generalize the system responses in the frequency domain. Perturbation signals of different

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frequencies are then fed into the trained RNN to determine its frequency responses, which are very close to those of the tested system, as demonstrated by simulation results.

II. Impedance Measurement with Injection

For the purpose of small-signal stability analysis, a power system can normally be divided into two halves at a common interface, with the two sides designated as the source and the load. Fig. 1 shows an example of a system used to illustrate the concept of impedance measurement in a dc system. Therein, a perturbation current is injected at the interface of the source and load. To determine the impedances of the two sides, current signals i_s and i_l, together with voltage signal v, are measured and recorded. The length of the recorded signals depends on the sampling frequency and the impedance frequency range. Let the injected current contain a single component of frequency f_i. Once the signals are obtained, a Fourier transform can be performed on them to extract the magnitude and phase information in the voltage and currents at the frequency f_i. The small-signal source impedance and load admittance at f_i can then be calculated using

$$Z_s(f_i) = -\frac{V(f_i)}{I_s(f_i)} \tag{1}$$

and

$$Y_l(f_i) = \frac{I_l(f_i)}{V(f_i)}, \tag{2}$$

where $V(f_i)$, $I_s(f_i)$ and $I_l(f_i)$ are complex numbers and denote the Fourier transform results of the signals. To obtain the impedance/admittance of the system at another frequency, the current injection should be adjusted and a new set of measured signals are needed for the calculation. In practice, it is often necessary to perform the injection test dozens of times to create an impedance curve over the desired frequency range.

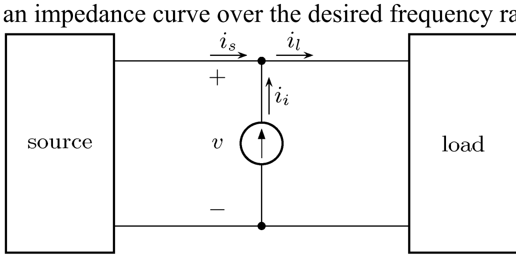

Fig. 1. Impedance Measurement in dc/single-phase system.

The impedance measurement of a three-phase ac system is more complicated. As shown in Fig. 2, a three-phase perturbation current is injected into the system. The actual injection device is usually not a three-phase current source. For low-power systems, three-phase power amplifiers can be used. For high-voltage or high-power systems, wound-rotor induction machines or switching circuits are often used. In many cases the system is very likely phase-wise unbalanced, and mutual coupling may exist between the phases. So the impedances/admittances are represented by 3×3 matrices at different frequencies. Furthermore, if the source contains synchronous generators, the impedance of each phase is also time-varying. In [5], these problems are solved by transforming the *abc* quantities into the synchronous *d-q* reference frame. At steady state, the source impedances and load admittances are related to the voltages and currents by

$$\begin{bmatrix} V_q \\ V_d \end{bmatrix} = \begin{bmatrix} Z_{qqS} & Z_{qdS} \\ Z_{dqS} & Z_{ddS} \end{bmatrix} \begin{bmatrix} I_{qs} \\ I_{ds} \end{bmatrix} \tag{3}$$

and

$$\begin{bmatrix} I_{qL} \\ I_{dL} \end{bmatrix} = \begin{bmatrix} Y_{qqL} & Y_{qdL} \\ Y_{dqL} & Y_{ddL} \end{bmatrix} \begin{bmatrix} V_q \\ V_d \end{bmatrix} \tag{4}$$

where all the variables are complex quantities corresponding to a specific frequency.

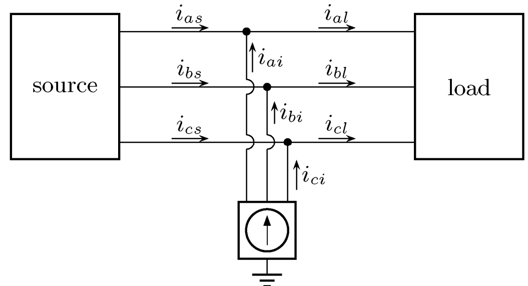

Fig. 2. Impedance Measurement in three-phase system.

III. Impedance Identification with Recurrent Neural Networks

A. Recurrent Neural Networks

Artificial neural networks have been proven to be an effective tool in system modeling [8-9]. Unlike the widely used multilayer perceptron feedforward network where data flow is only in the forward direction, recurrent neural networks are feedback networks in which the present activation state is a function of the previous activation state as well as the present inputs. The feedback mechanism provides a memory to the RNNs so that they are capable of modeling systems with internal dynamics. The capability makes this type of neural networks superior to conventional feedforward neural networks in modeling dynamic systems.

The block diagram of a two-layer RNN with voltages as input and one current as output is shown in Fig. 3, where m neurons are used in the hidden layer. The topology is similar to that of a feedforward network, except that the outputs of the hidden layer are used as the feedback signals. Although not shown in the diagram, there is a one-step time delay in the feedback path so that previous outputs of the hidden layer, also called the states of the network, are used to calculate new output values. The input voltages, together with the feedback vector **d** from the hidden layer, are first passed through an input weight matrix **W** to every node in the hidden layer.

A sigmoid function is then used to calculate the hidden layer decision vector **d**.

$$d_k(t) = \mathrm{sgm}(s_k(k)) \tag{5}$$

and

$$s_k(t) = \sum_{i=1}^{l} w_{ik}^{(1)} x_i(t) + \sum_{j=1}^{m} w_{jk}^{(2)} d_j(t-1) \qquad (6)$$

where $\boldsymbol{x}(t)$ is the input vector, $\mathbf{W}^{(1)}$ is the weight matrix associated with the inputs and hidden neurons, and $\mathbf{W}^{(2)}$ is the weight matrix associated with the states and hidden neurons. The hyperbolic tangent sigmoid function is selected as the nonlinear activation function sgm(·) of the hidden layer because it can provide a bipolar signal to the output.

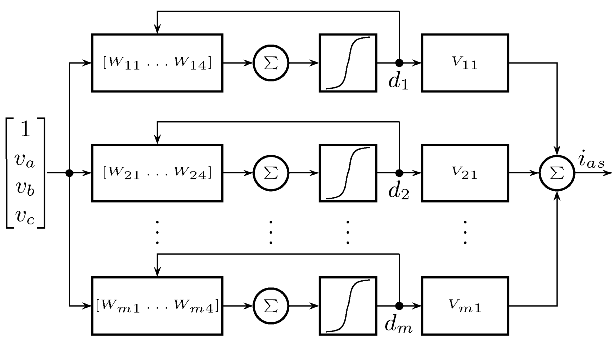

Fig. 3. Two-layer RNN architecture.

The output of the RNN is computed with output weight matrix **V**. Linear neurons are used in the network's output layer. The outputs are determined by

$$y_k(t) = \sum_{i=1}^{m} v_{ik} d_i(t) \qquad (7)$$

where **V** is the weight matrix associated with the hidden neurons and the outputs.

Various algorithms exist for the training of RNN [10-13]. The backpropagation algorithm can be used to modify the weight matrices **W** and **V** such that the error between the desired current signal and the RNN estimated current output is minimized. Fig. 4 shows a diagram of the training scheme, where the inputs to the system are three-phase voltages, and the outputs are currents. Evolution-based stochastic algorithms such as genetic algorithm (GA) and particle swarm optimization (PSO) method can also be used to train RNNs.

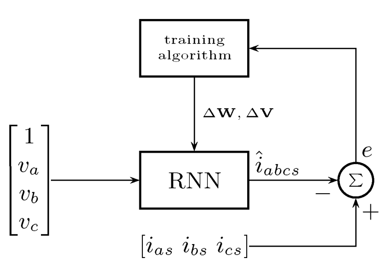

Fig. 4. Back-propagation training scheme of RNN.

B. RNN-based Impedance Identification

To identify the frequency response of a system, the proposed method also relies on current or voltage injection as used in previous measurement techniques. However, instead of sinusoidal signals, a sampled uniform random signal is injected to perturb the system with a wide range of frequencies. The randomness of the injected signal ensures that a relatively equal distribution of energy spreads over all frequencies so that the dynamic behaviors of the system can be characterized. Analog low-pass filters are needed to remove components at frequencies outside of the range of interest. The filters are also necessary to prevent aliasing when the signals are sampled for digital processing. The sampling frequency of the injection signal is determined based on the frequency range over which the impedance/admittance is to be measured. The magnitude of the injection signal should be large enough so that the effects of measurement errors are negligible.

With such an injection signal, only one time of on-line injection is needed, and the rest of the identification process only requires off-line calculations. The measured voltage and current signals are first normalized so that they are in the range of -1 to 1 to be used as the input and target output to train a RNN. Either the voltage or the current can be used as the input, and the other as the output. In the following description, it is assumed that the voltage signals are the input and the current signals are the target output.

Since both the source and load signals are measured, two independent RNNs are needed to model the two subsystems. The number of hidden layers and the number of neurons in each layer are related to the complexity of the system. Generally high-order nonlinear systems require more layers and neurons to model, and the number of feedback states in the RNN should be at least higher than the order of the system. However, as the number of hidden neurons increases, so does the computational effort required to train the network. Thus a trade-off has to be made between model accuracy and time required to complete the RNN training.

Initially the weight matrices of the RNN contain random numbers. To train the RNN with backpropagation algorithm, the recorded and normalized input data points are fed to the network one by one. With each input point, (5)-(7) are used to update the internal states and calculate the output. The output of the network is then compared with the target output data, which are also recorded and normalized test signals. Elements in the weight matrices **W** and **V** are then adjusted based on the output errors. When the next input data point is fed to the network, the updated weights and states are used to calculate the new states and output, and errors are again backpropagated to adjust the weights. This process starts all over when the calculation on the last input data point is finished.

It should be noted that the initial states of the RNN are reset to zero each time the first input point is used. This is done because only the weight matrices are updated during the backpropagation training process and it is generally not possible to determine the internal states of the power system at the beginning of the test. Obviously the zero-initial-states assumption is not valid in most cases and will cause the RNN model to be less accurate. To minimize the effects of non-zero initial states, longer period of test data should be recorded and used in the training. Another approach is to use GA or PSO algorithms to train the network, and include both the weights and initial states in the chromosomes or particles.

A well trained RNN has the ability to approximate the time-domain dynamic responses of the system to different input voltage signals. To extract the frequency-domain information, simulated voltage signals are fed into the network to obtain its current output. The input voltages consist of a pure sinusoidal perturbation signal of a specific frequency f_i. The perturbation signal is used as an ideal small-signal source to obtain the response of the system at frequency f_i.

To minimize the effects of network initial states, the first portion of the input voltages and RNN output currents are truncated. The rest of the signals are then processed with Fourier transform to obtain the magnitude and phase information at the injection frequency f_i. The impedances of the system are determined in the same way as detailed in Section II. To obtain system impedances at other frequencies, the above calculation should be repeated with simulated voltage injection signals at these frequencies. The impedance identification process can thus be automated by feeding the trained neural network with signals of desired frequencies one at a time.

A significant advantage of the proposed method is that real perturbation signals only need to be injected to the hardware system once, and the rest of the impedance identification process is off-line, as shown in the flow chart in Fig. 5. The reduced test time makes it less likely for the system operating point to change during the test, so the impedances at different frequencies are more consistent. Also, the signals used for Fourier transform are free of noise and unwanted frequencies, because the input voltage is a simulated signal that contains ideal injection components. This avoids frequency leakage and helps increase the accuracy of the Fourier transform.

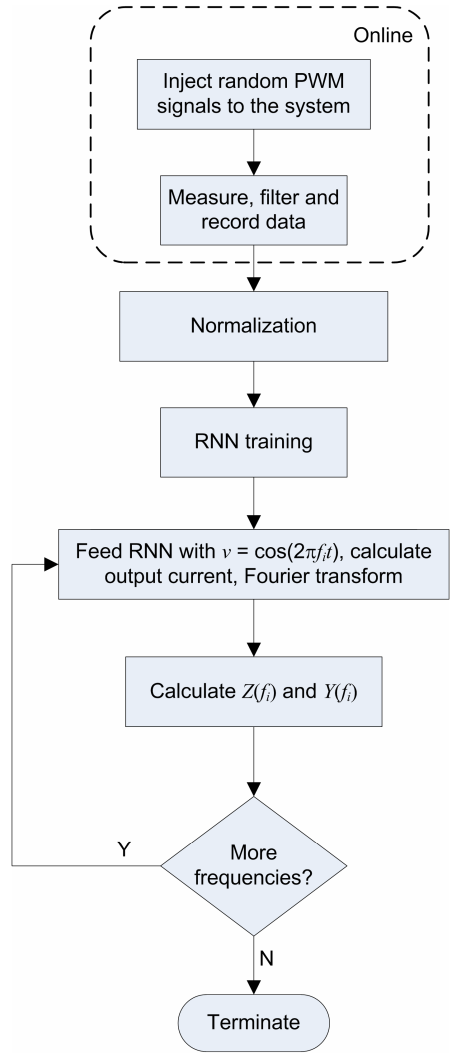

Fig. 5. Flow chart of the impedance identification process.

IV. Simulation Results

To demonstrate the effectiveness of the proposed method, the dc link interface of a rectifier-inverter-induction motor system is used for the dc test. The diagram of the system is shown in Fig. 6. To measure the impedance of the subsystem to the right of the injection point, both v_{dc} and i_{load} are recorded and saved.

The recorded signals are filtered to avoid aliasing, and sampled at a frequency of 10 kHz. The data is then normalized to be within the range from -1 to 1. A RNN is trained with the voltage data as input and current data as output. Fig. 7 shows the normalized dc-link voltage and load current.

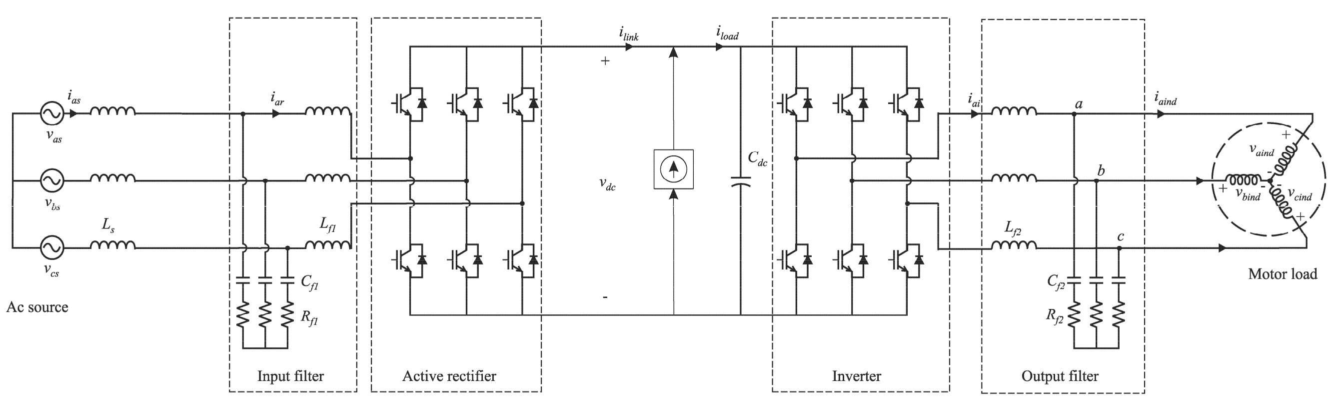

Fig. 6. Test system for dc impedance measurement.

The training of RNN uses the mean squared error as the convergence criterion. After 100 epochs of training, the network can output a signal that is very close to the measured load current. Further test shows that it can also approximate very well the current responses to other input voltages.

To determine the impedances of the inverter load, simulated voltage signals with 2% fixed-frequency perturbation are fed into the network. The frequency range of interest is from 10 Hz to 1000 Hz, with a 20 Hz interval. The output signals are then processed with an FFT, and impedances are readily obtained by (1). Fig. 8 shows the magnitude and phase angles of the load impedance as calculated according to the linearized model and as identified by the proposed method. It can be seen that the impedance magnitudes and phase angles match very well over the whole frequency range.

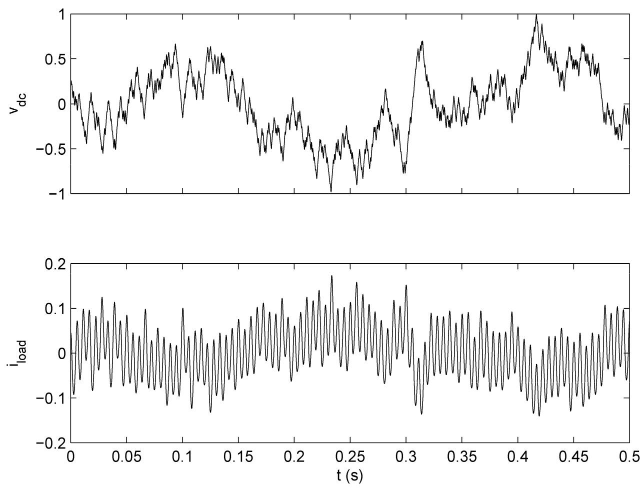

Fig. 7. Normalized dc voltage and load current used for RNN training

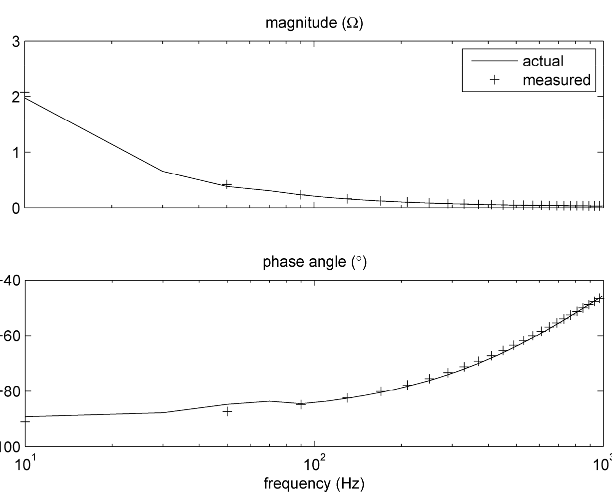

Fig. 8. Actual and measured impedances of the dc subsystem.

V. CONCLUSIONS

Impedance measurement of power components for stability determination is a common practice in shipboard power systems. In this paper, a novel technique for impedance identification is proposed. The technique is based on injecting a random current disturbance and using the results to train a recurrent neural network. The trained neural network is then used to obtain the impedance off-line. This method has the potential to reduce the on-line experimentation time. Simulation results demonstrate the ability of recurrent neural networks to learn source/load dynamic behaviors and identify frequency-dependent impedances/admittances. In addiction to applications in stability analysis, the proposed method can also be used to determine power network harmonic impedances, which is important for the designing of harmonic filters and prediction of system resonance.

VI. REFERENCES

[1] A. Emadi, A. Khaligh, C. H. Rivetta, et. al., "Constant power loads and negative impedance instability in automotive systems: definition, modeling, stability, and control of power electronic converters and motor drives," *IEEE Transactions on Vehicular Technology*, vol. 55, Issue 4, pp.1112-1125, July 2006.

[2] R. D. Middlebrook, "Input filter considerations in design and application of switching regulators," *IEEE Proceedings of IASAM*, October 1976.

[3] C. M. Wildrick, F. C. Lee, B. H. Cho, et. al., "A method of defining the load impedance specification for a stable distributed power system," *IEEE Transactions on Power Electronics*, vol. 10, issue 3, pp. 280-285, May 1995.

[4] S. D. Sudhoff, S. F. Glover, P. T. Lamm, et. al., "Admittance space stability analysis of power electronic systems," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 36, issue 3, part 1, pp. 965-973, July 2000.

[5] Y. L. Familiant, K. A. Corzine, J. Huang, et. al., "AC Impedance Measurement Techniques," in *Proc. IEEE International Conference on Electric Machines and Drives*, pp. 1850-1857, May 2005.

[6] M. Belkhayat and M. L. Williams, "Impedance Extraction Techniques for Dc and Ac Systems," in *Proceedings of the Naval Symposium on Electric Machines*, Philadelphia PA, December 2000.

[7] J. Huang and K. A. Corzine, "AC Impedance Measurement by Line-to-Line Injected Current," in *Proceedings of IEEE IAS Annual Conference*, October 2006.

[8] M. Rukonuzzaman, A. M. Zin, H. Shaibon, and K. L. Lo, "An application of neural network in power system harmonic detection," *Proceedings of the IEEE International Joint Conference on Neural Networks*, vol. 1, pp. 74-78, May 1998.

[9] J. Mazumdar, R. G. Harley, F. Lambert, and G. K. Venayagamoorthy, "Neural network based method for predicting nonlinear load harmonics," *IEEE Transactions on Power Electronics*, in press.

[10] D. J. Janson and J. F. Frenzel, "Training product unit neural networks with genetic algorithms," *IEEE Intelligent Systems and Their Applications*, vol. 8, issue 5, pp 26-33, Oct. 1993.

[11] R. Mendes, P. Cortez, et al., "Particle swarms for feedforward neural network training," *Proceedings of the 2002 International Joint Conference on Neural Networks*, vol. 2, pp. 1895-1899, May 2002.

[12] J. Salerno., "Using the particle swarm optimization technique to train a recurrent neural model," in *Proc. Ninth IEEE International Conference on Tools with Artificial Intelligence*, pp. 45-49, Nov. 1997.

[13] V. G. Gudise, and G. K. Venayagamoorthy, "Comparison of particle swarm optimization and backpropagation as training algorithms for neural networks," *IEEE Swarm Intelligence Symposium*, pp. 110-117, April 2003.