

## Background Information on our Neural Network–Based System of Leading Indicators

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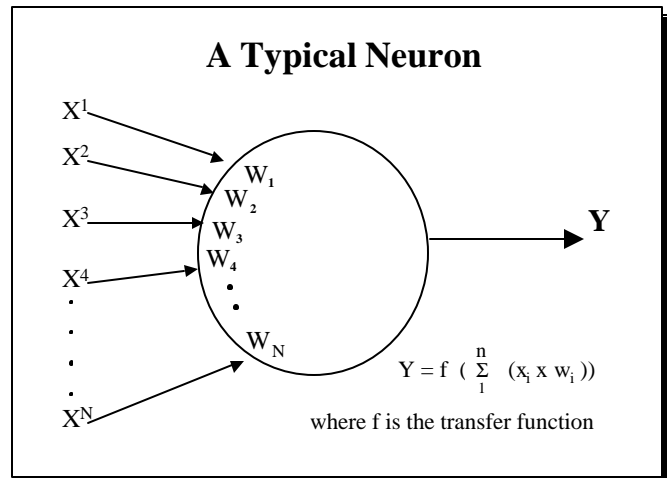
CIBCWM leading indicators of economic activity and inflation are designed to signal any notable change in trends in overall GDP growth and inflation. The indicators are based on Artificial Intelligence -- Neural Network technology. Neural networks have been used in various fields such as medicine and robotics for several years, but only recently have they made an impact as a serious business tool. In the financial sector, neural networks are mainly used for stock selection, stock ranking, credit analysis, risk assessment and asset allocation. Neural networks can be also utilized in both macro- and microeconomic analysis, with clear potential to improve the timeliness and quality of economic forecasting. This is especially true in cases where there is a significant non-linear relationship between the dependent and independent variables

### What are Neural Networks?

Neural network technology is an advanced computerized system of information processing. In many discussions they are credited with operating in the same way as the human brain. This is clearly an overstatement. Although loosely inspired by the structure of the brain, current neural network technology is far from being able to simulate even a simple brain function. Nevertheless, neural networks do offer a computational approach that is potentially very effective in solving problems which do not lend themselves to analysis by conventional means. The key difference between neural networks and other problem-solving methods is that neural networks in a real sense learn by example and modify their structure rather than having to be programmed with specific, preconceived rules. In other words, neural networks can be seen as a non-parametric statistical procedure that uses the observed data to estimate the unknown function.

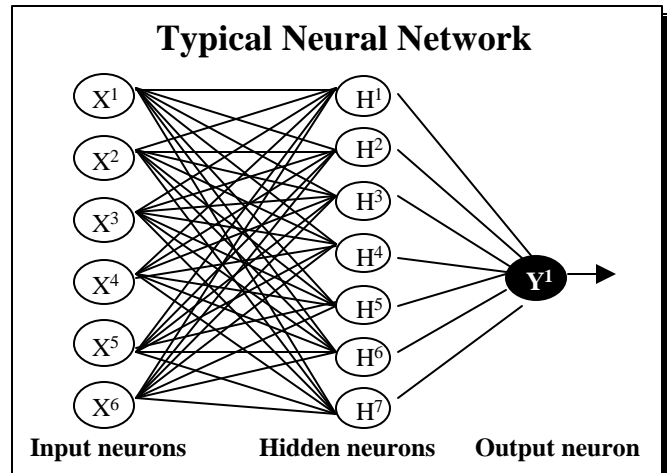
The base unit of any neural network is the neuron (processor). Each neuron is able to sum many inputs, whether these inputs are from a database or from other neurons, with each input modified by an adjustable weight (Chart 1). The sum of these weighted inputs is added to an adjustable threshold for the neuron and then passed through a modifying (transfer) function that determines the final output.

Chart 1



Neurons are arranged in several layers called input, hidden, and output layers (Chart 2). Simply put, the input layer is similar to a matrix of independent variables in a regression while the output layer is the dependent variable. The hidden layer is the series of relationships calculated in the network's training process. There is no theoretical limit on the number of hidden layers in a given network. Typically there will be one or two.

Chart 2



A simple way to look at the nature of the connection of the different neurons in the network is to focus on a single neuron (say  $H^1$  in Chart 2). This neuron receives “signals” from each one of the neurons in the input layer. For each case these signals are the input value of the independent variable, multiplied by a given weight. After receiving all the signals, neuron  $H^1$  sums them up. This weighted sum is its input. The output of this neuron (namely the signal that it submits to the output layer) is a nonlinear transformation of its input.<sup>i</sup> This process takes place simultaneously in each neuron in the network. In most cases there are no interconnections among neurons of the same layer, a fact that provides the network with a great potential for parallelism.

Most neural networks have some sort of training rule whereby neural networks learn from examples and exhibit some structural capabilities for generalizing and forecasting.<sup>ii</sup> During training, the neural networks program seeks to find a system of connective weighting among the layers that results in a minimum of error between the network’s outcome and the actual answer. Each outcome generated by the network is compared to the actual figure at any point in time. If the network gives the “correct” answer (an outcome that is close enough to the actual figure), no changes are made to the weights. If the network makes an incorrect prediction, the internal values of the neuron links are automatically adjusted via a training algorithm.<sup>iii</sup> Training continues until the network learns to make the correct prediction, at least to the user’s specified accuracy. If the relationship can be learned, a stable set of weights adaptively evolves and eventually will produce satisfactory answers for all the sample decisions of predictors.

## Neural Networks versus Econometrics

In theory, neural networks should be able to duplicate, and in some cases, exceed the performance of regression techniques. Neural networks can be seen as a wide class of flexible nonlinear regression and discriminant models, data reduction models and nonlinear dynamical systems. For the purpose of economic forecasting neural networks have some clear advantages over regression analysis:

- *Flexibility:* As opposed to a simple regression where linearity in parameters is imposed on the data, neural networks are non-linear in nature. As for non-linear econometrics procedures, while significant work has been done on non-linear minimization problems in applied mathematics, these, in most cases, require specific assumptions regarding the non-linearity structure of the investigated relationship. A neural network-based system does not require such prior knowledge. This characteristic enables the neural network approach to capture relationships with a higher degree of complexity.

- *Simplicity:* Given the non-parametric character of neural networks, no subject-domain knowledge is incorporated in the modelling process. This means, for example, that no prior knowledge and assumptions regarding the probability distribution of the data are needed when using neural networks. Such assumptions are necessary in regression analysis.

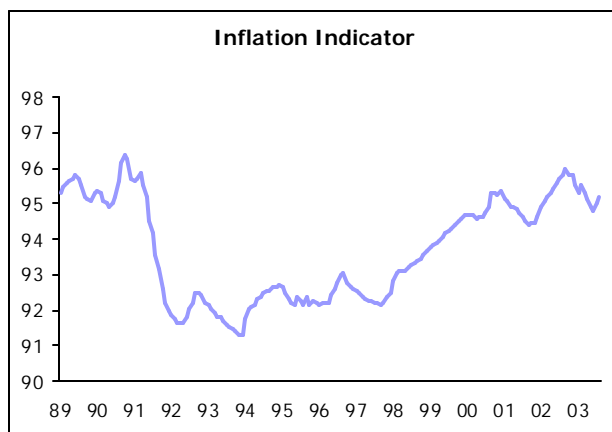
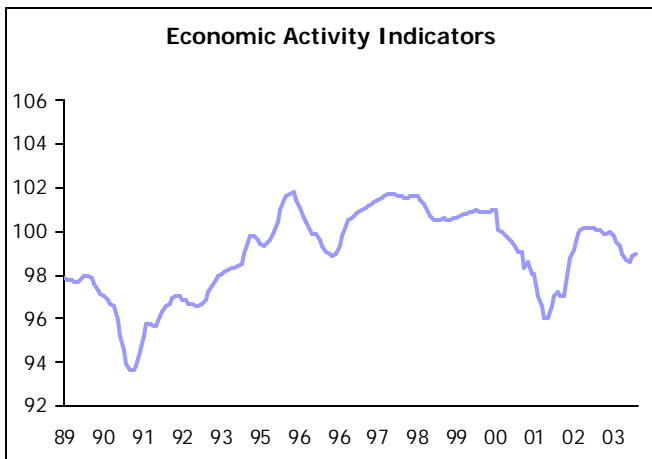
Disadvantages of neural networks compared to regression analysis include:

- *Interpretation:* In some cases, it can be difficult to interpret the output generated by a neural network. There is no straightforward measure of confidence, and sensitivity analysis is also more difficult.
- *“Black Box” Aspects:* As opposed to regression analysis, where the process of producing outcomes can be duplicated, a neural network is still, to some extent, a “black box”, as the process of generating the outcome is not explicitly stated.

## The CIBCWM Neural Network Indicators

EcoNet the leading Indicator of economic activity focuses on the real side of the economy. PriceNet looks at inflation and potential price pressures. The motivation to use Neural Network Technology to construct these indicators as opposed to an indexed-based forecasting systems is the following: First, index-based or fixed-weight systems are necessarily unsophisticated. They consist of various economic indicators summed, smoothed and indexed. The changes in the index serve as the forecasting tool. With neural networks, we are able to introduce a new sophisticated technique into the forecasting process. Second, using an index-based system presents practical problems regarding timeliness. For example, the requirement that final data be available typically meant that the February leading indicator would not be published until the middle of May. Using neural networks, it is possible to mix different months of data and put together a February indicator on February or early March.

The neural networks have been designed to be a guide to the future. Having trained the networks on the past, we are able now to put in the data corresponding to a particular month and create the current indicator you. The model was trained on a year-over-year percentage changes as opposed to absolute levels. The first step in building the model was to choose the output variable whose past behavior would be used to train the neural network system. In the case of economic activity, gross domestic product was chosen as the output neuron while for inflation, the output neuron chosen was inflation as measured by the consumer price index.



The next step was to choose appropriate economic indicators to forecast economic activity and inflation. For economic activity (EcoNet), the following indicators were chosen – U.S. leading indicators, consumer credit, exports, housing index, business/service employment, yield curve, Avg. manufacturing workweek, Canada-U.S. exchange rate, and the TSX index. For inflation (PriceNet), the following indicators were used – Avg. weekly wage, the Paasche import price index, real gross domestic product, the industrial product price index, the number of persons unemployed for four weeks or less, the number of persons unemployed 5-13 weeks, treasury bill yields, bond yields, the Canada-U.S. exchange rate, and growth in money supply (M2). This step is similar to the process economists employ in choosing inputs for regression models.

The next step was specifying the time lags for each variable. In this, neural networks provide a great deal of flexibility. The lag specifications were based on the specific nature of the relationship between a given input and the output (for example, whether a rise in import prices in March showed up as higher consumer inflation in June or in September). As well, practical considerations regarding data availability were taken into account.<sup>iv</sup>

When the model was specified, each network was ready to be trained. It is impossible to gauge how long the training process will take for any particular application, and whether or not any particular model is “trainable”. In the case of EcoNet and PriceNet, the initial models underwent training for up to 24 hours. Most software packages, however, provide information on an on-going basis, so the user always has a sense of how close the model is to converging.<sup>v</sup>

Some of the input variables were judged as too erratic to be of use in the model. For example, although various specifications of manufacturing shipments were tried as an input into EcoNet, none of them was found to be able to provide a stable model.

Testing is the final step in building a neural network. The real power of neural networks is evident when the trained network is able to provide good results for data which the network has never seen before, data that were not included in the training process. This set of observations is called the test data. A high correlation between the test data and the network prediction indicates that the model has not only been able to learn the nature of the economic relationships, but also has succeeded in generalizing the relationships and providing successful results. It is important to monitor the performance of the testing sample at different stages of the training process and stop the training at the point where the test sample provides the best result. (i.e. the highest R<sup>2</sup> figures, which suggest that the forecast error is at its minimum). In order to increase the probability of a stable model, a minimum of two test samples is required.

Of course, as in any other mathematical model, predicted outcomes can only be as good as the data used in the models. A neural network, like a traditional economic forecasting model, cannot foresee random events. An oil shock or a political crisis can overshadow the most careful projections. Neural networks, like regression models, should be thought as a forecasting tool to be used alongside other tools.

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## Notes

- i The non-linear specification used in our models was a sigmoidal (i.e. bounded above and below, but differentiable) function of the weighted sum of the inputs. This function is called the transfer function.
- ii "Generalization" refers to the process of calculating a stable set of weights which is consistent with the past relationship between the predictors and the output.
- iii The most widely used is the "Back-Propagation" training process which, simply put, allows the network's errors to be *fed back* through the network until they are reduced to an acceptable level.
- iv The data were converted to a year-over-year rate of change and in some cases smoothing procedures were used.
- v The software we used for developing the model was "BrainMaker Professional", developed by California Scientific Software (1992).

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