Masthead Logo

Journal of Transportation Management

Volume 21 | Issue 3 Article 4

10-1-2010

Using artificial neural networks for transport decisions: Managerial guidelines

Robert L. Cook
Central Michigan University, Robert.cook@cmich.edu

Lawrence O. Jenicke
Central Michigan University, Jenkilbj@cmich.edu

Brian Gibson
Auburn University, brian.gibson@auburn.edu

USING ARTIFICIAL NEURAL NETWORKS FOR TRANSPORT DECISIONS: MANAGERIAL GUIDELINES

Dr. Robert L. Cook
Central Michigan University

Dr. Lawrence O. Jenicke
Central Michigan University

Dr. Brian Gibson
Auburn University

ABSTRACT

One information technology that may be considered by transportation managers, and which is included in the portfolio of technologies that encompass TMS, is artificial neural networks (ANNs). These artificially intelligent computer decision support software provide solutions by finding and recognizing complex patterns in data. ANNs have been used successfully by transportation managers to forecast transportation demand, estimate future transport costs, schedule vehicles and shipments, route vehicles and classify carriers for selection. Artificial neural networks excel in transportation decision environments that are dynamic, complex and unstructured. This article introduces ANNs to transport managers by describing ANN technological capabilities, reporting the current status of transportation neural network applications, presenting ANN applications that offer significant potential for future development and offering managerial guidelines for ANN development.

INTRODUCTION

In today's intensely competitive and dynamic global market, serviced by complex, global supply chains, improving the quality of transportation management decisions will result in significant increases in corporate profitability and customer service performance (Holcomb and Manrodt, 2007). As the largest logistics cost component, representing 62.8 percent of U.S. total logistics costs in 2010 (Wilson, 2011), transportation can affect profits significantly. Additionally, transportation management decisions affect the length and variability of material and finished goods delivery leadtimes which directly impacts operational and customer service performance.

Improving transportation management decision quality in the current complex, turbulent supply chain environment is a substantial challenge. It is not surprising that many transportation managers in recent years have adopted transportation management systems (TMS) (Griffis and Goldsby, 2007). These systems are information technologies used to plan and execute transportation operations (Coyle, et al., 2009).

One information technology that may be considered by transportation managers to be included in the portfolio of technologies that encompass TMS is artificial neural networks (ANNs). These artificially intelligent computer decision support software provide solutions by finding and recognizing complex patterns in data. Based on a computing model similar to the underlying structure of the human brain, ANNs share the brain's ability to learn or adapt in response to external inputs. When exposed to data, ANNs discover previously unknown relationships in the data (Kamruzzaman et al., 2006; Smith and Gupta, 2000).

ANNs have been used successfully by transportation managers to make decisions in a number of critical decisions areas including: transport demand forecasting, transportation cost estimation, vehicle and shipment scheduling, vehicle routing and carrier classification and selection. In addition, when faced with challenging decision environments, transport managers who utilized ANNs were rewarded with excellent results (Duliba, 1990). For example, Victory Shipping Company employed an ANN to route leased container shipments from Shanghai, China to global destinations using a myriad of databases. The ANN reduced costs and achieved 100 percent on-time delivery (Lau et al., 2004). Also, by using an ANN to select containers to inspect, Chinese customs inspectors were able to maintain the same level of security while decreasing the number of container inspections to only 30 percent of the pre-ANN total (Hua, Li and Tao, 2006).

This article introduces ANNs to transport managers by describing ANN technological capabilities, reporting the current status of transportation neural network applications, presenting ANN applications that offer significant potential for future development and offering managerial guidelines for ANN development.

ANN TECHNOLOGICAL CAPABILITIES

Artificial neural networks are capable of performing several generic tasks that transport managers perform. These generic tasks involve interpreting, predicting, diagnosing, designing, planning, monitoring, repairing and controlling

When transport managers must perform any of these generic tasks in a very challenging decision environment, ANN technology may be very useful. Specifically, artificial neural networks excel in transportation decision environments that are: (1) dynamic- involving data that is incomplete, non-linear and/or rapidly changing (e.g. forecasting demand for transportation (Nijkamp, Reggianni and Tsang, 2004)); (2) complex- involving numerous alternatives, large amounts of data and many variables (e.g. designing routes for pickup and delivery (Ghaziri and Osman, 2006)); and (3) unstructured- involving variables that are both quantitative and qualitative (e.g. selecting a third party transportation partner). In contrast, traditional TMS decision support tools such as linear regression, mathematical optimization and linear programming are better suited to transport decision environments where: (1) data is linear, less dynamic and more complete and (2) there are fewer variables that are all quantitative in nature.

ANNs excel in very challenging transportation decision environments because they possess the following capabilities:

- **Reaches conclusions in problem domains that are not well understood**: enables managers to solve problems when no exact model of the underlying process exists (e.g. using an ANN to forecast European inter-regional truck freight flows for food and chemicals (Nijkamp et al., 2004));

- **Rapid knowledge acquisition**: enables managers to leverage numerous, large, existing databases to solve problems (e.g. an ANN was used to forecast VLCC freight rates for 3, 6, 9 and 12 month periods using numerous large databases involving: demand for oil transport, crude oil pricing, time charter rates, and crude oil production among others (Lyridis et al., 2004));

- **Rapid processing and response**: enables managers to receive decision support quickly despite the dynamic, complex, unstructured nature of the data and problem environment (e.g. an ANN is being used to control a gasoline engine fuel-air ratio between cycles to decrease NO_2 emissions (Editor, The Engineer, 2004)); and

- **Learns from previous applications**: enables managers to receive better solutions over time (e.g. an ANN learns and makes better decisions over time as it schedules daily assignments of inland barges to pusher tugs at a loading port and provides decision support to dispatchers when changes are necessary (Vukadinovic et al., 1997)).

TABLE 1
GENERIC TASKS PERFORMED BY ARTIFICIAL NEURAL NETWORKS

Task	Definition	Potential Application
Interpreting(classifying)	Infer situation description from observations	Classifying carriers for consideration in a carrier selection decision
Predicting (forecasting, estimating)	Infer likely consequences of given situations	Forecasting transportation demand in a dynamic market
Diagnosing	Infer malfunctions from observations	Diagnosing vehicle malfunctions from vehicle operating data
Designing	Configure objects under constraints	Designing facility locations (network design) and optimizing routes
Planning	Designing actions	Optimizing scheduling of vehicle arrivals/loading at facilities
Monitoring	Compare observations to plan vulnerabilities	Monitoring vehicle/pipeline operations
Repairing	Prescribe malfunction remedies and plans to implement remedies	Prescribing vehicle repairs that are timely and cost effective
Controlling	Interpret, predict, repair and monitor system behavior	Controlling engine performance for improved energy use

ANN Advantages and Disadvantages

The application of ANN technology to transportation management decision making may result in significant improvements in transportation effectiveness and efficiency when compared to traditional TMS mathematical tools. Examples of potential improvements include the following:

- **More effective decisions**: In complex operating environments, ANNs can provide better scheduling and routing of shipments (Schwardt and Dethloff, 2005) and better monitoring of operations (Rahmat et al., 2010);

- **Faster response**: In complex operating environments, ANNs can prescribe flight corrections in seconds to help pilots land aircraft during in-flight emergencies (Corder, 2004);

- **Improved accuracy**: In unstructured environments, ANNs can provide more accurate transport demand forecasts (Nam et al., 1995), more accurate price forecasts (Lyridis et al., 2004) and more accurate cost estimates (Williams, 2002); and

- **More efficient decisions**: In dynamic environments, ANNs can design more cost efficient loading schedules (Zeng and Yang, 2009).

There are some drawbacks to developing and using neural networks. Some disadvantages of ANNs are as follows (Kamruzzaman et al., 2006; Bigus, 1996):

● **No explanation of solution**: ANNs will not provide an explanation of the functional relationships among the variables involved;

● **Large data preparation effort**: 50 to 75 percent of development time is spent accessing, cleansing and coding data for use by the ANN; and

● **Training ANNs can be challenging**: Usually, an ANN is trained for a specific problem and for some complex problems might require hundreds of iterations before it is sufficiently trained.

Despite these drawbacks, ANN development for use in transportation management has grown in the last two decades.

ANN TRANSPORTATION APPLICATIONS

In the past twenty years, numerous ANNs have been developed and used to improve transportation management decisions. In fact, ANNs have been applied effectively to numerous transportation areas including: transport planning, operations, operations support, international transportation, transport equipment manufacturing, infrastructure development, transport energy and security. Table 2 provides a list of several recent ANN applications.

Current Applications

The leading transportation management category for ANN applications is transport operations. The primary focus of operations applications has involved vehicle or shipment scheduling and routing. Transport operations support ANNs have been primarily developed to monitor vehicle operations, detect vehicle operational malfunctions and support vehicle repair. Transport planning and international transport ANNs have focused on forecasting applications in three areas: (1) transport demand forecasts (e.g. global, country, regional, local, and modal); (2) transport rate forecasts (e.g. freight rates, monetary exchange rates); and (3) transport project cost forecasts (e.g. long-term construction projects such as roads, building, and bridges). Transport equipment manufacturing ANNs have supported various aspects of vehicle production while transport infrastructure development ANNs have focused on forecasting costs. Transport energy ANNs have been developed to forecast fuel demand/consumption and improve vehicle energy use. Finally, transport security applications have addressed border, transport asset and shipment security.

Future Applications

There are many significant opportunities to utilize ANN technology to improve transportation effectiveness and efficiency given the dynamic, complex, and unstructured decision environment often facing transportation managers. Table 1 provides a potential transportation application for each generic task. In addition, the following set of more detailed applications is provided to illustrate the significant opportunities for future ANN development.

Fuel Price Forecaster: An ANN may be developed to forecast future gasoline or diesel fuel prices to help transportation managers develop fuel procurement strategies and serve as an input to transportation planning. The neural network could analyze data such as: global fuel consumption patterns, fuel production and inventory levels, fuel production capacities, risk of supply shortage due to global events/disasters, and pricing data to predict future fuel prices. A fuel price forecast ANN could enable managers to develop effective and efficient transport plans.

Global Route Assessor: An ANN may be developed to assess a proposed global shipment route to determine if it is viable. Factors considered could include likely leadtime length and variability; expected vehicle operating costs; and likely risk factors such as natural disasters, piracy, terrorism, and political unrest among others. A global route assessment ANN could enable managers to select global routes that are efficient and sustainable.

TABLE 2
CURRENT TRANSPORTATION APPLICATIONS

Category	Transportation Neural Networks
Transport Planning	Predicts global requirements for logistics expenditures (Bowersox et al. 2003 Predicts individual country logistics expenditures (Rodriques et al. 2005) Predicts regional Europe road food & chemical commodity freight flows (Nijkamp et al. 2004) Predicts oil tanker(VLCC) spot freight rates for specific routes (Lyridis et al. 2004) Predicts short-term traffic flow for Hong Kong to improve city planning (Lam et al. 2006) Predicts vehicle travel time on a congested 17 mile 2 lane highway (Innamaa, 2005)
Transport Operations	Schedules vessels to optimize port capacity utilization (Lokuge and Alahakoon, 2007) Predicts unexpected events to improve aircraft container loading/scheduling (Lau et al. 2004) Schedules daily assignment of barges to pusher tugs at the port (Vukadinovic et al. 1997) Designs routes for pickup delivery from customers from 1 site (Ghaziri and Osman, 2006) Designs vehicle routes among a fixed set of bus stops (Creput and Koukam, 2007) Designs routes from 1 location to multiple customers (Schwardt and Dethloff, 2005) Identifies facility locations and assigns customers to a specific facility (Aras et al. 2006) Prescribes flight correction to help pilot land aircraft during in-flight emergency (Corder, 2004) Helps simulation model schedule container loading at terminals (Zeng and Yang, 2009) Controls isolated road intersection traffic light changes & traffic flow (Teodorovic et al. 2006) Improves outcomes of a shipper negotiation with a freight forwarder (Rau et al. 2006)
Transport Operations Support	Predicts part failures and provides inspection schedules for aging aircraft (Luxhoj et al. 1997) Detects railcar bearing defects from shock impulse data (Editor, 1996) Improves monitoring of solid particles flow in a pipeline (Rahmat et al. 2010) Monitors oil platform leak detection systems on submerged oil transfer lines (Harrold, 1998) Predicts vehicle downtime (Wang, Chen and Bell, 2005) Predicts bus equipment/part failure rates and resulting repair costs (Bellandi et al. 1998)
International Transport	Identifies critical customer services desired by ocean freight shippers (Durvasula et al. 2007) Identifies import shipments to inspect for Chinese custom inspectors (Hua, Li and Tao, 2006) Predicts daily exchange rates for US dollar with Euro and Canadian dollar (Jamal, 2005) Predicts airline passenger traffic for flights between US and S. Korea (Nam et al. 1995) Predicts Thailand's rice export quantity (Co and Boosarawongse, 2007) Estimates political risks/predicts cost of intl construction projects (Al-Tabtabai and Alex, 2000)
Transport Equipment Manufacturing	Monitors quality of principal components used in auto body assembly (Jang and Yang, 2001) Estimates unit manufacturing cost of a new type of auto disk brakes (Cavalieri et al. 2004) Identifies 3D weld seams in ship blocks during hull assembly process (Yoo and Na, 2003)
Transportation Infrastructure Development	Predicts pavement stress from truck radial-ply & bias-ply tires-FHA study (DeGaspari, 1999) Predicts completed cost of competitively bid highway projects for NJ DOT (Williams, 2002) Predicts state DOT highway construction project costs and duration (Hassanein, 2006)
Transport Energy	Forecasts global consumption of non-fossil fuel energy (Ermis et al. 2007) Forecasts national transport energy demand (Murat and Ceylan, 2006) Predicts fuel consumption of a Boeing 757 aircraft (Stolzer and Halford, 2007) Controls gas engine fuel-air ratio between cycles to decrease NO_2 emissions (Editor, 2004)
Transport Security	Designs packaging for products in transit to minimize shock damage (Somchai et al. 2000) Detects explosives in baggage staged for loading onto aircraft (Glatzer, 1992) Predicts induced voltage on gas pipeline from nearby transmission lines (Al-Alawi et al.2005)

Carrier Selector: An ANN may be developed to analyze alternative transportation providers and classify potential providers to aid transportation managers in the selection of a carrier. The ANN could analyze a wide range of data pertaining to the carrier evaluation including: customer service and cost goals, prices, service capabilities for moving and storing products, quality of service provided, level of information technology, management experience and capabilities, cultural fit and financial stability among others. A carrier selection ANN could enable managers to select an efficient and effective carrier.

Global Production Site Selector: An ANN could be developed to analyze alternative plant site locations to support transportation managers in determining optimum production site locations. The ANN could analyze data regarding the following areas to aid managers in site selection: material source and market locations, labor and transportation availability and cost, import-export tariffs, monetary exchange rates, government risk, government policies and taxation, labor quality, trends in foreign investment, and energy utility support among others. A global production site selection ANN could enable managers to select optimum sites.

ANN MANAGERIAL IMPLICATIONS AND DEVELOPMENT GUIDELINES

This section provides guidelines to assist transportation managers in ANN development. The ANN development process consists of five stages: project planning, application selection, design, development and implementation.

Project Planning

A project plan should be developed to formalize the project and guide the development team through the remaining stages of the development process. A project plan should include a description of the project goals, resources required, benefits, development stages, costs, and time schedule. Large projects should have a champion and be fully supported by top management.

The resources required to develop a neural network should be identified and their availability and cost determined. Typical resources include: a knowledge engineer, experienced supply chain managers, problem domain data and appropriate hardware and software.

A productivity analysis should be performed to determine the expected return on investment for the selected application. The initial application should yield easily demonstrated, measurable and quantifiable benefits such as faster decision response time, lower error rates, or more effective and efficient transportation decisions.

Application Selection

A potential ANN application should have the following characteristics (Kamruzzaman et al., 2006; Bigus, 1996):

- Problem area data are non-linear;
- Problem area knowledge is incomplete;
- Problem area knowledge is uncertain (dynamic/ever-changing);
- Problem area data are large and involves many variables;
- Problem area variables are quantitative and qualitative;
- Problem area variable relationships are not well-defined;
- Applying regression, mathematical optimization and linear programming provides unsatisfactory solutions; and
- Applying expert systems or case based reasoning provides unsatisfactory solutions.

In addition, the goal of the ANN application should be to perform one of the generic tasks listed in Table 1 such as predicting (e.g. forecasting tank truck demand).

Design

A major aspect of ANN design involves selecting an ANN model that fits the specific application selected in the previous step. Three of the better known ANN models that are useful for transportation ANN development are: multilayered feedforward model (MF), optimization model, and self-organizing model (SO) (Smith and Gupta, 2000).

An overwhelming majority of transportation ANNs have been developed utilizing an MF model with a backpropagation learning rule. MF has broad applicability to many generic transportation tasks including: classifying, predicting, and modeling non-linear functions pertaining to diagnosing, designing, and monitoring among others.

The MF model consists of a multi-layered network of artificial neurons plus an adjustment algorithm (see Figure 1). The primary building block of the MF ANN is the artificial neuron (see Figure 2). Each neuron receives weighted inputs and sums them. Then, the summed value is fed to the neuron's on-off switch. If the summed value is greater than the threshold value, the neuron fires ... sending a weighted output to succeeding neurons in the network. However, if the summed value is less than the threshold value, the neuron does not fire.

As an example, if the MF ANN depicted in Figure 1 was being developed to forecast U.S. tank truck demand for 2012, transport managers would feed a series of weighted inputs (e.g. data from previous years such as demand for oil transport, crude oil production, crude oil prices) into the neural network. Some neurons would fire providing weighted outputs to other neurons. Some of the neurons receiving the weighted output would fire, others would not. Ultimately, actual outputs (demand forecasts for previous years) would be determined and compared to the desired outputs (actual demand in previous years) given the specific set of inputs. An error signal (forecast error) would be generated and fed through an adjustment algorithm which is used to train the ANN. The adjustment algorithm would direct the ANN to adjust some neuron weights and threshold values so that during the next iteration, the forecasts would be closer to the actual demands (learning). After much iteration, the ANN error signal (forecast error) would be small enough to be acceptable to management. At that point, the ANN has been trained and can be used to forecast tank truck demand for 2012 (Behara et al., 2002; Bigus, 1996).

A second model is principally used to solve optimization problems. As a result, the optimization model (e.g. Hopfield) is very useful in designing, planning, and control tasks. Like the MF model, the optimization model involves a set of inputs and known outputs and supervised learning (training).

A third model involves a self-organizing neural network. SO models are primarily used as a clustering technique. Therefore, SO models are developed to perform classification tasks. The primary difference between the SO model and models discussed previously is that learning is unsupervised because the desired outputs are unknown. The SO model identifies previously unknown patterns in data. Potential applications include identifying new transport market segments or new vehicle routes.

Another major aspect of ANN design involves the selection of a neural network software development tool. Software development tools include: (1) computer languages such as C or C++, that allow significant design flexibility but result in long development time and (2) specialized neural network software development tools that allow rapid prototyping, facilitate ANN training and provide a platform for operations but limit design flexibility to a degree. There are many software development tools available commercially. Table 3 displays a sample of available tools that range in price from thousands of dollars to zero. Some software providers offer free downloads of sample packages so that

FIGURE 1
ARTIFICIAL NEURAL NETWORK

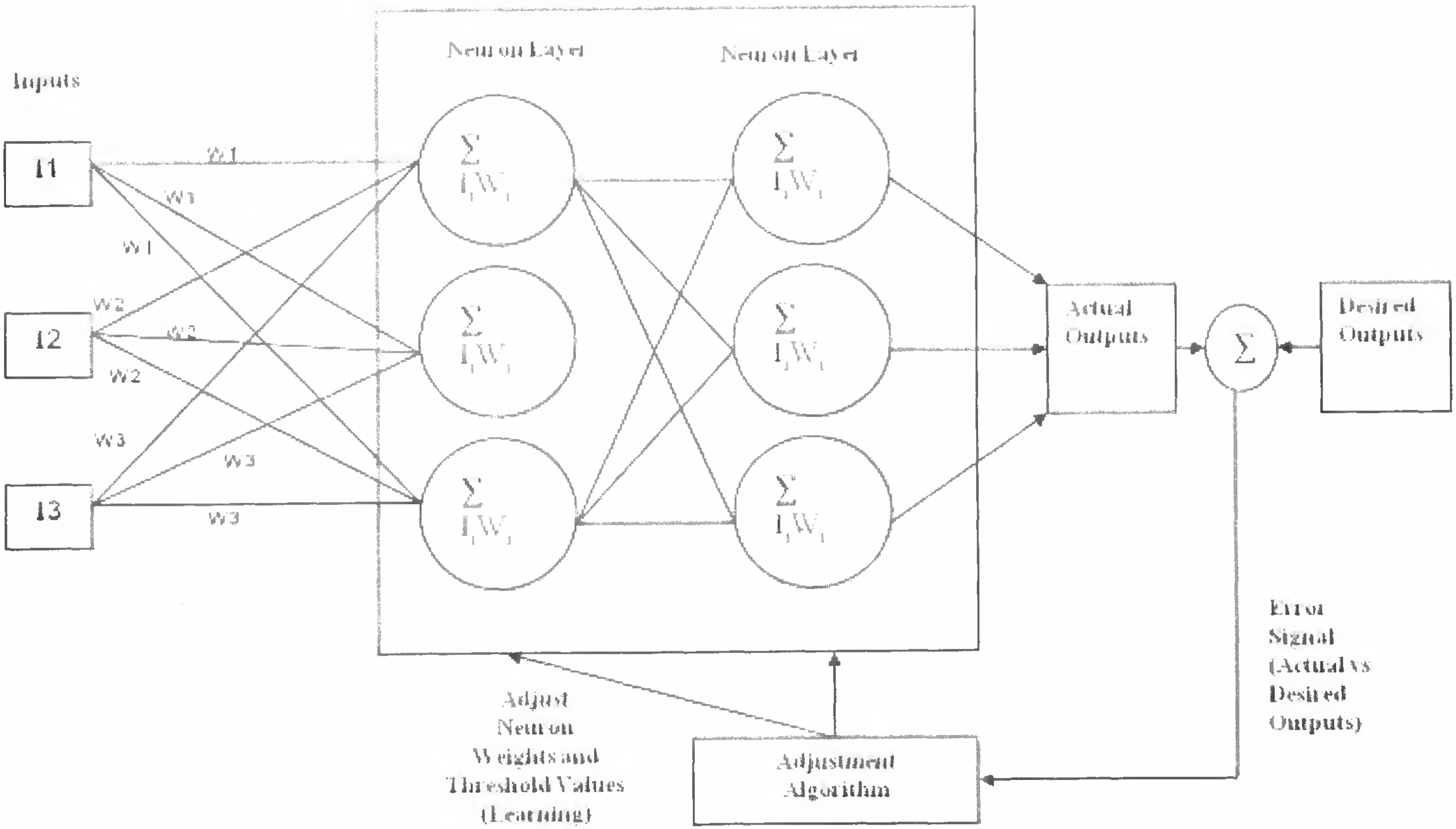

FIGURE 2
ARTIFICIAL NEURON

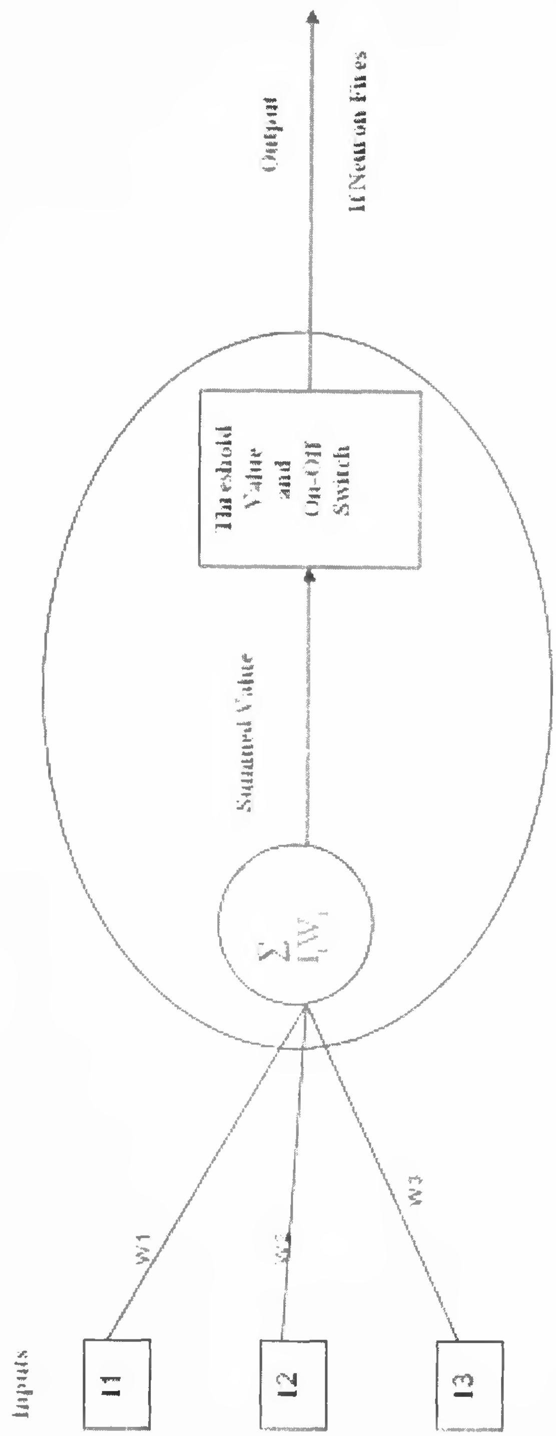

TABLE 3
REPRESENTATIVE ARTIFICIAL NEURAL NETWORK DEVELOPMENT TOOLS

Company/E-Mail	Software Name	Price as of 7/20/11	Generic Tasks
Alyuda www.contacts@alyuda.com	Neuro Intelligence	$497-$4,970	Classification, prediction, function modeling
California Scientific sales@calsci.com	BrainMaker Professional	$795	Classification, prediction, network design
NeuraWare www.neuralware.com	NeuralWorks Professional II/+	$2,495-$4,995	Classification, prediction, function modeling
NeuroDimension, Inc. www.info@nd.com	NeuroSolutions	$295- $2,495	Classification, prediction, qulaity control
NeuroXL support@neuroxl.com	PredictorClusterizer	$49.95and up	Classification, prediction, pattern recognition
Palisade www.sales@palisade.com	NeuralTools Standard	$495	Classification, prediction, control
Peltarion www.info@peltarion.com	Synapse	$1,419	Classification, prediction, function modeling
Runtime Software Support europe@runtime.org	Pythya	Free	Classification, prediction
Statsoft info@statsoft.com	Statistica Neural Networks	varies	Classification, prediction, monitoring, control
The Mathworks www.mathworks.com	Neural Network Toolbox	varies	Classification, prediction, function modeling
Ward Systems Group, Inc. sales@wardsystems.com	AI Trilogy	$1,395	Classification, prediction, function modeling, optimization

potential users can interact with the tool prior to purchase.

Development

Once an application has been identified and an ANN model and software development tool selected, ANN development can start. Two critical aspects of ANN development involve data preparation and network training.

Data preparation There are two basic data preparation tasks to perform. The first task is to cleanse the data of inaccurate values, missing data or other inconsistencies. The second task is data representation. Most neural networks accept input values in the range of 0 to 1 or -1 to +1. Therefore, data representation must fit these parameters (Kamruzzaman et al., 2006; Bigus, 1996).

Most data can be classified as one of three types: continuous numeric values, discrete numeric values or symbolic values (Kamruzzaman et al., 2006; Bigus, 1996). For continuous numeric values, the most common representation approach is data scaling. For example, data that has a range of values from 0 to 100 can be linearly scaled from 0.0 to 1.0 so that .3 represents a value of 30. For discrete numeric and symbolic values, the most common representation codes are one-of-N codes, binary codes and thermometer codes.

- One-of-N codes are used most often and represent each distinct discrete value. For example, (air, rail, truck) can be represented as air=001, rail=010, and truck=100. One-of-N codes are easy to use and easy for ANN to understand.

- Binary codes are used to represent discrete variables. For example, yes/no can be represented as yes=1, n=0.

- Thermometer codes are used most often when discrete values are related. For example, excellent, good, fair and poor customer service performance can be represented by the following: excellent=1111, good=1110, fair=1100, and poor=1000. Using these codes ensures that the neural network recognizes that excellent is similar to good but excellent is not similar to poor.

Many software development tools are capable of interfacing with common spreadsheet and database programs. For example, Microsoft Excel and Access can facilitate initial data processing.

ANN training. Most ANNs require some form of supervised training. The amount of training required varies widely depending on the number of variables involved, the number of data patterns to learn (problem complexity), and the level of solution accuracy desired. For most ANNs, training begins with ANN weights initialized to small random values. Next, training control parameters are set. Then, training data patterns are fed through the ANN, one after another. Knowledge engineers monitor ANN output error and adjust weights to reduce output errors. In most cases, knowledge engineers should train the ANN with a subset of data patterns (examples) and then test the ANN performance with a separate smaller subset. Alternating between training and test data patterns ensures good generalization for the ANN application area.

Successful training (small error signal) depends, to a large extent, on how the training control parameters (learning rate, momentum, error tolerance) are set and troubleshooting. First, knowledge engineers must set learning rates to control the magnitude of weight adjustments prescribed by the adjustment algorithm. A large learning rate, to make major corrections, is acceptable early in the training process. However, it is beneficial to lower the learning rate as the training progresses to fine-tune the ANN. Remember, the ANN goal is not to have a perfect answer to each training data pattern but to be able to accurately generalize to data patterns that have not been seen before.

Second, a momentum parameter must be set to control oscillation of the weight values. This parameter dampens oscillation by averaging the output error of several previous training iterations. As a result, the ANN weighted adjustments are less likely to be driven back and forth in alternate directions based on a single training experience.

Third, an error tolerance level must be set to create an acceptable accuracy goal for the ANN. When ANN outputs are less than or equal to the error tolerance levels set, ANN training has been completed. For ANN, with a range of outputs from 0.0 to 1.0, a learning tolerance level of 0.1 is commonly used. Accepting output solutions at .10 or .90 avoids pushing the ANN weight values to extremes to reach extreme outputs approaching 0.0 or 1.0 which might paralyze the ANN.

If training progress stalls, these troubleshooting actions should be considered:

- If the error signal falls quickly then stays flat or oscillates up or down, add some random noise to the weights or reset the weights to new random values and start over;

- If the learning tolerance level is not reached after many iterations, add more neurons or neuron layers to boost the computational power; and

- If the learning tolerance level is not reached after many iterations, check key variables for improper data scaling or coding and use a domain expert to check for missing key variables

Implementation

The fully developed transportation ANN should be validated in the field. A field test will ascertain performance regarding user interface, corporate information systems interface, and decision support effectiveness and efficiency.

ANN maintenance is a necessary, on-going task. Primary maintenance activities include: adding new variables based on new experiences, deleting obsolete variables, and retraining the ANN, when necessary.

Training must be provided to transportation managers regarding the ANNs purpose, capabilities, and operational instructions. Potential ANN users should be involved early in the development effort to facilitate a smooth deployment transition.

CONCLUSION

In today's highly competitive and volatile global marketplace, transportation managers must make more effective and efficient decisions if corporate profitability goals are to be achieved. Artificial neural networks may provide significant improvements in many transportation management decision environments that are dynamic, complex and unstructured. Transportation ANNs can result in faster, more accurate, more effective, and less expensive decisions. As a result, transportation managers should focus some of their TMS decision support efforts and resources on understanding ANN technology and developing appropriate applications to improve transportation management decision making.

REFERENCES

Al-Alawi, S., Al-Badi, A. and Ellithy, K. (2005), "An Artificial Neural Network Model for Predicting Gas Pipeline Induced Voltage Caused by Power Lines Under Fault Conditions," *Compel*, 24(1): 69-81.

Al-Tabtabai, H. and Alex., A. (2000), "Modeling the Cost of Political Risk in International Construction Projects," *Project Management Journal*, 31(3): 4-13.

Aras, N., Ozkisacik, K. C. and Altinel, I. K. (2006), "Solving the Uncapacitated Multi-facility Weber Problem by Vector Quantification and Self-organizing Maps," *The Journal of the Operational Research Society*, 57(1): 82-93.

Behara, R., Fisher, W. and Lemmink, J. (2002), "Modelling and Evaluating Service Quality Measurement using Neural Networks," *International Journal of Operations & Production Management*, 22(9/10): 1162-1186.

Bellandi, G., Dulmin, R. and Mininno, V. (1998), "Failure Rate Neural Analysis in the Transport Sector," *International Journal of Operations & Production Management*, 18(8): 778-793.

Bigus, J. (1996), *Data Mining with Neural Networks*, New York, NY: McGraw-Hill Companies, Inc.

Bowersox, D. J. Calantone R. J. and Rodriques, A. M. (2003), "Estimation of Global Logistics expenditures Using Neural Networks," *Journal of Business Logistics*, 24(2): 21-36.

Cavalieri, S., Maccarrone, P. and Pinto R. (2004), "Parametric vs Neural Network Models for the Estimation of Production Costs: A Case Study in the Automotive Industry," *International Journal of Production Economics*, 91(2): 165-177.

Co, H. C. and Boosarawongse, R. (2007), "Forecasting Thailand's Rice Export: Statistical Techniques vs. Artificial Neural Networks," *Computers & Industrial Engineering*, 53(4): 610-627.

Corder, M. (2004), "Crippled but not Crashed," *Scientific American*, 291(2): 94-95.

Coyle, J., Langley, Jr., C., Gibson, B., Novack, R. and Bardi, E., (2009), *Supply Chain Management: A Logistics Perspective,* 8th Edition, Mason, OH: South-Western College Publishing.

Creput, J. and Koukam, A. (2007), "Transport Clustering and Routing as a Visual Meshing Process," *Journal of Information & Optimization Sciences*, 28(4): 573-601.

DeGaspari, J. (1999), "Measuring the Effect of Rubber on the Road," *Mechanical Engineering*, 121(10): "p.12"

Duliba, K. (1990), "Contrasting Neural Nets with Regression in Predicting Performance in the Transportation Industry," *NYU Working Paper Series*, IS-90(17): 1-17.

Durvasula, S., Lysonski, S. and Mehta, S. (2007), "Competitive Positioning in International Logistics: Identifying a System of Attributes Through Neural Networks and Decision Trees," *Journal of Global Marketing*, 20(1): 75-89.

Editor. (2004), "More Brain Power to Your Engine," *The Engineer*, April(16): "p.12"

Editor. (1996), "New Defective Bearing Detection Techniques," *Railway Age*, 197(3): 69-71.

Ermis, K., Midilli, A, Dincer, I and Rosen, M. A. (2007), "Artificial Neural Network Analysis of World Green Energy Use," *Energy Policy*, 35(3): 1731-1743.

Ghaziri, H. and Osman, I. (2006), "Self-organizing Feature Maps for the Vehicle Routing Problem with Backhauls," *Journal of Scheduling*, 9(2): 97-114.

Glatzer, H. (1992), "Neural Networks Take on Real-world Problems," *Computerworld*, 26(32): "p.21"

Griffis, S. and T. Goldsby (2007), "Transportation Management Systems: An Exploration of Progress and Future Prospects," *Journal of Transportation Management*, 18(1): 18-32.

Harrold, D. (1998), "Do You Know What's Leaking?," *Control Engineering*, 45(10): 81-82.

Hassanein, A. (2006), "Conceptual Planning of Highway Construction Projects," *AACE International Transactions*, PS171-177.

Holcomb, M. and K. Manrodt (2007), "The Changing State of Transportation," *Journal of Transportation Management*, 18(2): 17-37.

Hua, Z., Li, S. and Tao, Z. (2006), "A Rule-based Risk Decision-making Approach and its Application in China's Customs Inspection Decision," *Journal of the Operational Research Society*, 57(1): 1313-1322.

Innamaa, S. (2005), "Short-term Prediction of Travel Time Using Neural Networks on an Interurban Highway," *Transportation*, 32(6): 649-669.

Jamal, A. M. (2005), "The Neural Network and Exchange Rate Modeling," *International Journal of Management*, 22(1): 28-32.

Jang, K. and Yang, K. (2001), "Improving Principal Component Analysis (PCA) in Automotive Body Assembly Using Artificial Neural Networks," *Journal of Manufacturing Systems*, 20(3): 188-198.

Kamruzzaman, J., Begg, R. and Sarker, R. [Ed.] (2006), *Artificial Neural Networks in Finance and Manufacturing*, Hershey, PA: Idea Group Publishers.

Lam, W., Tang, Y.F., Chan, K. S. and Tam, M. (2006), "Short-term Hourly Traffic Forecasts Using Hong Kong Annual Traffic Census," *Transportation*, 33(1): 291-310.

Lau, H., Choy, K. L., Lau, P., Tsui, W. T. and Choy, L. C. (2004), "An Intelligent Logistics Support System for Enhancing the Airfreight Forwarding Business," *Expert Systems*, 21(5): 253-268.

Lokuge, P. and Alahakoon, D. (2007), "Improving the Adaptability in Automated Vessel Scheduling in Container Ports Using Intelligent Software Agents," *European Journal of Operational Research*, 177(3): 1985-2015.

Luxhoj, T., Williams, T., P. and Shyur, H. (1997), "Comparison of Regression and Neural Network Models for Prediction of Inspection Profiles of Aging Aircraft," *IIE Transactions*, 29(2): 91-102.

Lyridis, D., Zacharioudakis, P., Mitrou, P. and Mylonas, A. (2004), "Forecasting Tanker Market Using Artificial Neural Networks," *Maritime Economics & Logistics*, 6(1): 93-108.

Murat, Y. S. and Ceylan, H. (2006), "Use of Artificial Neural Networks for Transport Energy Demand Modeling," *Energy Policy*, 34(17): 3165-3172.

Nam, K. and Schaefer,T. (1995), "Forecasting International Airline Passenger Traffic Using Neural Networks," *Logistics and Transportation Review*, 31(3): 239-252.

Nijkamp, P., Reggianni, A. and Tsang, W. F. (2004), "Comparative Modeling of Interregional Transport Flows: Applications to Multi-modal European Freight Transport," *European Journal of Operational Research,* 155(3): 584-602.

Rahmat, M., Sabit, H. and Rahim, A. (2010), "Application of Neural Network and Electrodynamic Sensor as Flow Pattern Identifier," *Sensor Review*, 30(2): 137-141.

Rau, H., Tsai, M., Chen, C. and Shiang, W. (2006), "Learning-based Automated Negotiation Between Shipper and Forwarder," *Computers & Industrial Engineering*, 51(3): 464-481.

Rodriques, A. M., Bowersox, D. J. and Calantone, R. J.,(2005), "Estimation of Global and National Logistics expenditures: 2002 Data Update," *Journal of Business Logistics*, 26(2): 1-16.

Schwardt, M. and Dethloff, J. (2005), "Solving a Continuous Location Routing Problem by Use of a Self-organizing Map," *International Journal of Physical Distribution & Logistics Management*, 35(6): 390-409.

Smith, K. and Gupta, J. (2000), "Neural Networks in Business: Techniques and Applications for the Operations Researcher," *Computers & Operations Research*, 27(11-12): 1023-1044.

Somchai, C., Lye, S. and Yeong, H. (2000), "An Integrated Design Approach for Protective Packaging," *Integrated Manufacturing Systems*, 11(5): 321-330.

Stolzer, A. and Halford, C. (2007), "Data Mining Methods Applied to Flight Operations Quality Assurance Data: A Comparison to Standard Statistical Methods," *Journal of Air Transportation*, 12(1): 6-25.

Teodorovic, D., Varadarajan, V., Popovic, J., Chinnaswamy, M. R. and Ramaraj, S. (2006), "Dynamic Programming—Neural Network Real-time Traffic Adaptive Signal Control Algorithm, *Annals of Operations Research*, 143(1): 123-131.

Vukadinovic, K., Teodorovic, D. and Pavkovic, G. (1997), " A Neural Network Approach to the Vessel Dispatching Problem," *European Journal of Operational Research*, 102(3): 473-488.

Wang, W., Chen, H. and Bell, M. (2005), "Vehicle Breakdown Duration Modeling," *Journal of Transportation and Statistics*, 8(1): 75-84.

Williams, T. (2002), "Predicting Completed Project Cost Using Bidding Data," *Construction Management and Economics*, 20(3): 225-235.

Wilson, R. (2011), "22nd Annual State of Logistics Report: Navigating through the Recovery," Lombard, IL: Council of Supply Chain Management Professionals.

Yoo, W. S. and Na, S. J. (2003), "Determination of 3-D Weld Seams in Ship Blocks Using a Laser Vision Sensor and a Neural Network," *Journal of Manufacturing Systems*, 22(4): 340-347.

Zeng, Q. and Yang, Z. (2009), "Integrating Simulation and Optimization to Schedule Loading Operations in Container Terminals," *Computers & Operations Research*, 36(6): 1935-1944.

AUTHOR BIOGRAPHIES

Robert Lorin Cook is Professor of Marketing and Logistics at Central Michigan University. He received a Ph.D. in Marketing at Michigan State University. His primary research interests are in the areas of supply chain design, applying information system technologies to logistics systems and logistics education. Robert.cook@cmich.edu.

Lawrence O. Jenicke is Professor of Management at Central Michigan University. He received a Ph.D. in Management Science at Michigan State University. His primary research interest is in the area of modeling operations, supply systems and quality management processes. Jenki1bj@cmich.edu.

Brian J. Gibson is Professor of Supply Chain Management and Program Coordinator at Auburn University. He received a Ph.D. in Logistics and Transportation from the University of Tennessee. Dr. Gibson is co-author of the market-leading textbooks *Supply Chain Management: A Logistics Perspective* and *Transportation: A Supply Chain Perspective*. He has published over 50 articles in leading journals and spearheads the State of Retail Supply Chain Annual Study. His primary research interests are in the area of supply chain performance analysis, the role of logistics in e-commerce and Logistics education. Brian.gibson@auburn.edu.