# Feed Forward Enabled Interface of Artificial Neural Network To System Dynamics Modeling For Developing Experiential Expert System For Decentralized Marketing Logistics

*** Dr. Sanjay Bhushan***

## INTRODUCTION

As a component function of "Supplier to End User" Supply chain, Marketing Logistics handles the flow of finished goods or services originated from the factory and linking up to consumers via intermediaries by means of performing outbound marketing functions of Inventory, Transportation, Warehousing and Order-Processing in a cyclical manner.

Marketing logistics designing, integration and optimization is of paramount importance. The diversity in production systems and demand structures noticeable nearly through all the manufacturing sectors leads to many layers of demand for products particularly in sectors like FMCG, Consumer Electronics, Telecommunication, Automobile etc. which are conventionally characterized by having 'Decentralized marketing distribution network i.e. outbound marketing logistics'.

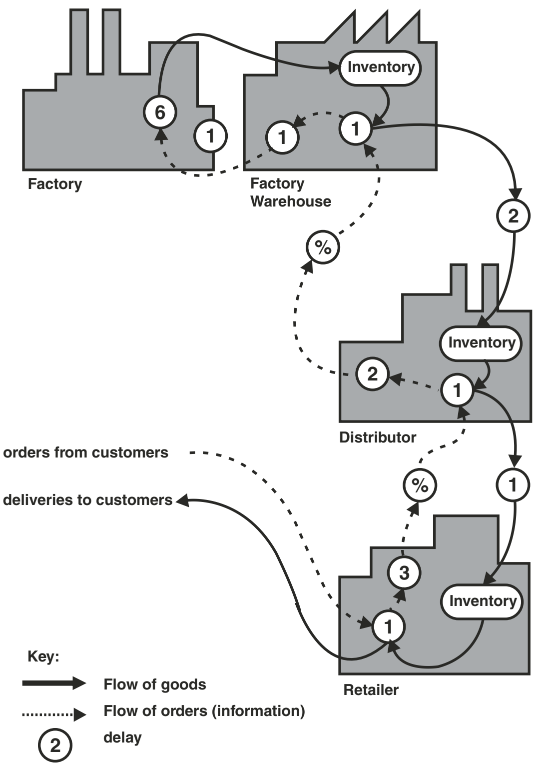


**Figure 1: Flow Diagram of a typical Four-level Marketing Logistics System**
**(Source: Forrester Supply-chain, Forrester 1961)**

Decentralized marketing logistics has a downstream flow of material from the factory via the factory warehouse, the distributor and the retailer to the customer. Orders (information flow) flow upstream and there is a delay associated with each echelon in the chain, representing, for instance, the production lead-time or delays for administrative tasks such as order processing. (Figure 1)

Such type of decentralization is prone to 'delays' where each intermediate level in the marketing logistics system places order to its next level and receives the material after a delay period. For instance, in consumer non-durable sector, logistics cost impacts substantially over the total product-cost and the 'stock-outs' often lead to big losses to companies.

* *Department of Management,* Faculty of Social Sciences, Dayalbagh Educational Institute (Deemed University), Dayalbagh, Agra-282005, Uttar Pradesh. E-Mail: sanjaybhushan@lycos.com, dei@sancharnet.in

## REQUIREMENT OF SYSTEMS PROBE INTO MARKETING LOGISTICS SYSTEM AND PRE-EMINENCE OF SD OVER OTHER DECISION- TOOLS

In the above context, an enterprise must design and implement a 'logistics system' that coordinates the components of the entire outbound marketing system and effectively reduce sub-optimization in the system. One promising method to investigate inter-organizational decentralized supply chains is by using systems approach through formal modeling and simulation in system dynamics.

Historically, system dynamics can take credit for being the first branch of mathematical research that has investigated management policies for decentralized supply chains. The application of System Dynamics Modeling to Supply Chain Management has its roots in Industrial Dynamics (J.W. Forrester 1958, 1961 et al). Forrester's *Industrial Dynamics* and the famous "Beer Game" (Sterman 1989 et al.) that was developed on the basis of this work, have for decades, been dominant in our understanding of amplification effects in decentralized logistics.

"SD methodology provides the dynamic simulation capability and considers the feedback relationships among different constituents of urban system explicitly…. Graphic tools of SD, namely causal loops and flow diagrams offer powerful communicability between modeler and decision maker. Its characteristics as a learning tool finds favor with the policy planners. …It is prudent to make use of the multiple simulation experiments with the help of SD model for acquiring capability for alternative policy formulations…." *(Prof.P.S. Satsangi 2002 et al.)*

System Dynamics approach lies in modeling complex real world systems as flow rates and accumulations linked by information feedback loops involve delays and non-linear relationships. Added to this, the fact that decentralized logistics contains many non-linear relationships; an analytical solution to solving model equations is not feasible. Hence, it leads to realization of the need of experimental or simulation approach. Methodologically, system dynamics has always placed a strong emphasis on the notion of counter-intuitive behavior of complex dynamics systems. That is, due to the intricate interplay between many interrelated factors and the non-linearity of their relationships, the dynamic behavior of complex systems is becoming practically very difficult to predict from a description of their static structure.

This approach has found favor amongst decision makers over other tools of Operations Research and Management Science which are limited to traditional mathematical formulas and analytical solutions and which do not account for variability and uncertainty of a decentralized supply chain representing complex interdependencies between organizations and help realistically analyze the performance trade-offs associated with different organizational decision making assumptions.

They don't as well infer the time evolutionary dynamics endogenously created by such system structures. (D.J.Thomas, P.M. Griffin. 1996 et al.). This is on account of the fact that mathematical analysis generally shows that such decentralized supply chains, where the constituent actors will strive to optimize their local performance, will have a performance which is sub-optimal to, or at best no better than, an integrated supply chain that is managed from one central position. (D.J.Thomas, P.M. Griffin. 1996 et al.) (A.M. Sarmiento, R. Nagi. 1999 et al.)

Therefore, it can be safely inferred here that system framework based decision making is essential in order to provide the basic building blocks necessary to construct decentralized logistical models that teach us how and why such multileveled complex systems behave the way they do over time. For a decision maker, the goal is to leverage this added understanding to design and implement more efficient and effective logistical policies.

## ARTIFICIAL INTELLIGENCE-ANN INTERFACE WITH SYSTEM DYNAMICS: SETTING A NEW DIRECTION FOR RESEARCH

In correspondence with the notion held by system scientists regarding the parallel occurance mechanism of systemic variables under a broader perspective, a new parallel modeling and optimization offshoot of science has developed as in Artificial Neural Network.

In the area of soft computation based dynamic modeling researches, Artificial intelligence based artificial neural netwok-popularly coined as ANN or NN (Neural Network) has emerged as a computational model based on biological neural network. Also referred to as Neuromorphic systems, artificial neural networks (ANNs) are an attempt at mimicking the patterns of the human mind.The framework of ANN consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation.

ANN offers remarkable opportunity for developing feedforward enabled experiential expert system for a complex system like one seen in decentralised logistics by making use of innumerable number of decision variables experienced, analysed or put into experimentation in the the model by a System modeler in order to arrive at the optimum decision-set for logistics-optimization.

Very significantly, ANN serves as an adaptive networking system which changes its structure based on external or internal information that flows through the network during its learning phase or as inferred in system dynamics as time-evolutionary path.
If we narrowly study the architect of ANN, we encounter a highly compatible interface between SD and ANN in terms of some remarkable structural resemblances between the two.

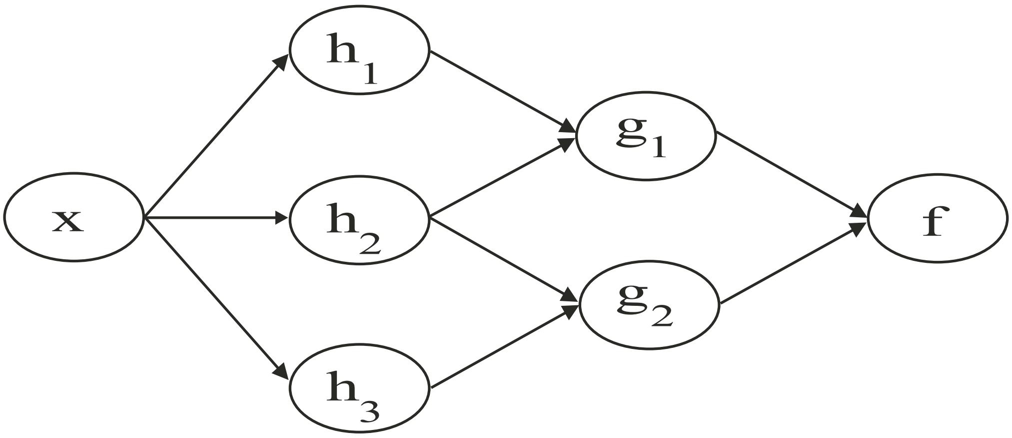


**Figure : 2**

Functionally, the above diagram (Figure 2) of the founding architect of ANN depicts a decomposition of *f*, with dependencies between variables indicated by arrows. In this architect, the input variable x is getting transformed into a 3-dimensional vector h, which is then transformed into a 2-dimensional vector g which is finally converted into f. Strikingly here, this is precisely what takes place in the SD-optimization process through the iterations of various decision variables.
Analyzing and interpreting the above ANN architect through the framework of feedback loop under SD-modeling, the above architect also depicts the dependency of variables f, g, h (can be considered here in congruence with stock or flow variables of SD causal loop) over x which might again be treated as the randomly independent indogeneous/ exogeneous inflow variable in the case of SD-causal modeling. As we understand, this form of Bayesian netwok based derivation of flow variables is common in SD causal models.

## INCLUSION OF FEEDFORWARD-INTERFACE COMPONENT INTO SD MODEL-ARCHITECT

Exploring further into the above ANN-network architect, the parellelisic placement of variables (as depicted above in h and g ) can be considered as a remarkable contribution of ANN to the field of dynamic modeling. This unique attribute of the network signifies to incorporate into a typical SD-model, an additional learning-cum-training component of **"FEEDFORWARD"** alongside the conventional Feedback causal component.
Specializing in feed forward assisted experiential knowledge, a neural network stores and expands its knowledge base via strikingly human routes-through a learning process and information storage involving interconnection strengths known as synaptic weights. Going by the ANN-architect, the basic feed forward network performs a non-linear transformation of input data in order to approximate the output data. The number of input and output nodes is determined by the logistical modeling problem being tackled, the input data representation and the form of the network output required.
The number of hidden layer nodes is related to the complexity of the logistics system being modeled. The interconnections within the network are such that every neuron in each layer is connected to every neuron in the adjacent layers. Each interconnection has associated with it a scalar weight that is adjusted during the training phase originally initialized from 0 training iterations. The hidden layer nodes typically have sigmoid transfer functions. Strikingly, these weights (network parameters) can be derived through the non-linear iterations based SD-optimization task where past process inputs and outputs can be used to predict the present process output.
Feed forward networks incorporating dynamical elements have important properties and are of use in many applications especially in the areas of control, signal processing, and various other time series analysis apart from System Dynamics.
Diagramatically, it could be shown in the following (Figure 3).

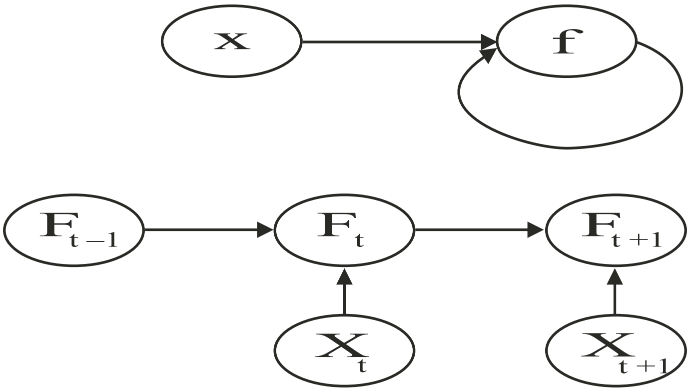


**Figure : 3: Feedforward Channel**

It can be safely assumed here that a feedforward loop is basically an open loop on its way. The upper side of the diagram shows a self-learning independent variable (stock or flow) which also temporally depends upon its own past value (say at zero) or the value at one or more other points in time (Lower part of the diagram). Models of this architect are no different than the SD-causal model.

This very segment of newly inducted feedforward structure into a SD model can be immensely useful in transforming a Decision-maker/ modeler dependent SD model into a self-learning and artificially trained decision network system.

## COMPLEMENTING FEEDFORWARD WITH FEEDBACK CONTROL LOOP

Now after re-designing such architect of feed forward component based logistics network, one can shift attention to fuse it with the recurrent feedback networks for the purpose of multi-step-ahead predictions. It can be done as a back propagation-in-time modeling where the hidden neuron outputs at the previous time step are fed back to its inputs through time delay units. It means that each feed forward logistics neuron has a one or more delayed feedback loop around itself. As we know of systems dynamics, feedback to a system might change not only its behavior but also the internal system structure since, a logistics system can be assumed to behave organically over an extended dynamic time-track.

## OTHER POSSIBLE INTEGRATIONS

Extending the above hypothesis further into a new domain of integration research, dynamic modeling coupled with advanced artificial neuro computing and genetic algorithm has the potential of becoming a highly potent decision making component of a broad logistics intelligence system. One of the major features of neural networks is their ability to generalize i.e. successfully classify patterns that have not been previously presented or explored. Moreover, a successfully trained ANN model is prudent to obtain quick response outputs within acceptable error for values of input covered by training input space. Hence, the ANN model provides excellent opportunity to store the knowledge contained in the variety of SD simulation results which would have otherwise been discarded after analysis, (Prof. P.S. Satsangi 2002). The need of such systemic integration is particularly pronounced on account of the easy compatibility offered by these system research domains and also the requirement of comprehensively diagnosing the intricate dynamic interplay between various endogenous and exogenous variables with the non-linearity of their relationships in a marketing logistics system. Hence, capturing the dynamics of such system and optimizing the decision variables is essential for robust decision-making and logistics policy design.

This type of research integration envisages the development of a hybrid intelligent decision support system using SD-ANN-GA interface and integration. The sequential integration of system dynamics, ANN and genetic algorithm methodologies to obtain the above objective could be proposed on the following lines:

• **Step 1:** Use system dynamics modeling to model and simulate a complex and decentralized outbound logistics system by clearly describing the causalities of state and decision variables*.

• **Step 2:** Capture the changes and dynamism of the modeled system by using the pattern recognition capabilities of neural networks trained by the voluminous amount of simulation experiments done at the previous step.

• **Step 3:** Use the potentials of genetic algorithm to modify the weights of decision variables by scanning complex & nonlinear search spaces in order to minimize the oscillatory behavior or eliminate undesirable behavior of the identified state variable/s.

*SD simulation clubbed with sensitivity analysis and eigen value analysis can help here in recognizing the causal relationship between undesirable state variables and corresponding decision variables in order to generate insight about a set of specific decision variable that are responsible for the fluctuations of state variables of interest. (Luis Rabelo, Magdy Helal & Chalermmon Lertpattarapong, 2007).

The proposed intelligent system is supposedly to initiate with one critical state variable and then gradually cover all critical variables of interest and apply stability conditions simultaneously to these variables to optimize the control parameters of an organizational logistics system. The combination of the NN calculating ability based on the heuristics and the ability of SD simulation to model and simulate the dynamics of a logistics system complemented by the application of genetic algorithm search in generating optimized simulation trajectories would, in the end, facilitate effective logistics policy formulation.

## ADVANTAGES

**(A):** One direct advantage of a feedforward based learning effort (as suggested in the first part of this paper) will cause a significant reduction in dynamic tracking error to an entirely feedback based logistics system as most of the logistics decisions are repeatable for a given learned sequence of activities or movments performed. Feed-forward logistics processing seems to maximize the logistics control system's responsiveness to sudden changes in the overall level augmented by market demand fluctuations, erratic business or other environmental events.

In this case, the ANN-control loop uses feed-forward to "anticipate" changes in the overall control level based on the derivative of the learned error by monitoring changes in the Control Response between control loop iterations. Without a feed-forward, or derivative term, in the control process, control performance is degraded, as the feedback gains must be reduced to insure the stability of the control loop. Reducing the feedback gains lengthens the time required to fully correct errors. Without this feed-forward processing, the time to re-equalize changes to the load dynamics can be unduly long.

Feed-forward processing allows the control system to adjust to the change in logistical structural response much faster than is possible if adjustments are based solely on spectral averaging in the main feedback loop. Thus, it greatly solves the response time problem of a feedback loop and in fact, could act as a quick response model as an expert decision making system. "...An artificial neural network (ANN) model can be successfully trained and used as a quick response model for fast feature extraction of the dynamics of the integrated urban energy-economy-environment system such that the outputs are within reasonable acceptable error for values of inputs covered by the input space of training patterns………" (Prof. P.S. Satsangi 2002 et al).

Added to this, if the logistical controller could learn the feed-forward effort to make a particular move from A to B as logistics strategic options, one could reduce the dynamic error to close to zero. This in turn means that the system is "fast" even if the feedback system is not "fast." Further, the learned control effort would minimize the systems oscillations even if the feedback system has a significant settling time. That is, the feed-forward would tend to introduce a compensating oscillatory input that would tend to make the dynamic error approach zero.

**(B):** On the other hand, as prescribed in the later part of the paper, system dynamics modeling and simulation would prove to be most effective methodology for logistics system design whereas ANN and Genetic algorithm shall be instrumental in the effective **melding** (modeling) and optimization of critical decision areas or variables. In this direction, it must be emphasized here that going beyond the current status of system researches, the proposed work also aims to analyze and integrate more than one decision variables in order to simultaneously apply the stability conditions in the given system.

## RELATED RESEARCHES

In the past, there have been segmented studies done as regards to the possibilities of neural network assisted dynamic modeling mainly in the areas like devising advanced Control Algorithm of engineering control systems, control designing (HH West et al), innovations in motion control, speed regulation in IC engines (Xiaoqiu Li et al) apart from other significant contributions made by researchers towards conceptualizing nonlinear dynamic systems under neural network perspectives (P.S. Satsangi 2002 et al), (Irwin W. Sandberg et al). However, any comprehensive research in the field of decentralized logistics modeling using feed forward neural approach has yet not been carried out.

## CONCLUSION

Neural networks have the potential of accurately describing the behavior of extremely complex systems such as

***(Cont. on page 31)***

have to keep consistency in his efforts to manage these global brands, which is not all that simple.

## BIBLIOGRAPHY


1. DOUGLAS B. HOLT, JOHN A. QUELCH, AND EARL L. TAYLOR, 2004, *How Global Brands Compete?,* Harvard Business Review, Pp 68-75.
2. SAURABH SHARMA, 2004, *Global for whom, local for whom?,* Indian Management, Pp 18-24.
3. MANJARI RAMAN, 2002, *Where Brands Fit Into Business Strategy?,* Indian Management, Pp 20-24.
4. EVIN LANE KELLER, Strategic Brand Management Building, Measuring, and Managing Brand Equity, Pearson Education, 2nd Edition, Pp680-688.
5. R.M. JOSHI, International Marketing, Oxford University Press, 2005 Edition, Pp350 355.
6. www.interbrand.com Best Global Brands 2006 A ranking by brand value.
7. http://bwnt.businessweek.com/brand/2005/ Top 100 Global Brands Scoreboard.


---

***(Cont. from page 20)***

being encountered in decentralized logistics. Learned feed-forward mechanism and ANN-Genetic Algorithmic integration are two great ways to reduce dynamic tracking error of a feedback based decentralized logistics control system as well as to optimize the logistical processes and decision variables. Hence, the above-deliberated possible interface offers a tremendous opportunity of developing an Experiential Expert System for logistics control, policy formulation and decision-making.

## BIBLIOGRAPHY


**1.** Chang, Yoon and Makatsoris, Harris., Institute for manufacturing, University of Cambridge, Cambridge, CB2 1RX, UK, International Journal of Simulation, Vol.2, No.1. ISSN 1473-804x on-line, pp.24-30, 2003.

**2.** Chen, F., Z.Drezner, J.K. Ryan, D. Simchi-Levi,"Quantifying the Bullwhip Effect in a Simple Supply Chain:The Impact of Forecasting, Lead Times and Information".*Management Science* v.46 n.3, 2000, pp.436-443.

**3.** Forrester, J. W. 1958. Industrial Dynamics: A Major Breakthrough for Decision Makers. *Harvard Business Review* 36 (4):37-66. .... 1961. *Industrial Dynamics*. Portland (OR): Productivity Press.

**4.** Forrester, J W., 'Industrial Dynamics', republished by Pegasus Communications, 1961, p.365

**5.** H. H. West and M. L. McGuire, Chemical Engineering and Material Science, University of Oklahoma, Norman, Oklahoma, USA

**6.** Irwin W. Sandberg, James T. Lo, Craig L. Fancourt, José C. Principe, Shigeru Katagiri, Simon Haykin Nonlinear Dynamical Systems: Feedforward Neural Network Perspectives, ISBN: 978-0-471-34911-2 , February 2001

**7.** Kelly, K. New Rules for the New Economy, 10 Ways the Network Economy is Changing Everything. Fourth Estate, London UK, 1998.

**8.** Luis Rabelo, Magdy Helal & Chalermmon Lertpattarapong, Analysis of supply chain using artificial neural net and eigen value, Winter simulation conference, USA 2004:

**9.** Moon, Young B., Phatak, Dinar., Enhancing ERP system's functionality with discrete event simulation, Industrial Management & Data Systems ISSN: 0263-5577, 2005, Vol.105 , , Emerald Group Publishing Limited, pp. 1206 1224

**10.** Richardson, G. P., and A. L. Pugh, III. 1981. Introduction to System Dynamics Modeling. Portland (OR): Productivity Press.

**11.** Satsangi,.P.S. "Integrated Urban Energy-Economy Environment-Transportation System Modelling And Simulation With Particular Reference to Soft-computing", Transportation Systems - Status & Directions, Phoenix Publications, IIT New Delhi Conference, 2002, pp. 369-384.

**12.** Sarmiento, A.M., R. Nagi. "A Review of integratedanalysis of production-distribution systems". IIETransactions 31, 1999, pp.1061-1074.

**13.** Sterman, J.D. Modeling managerial behavior:"Misperceptions of feedback in a dynamic decision makingexperiment". *Management Science* 35(3) 1989, pp. 321-339.

**14.** Thomas, D.J., P.M. Griffin. "Coordinated supply chainmanagement". European Journal of Operational Research,94, 1996, pp.1-15.

**15.** Towill, D. R. 1996a. Industrial dynamics modeling of supply chains. *Logistics Information Management* 9 (4): 43-56.

**16.** Vennix, J. A. M. 1996. Group Model Building: Facilitating Team Learning Using System Dynamics. Chichester: John Wiley & Sons.

**17.** Xiaoqiu Li and Stephen Yurkovich, Dynamic programming approach to optimal feedback-feed-forward controller design, Journal of Dynamic Systems, Measurement, and Control -- June 2000 -- Volume 122, Issue 2, pp. 269-275


---

***(Cont. from page 23)***

## BIBLIOGRAPHY


1. Berkowitz, E.N, Kerin, R.A, Hartley. S.W, & Rudelious, W. (2000). *Marketing.* (6th ed.). New York: Irwin McGraw-hill, p.325.
2. Partridge, M.V.B. (2003). *Guiding Rights: Trademarks, Copyright, and The Internet.* Retrieved from http://www.GuidingRights.com/resources/html.
3. The amazing Infosys Story. (2006). Retrieved October 30, 2006, from http://specials.rediff.com/money.
4. Sukumar, R. (2001, January 21). India's Best Employers: The Top 5. *Business Today*. Retrieved from http://www.india-today.com
5. Infosys recognized as a Globally 'Most Admired Knowledge Enterprise for 2004'. (2004, December 1). *A Teleos study*. Retrieved from http://www.infosys.com.
6. Building The Infosys Brand. (2008, February 7). *Hindustan Times,* p.5.
7. Starbucks. (2006). *Starbucks Foundation Grants.* Retrieved May 26, 2008, from http://www.starbucks.com/aboutus/grantinfo.asp
8. Intel News Release. (2006). *Intel Commits $1 Billion To Further Emerging Markets Strategy.* Retrieved May 26, 2008, from http://www.intel.com/pressroom