Applicability of Fuzzy Logic and Neural Networks to Logistics Control

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Abstract: The paper examines the issue of logistics control and applicability of fuzzy logic and neural networks to control of logistics performance. The author describes the elements of logistics control system, indicates the importance of performance measurement and areas of control where fuzzy logic and neural networks can improve the performance of controlling function. Illustrations and tables are used to enhance the argument.

Key words: logistics, control, systems, neural networks, fuzzy logic, performance parameters, Decision Support Systems

Introduction

Control is one of the basic management functions along with planning, organising and getting things done (or, briefly, implementation). The nature of this process is continuous comparison of what has been done with what has been planned and bringing those two more closely together, if required.

The need for a control activity is based on the future uncertainties that alter a plan's performance. Perfect planning and execution will not require control. This is seldom possible, though. Many internal forces affect a company's performance. Not all of them can be predicted with certainty. Changes in external forces such as legal environment and economic conditions can rarely be predicted but, nevertheless, may affect the plan. In addition to what can be considered a normal variation in conditions and external factors are contingencies (floods, strikes, earthquakes), that drastically affect a plan's performance.

The basic element of a control system is the monitor. It receives information about a process performance, compares it with the planned, and initiates corrective action. Though planning was never a simple matter, the measurement of the actual performance is not much easier, if at all. Development of measurement techniques started from engineering applications. Some engineering systems cost millions of pounds and are described by thousands of parameters. Business systems are usually not much simpler. Cross-functional borders, layers of decision-making, and a multitude of approaches to cost accounting make accurate measurement a real challenge. Accurate and timely measurement of performance is costly, but reward of being within control in terms of increased sales level and reduced operational expenses usually outweighs the cost of information about the actual performance.

Analysis of gaps between plan and the actual performance allows finding the cause of the problem and solution in terms of corrective action. Both require the knowledge of a system and experience in decision-making, qualities which are both rare and well paid.

Recent developments in the computer industry help to reduce the cost and increase the reliability of measurement and control. New computer technology makes possible the flourishing of Activity Based Costing and many other quality and productivity measure techniques. Some breakthroughs have been achieved in the field of decision-making with the introduction of Decision Support (DSS) and Expert Systems (ES), which can effectively replace a human manager in many areas of control. Despite the fact that current DSS and ES allowed increases in the overall productivity of decision-making in many areas, they lack the flexibility and learnability to be used for every management task.

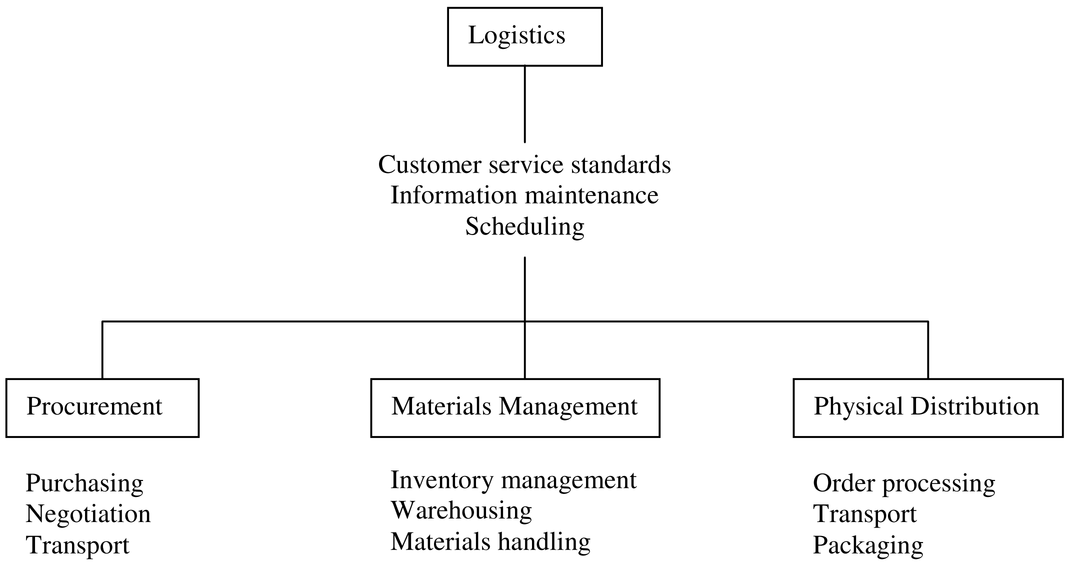
New developments in the area of Artificial Intelligence such as Fuzzy Logic and Artificial Neural Networks soon may dramatically change the way in which companies are run and controlled. The flexibility of Fuzzy Logic in dealing with uncertainty and vagueness, and the learnability of Neural Networks together with many other techniques of Computational and Artificial Intelligence will make control essentially an automatic activity.

Logistics Management

Logistics is the process of planning, implementing, and controlling the efficient, cost-effective flow and storage of raw materials, in-process inventory, finished goods and related information from point of origin to point of consumption for the purpose of conforming to customer requirements [Council of Logistics Management].

The key areas of Logistics are Procurement, Materials Management, and Physical Distribution (Figure 1). The task of Procurement is to acquire raw materials and components and bring them to the place of further processing by a company. Materials Management takes responsibility for in-plant storage and handling of raw materials, components and work-in-progress. The responsibility of Physical Distribution is reliable and cost-efficient delivery of finished products to the customers.

Figure 1. Logistics Management and basic logistics activities
(Adapted from R. Carter, P. Price "Integrated Materials Management", 1993)



Despite the functional division within Logistics Management the main objective continues to be the achievement of high level of customer service at the lowest total logistics cost. Minimisation of the total logistics cost is achieved through management of individual activities and trade-offs between different logistics activities and functions. The major prerequisites for achievement of these objectives are logistics organisational structure which facilitates and is constructively similar to the flow of materials from the suppliers through the organisation to the customers, and the effective and efficient backwards flow of timely and accurate information.

A number of primary activities have to be controlled by logistics management (Figure 1). Like any other control system Logistics Control System compares outcome of logistics activities with logistics standards and goals. The standards are typically expressed in the form of a cost budget, a customer service target level, or contribution to profit (Table 1). Though the tracking of logistics gaps is currently performed automatically, the gap analysis and finding of corrective action lies mostly in the human domain.

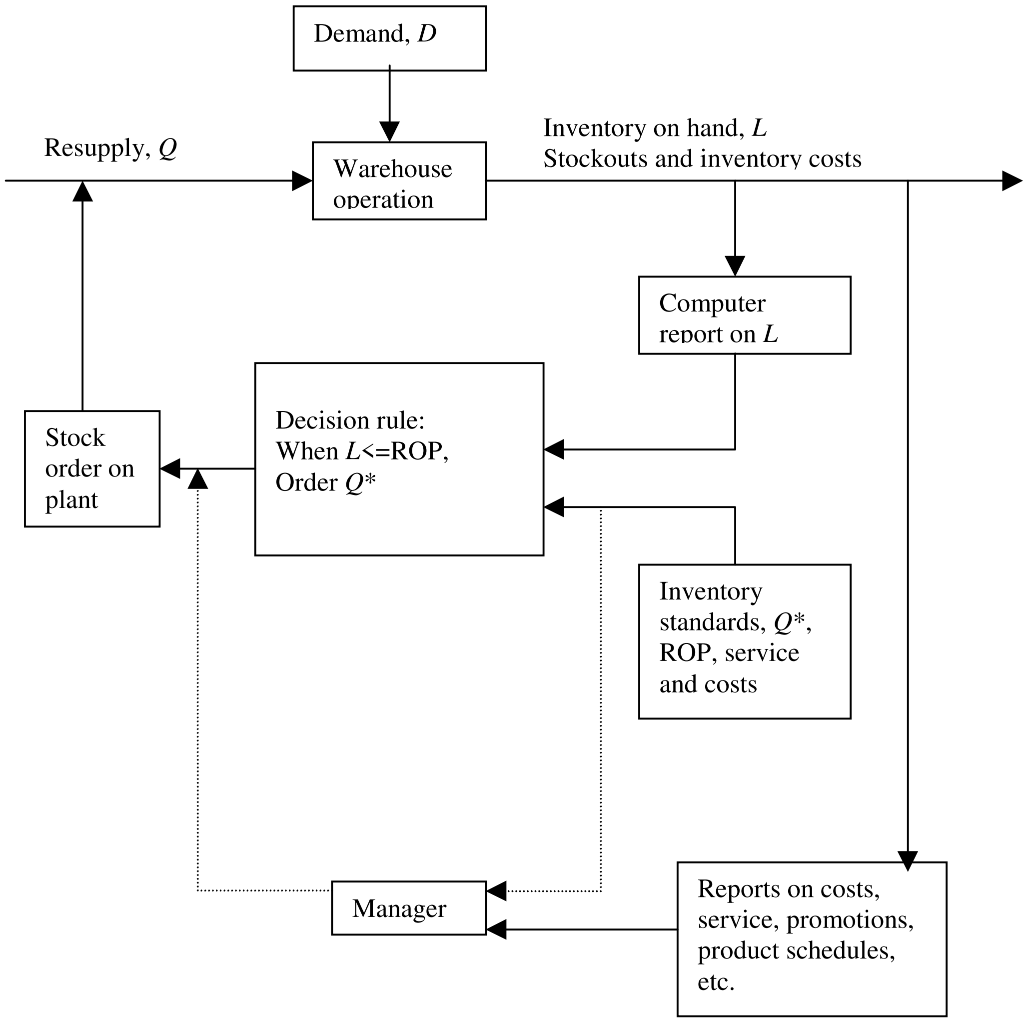
Table 1. Example of Logistics Cost-Service Variables used in Logistics Budgets (Adapted from Ronald H. Ballou "Business Logistics Management")

Physical Distribution (£)	Physical Supply (£)	Customer Service
Transportation of finished goods	Transportation of supply goods	Percentage of warehouse deliveries within one day
Freight charges inbound to warehouses	Freight charges inbound to plant	Average in-stock percentage
Delivery charges outbound from warehouses	Expedited freight charges	Total order cycle time
Freight charges on stock returns to plant	Supply goods inventories	(a) Normal processing
Extra delivery charges on back orders	Storage costs on raw materials	(b) Back-order-split delivery processing
Finished goods inventories	Material-handling costs on raw materials	Back orders and split deliveries
Inventories in transit	Order processing	(a) Total number
Storage costs at warehouses	Processing of supply orders	(b) Percentage of total orders
Materials-handling costs at warehouses	Costs of expedited orders	Orders filled complete
Costs of obsolete stock	Administration and overheads	Customer returns due to damage, dead stock, order processing errors, and late deliveries
Storage costs at plants	Proration of unallocated material expenses	Percentage of available production time shutdown due to supply out of stock
Materials-handling costs at plants	Depreciation of owned storage space	
Order processing costs	Depreciation of materials handling equipment	
Processing of customer orders	Depreciation of transportation equipment	
Processing stock replenishment orders		
Processing of back orders		
Administration and overhead		
Proration of unallocated material expenses		
Depreciation of owned storage space		
Depreciation of materials handling equipment		
Depreciation of transportation equipment		

The Inventory Control System based on the fixed order quantity-variable order interval inventory control model with constant demand and lead-time is one of the examples of such system (Figure 2).

The system places a stock order for Q* units when the inventory in stoch drops below the reorder point quantity (ROP). But because of the changes in short-term plans and environmental influences the automatic control system has to be watched over by a human manager. The manager may change the parameters of the system if new forces become active. For example, a promotion period will require a higher level of stock, which can be achieved by either increasing of reorder point ROP or economic order quantity Q*.

Figure 2. Inventory control system
(Ronald H. Ballou, Business Logistics Management)



An effective logistics control system requires accurate, relevant, and timely information about activity or function performance. This information is obtained in the form of Logistics Parameters (LP). Logistics Parameters measure the performance of each individual activity. The full set of LP depicts the behaviour of the logistics system as a whole. All logistics parameters can be assigned to 4 major groups: Logistics Financial Performance Parameters (LFPP), Logistics Productivity Parameters (LPP), Logistics Quality Parameters (LQP), and Logistics Cycle Time Parameters (LCTP). Examples of each of the parameter groups are given in Table 2.

Not many companies pay adequate attention to logistics parameters. Two major reasons account for this. First, not too many companies have adequate accounting systems to assign costs correctly to each logistics activity. Second, even when a company can collect all relevant information about their logistics system, they are not always capable of analysing it and putting the results of their analysis into action.

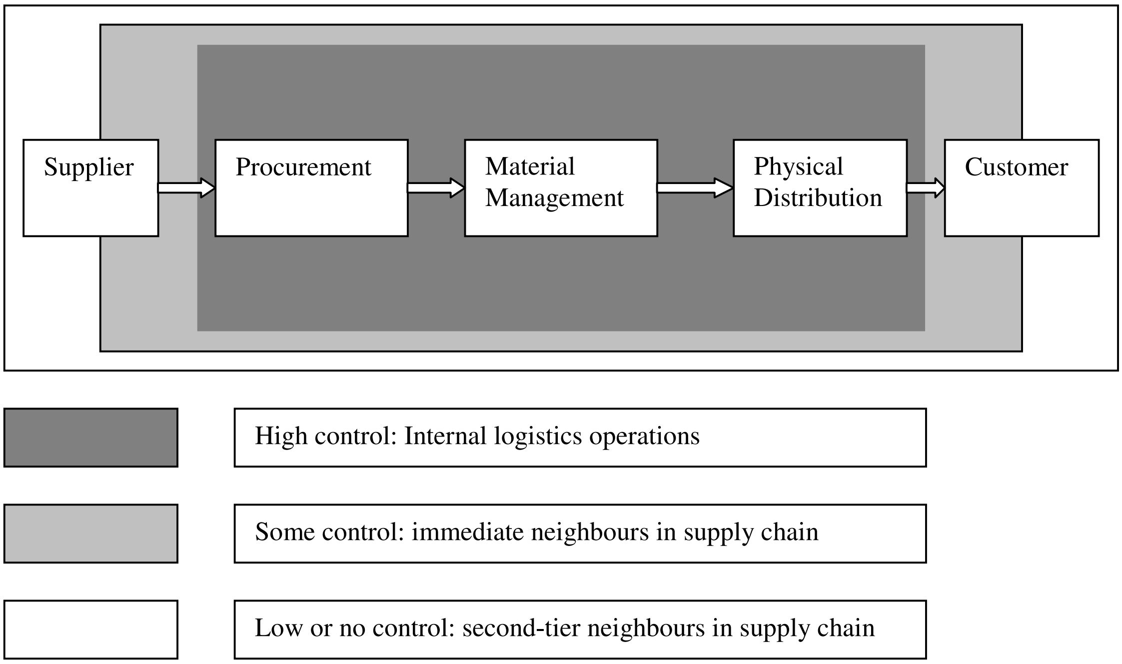
Table 2. Logistics parameters
(Adapted from Edward H. Frazelle "Logistics Performance, Cost, and Value Measures", 1997 LMC, Inc.)

Logistics Financial Performance Parameters	Logistics Productivity Parameters	Logistics Quality Parameters	Logistics Cycle Time Measures
Logistics Expenses	Logistics Workforce Productivity Parameters	Perfect Order Percentage	Order Entry Time
Logistics Profit	Customer Response Productivity Parameters	Customer Response Quality Parameters	Order Processing Time
Return on Logistics Assets	Inventory Management Productivity	Inventory Quality Indicators	Purchase Order Cycle Time
Logistics Asset Turnover	Supply Productivity	Fill Rate	In-Transit Time
Logistics Capital Charges	Transportation Productivity	Forecast Accuracy	Warehouse Order Cycle Time
Total Logistics Cost	DC Operations Productivity	Supply Quality Indicators	Total Logistics Cycle Time
Logistics Cost-Sales Ratio		Transportation Quality Parameters	
Logistics Value Added		DC Operations Quality Parameters	
Cost-Service Trade-offs		Inventory Accuracy	
		Picking Accuracy	
		Shipping Accuracy	

One more issue should be addressed in logistics control: configuration and boundaries of a logistics system. The boundaries of a logistics system define the scope of responsibility of company's logistics management. A company, adopting the Supply Chain Concept [Lar95] will define its logistics system more broadly than a company whose logistics system does not cross company boundaries. Indeed, a supply chain-driven organisation will have 'fuzzy' logistics system borders. These boundary activities may not be controlled in the same way as completely internal logistics activities, because a company will not be able to achieve the same level of controllability as for internal logistics operations (Figure 3).

Recent developments in computer technology have brought significant improvements to the area of logistics control. Computers became the essential part of complicated Management Information Systems (MIS), which allow the capturing and analysing of all around-organisation data. Lack of flexibility and learnability in MIS may be overcome by fast development in techniques of Computational Intelligence: Fuzzy Logic and Artificial Neural Networks.

Figure 3. Area of Control in Supply Chain - Driven Organisation



Artificial Neural Networks (ANN)

Artificial Neural Networks are computational structures which model the structure of human brains and can be trained to learn patterns from examples. ANNs attempt to mimic the way in which the human brain processes information. The basic computing device in the human brain is the *neuron.* A neuron consists of a cell body, branching extensions called *dendrites* for receiving input, and an *axon* that carries the neuron's output to the dendrites of other neurons. The junction between an axon and dendrite is called a *synapse*. The very simplest model of a neuron assumes that it carries out a simple threshold calculation. It collects signals at its synapses and sums them. If the combined signal strength exceeds a certain *threshold*, the neuron sends out its signal, which is a transformation of the original input signal [Ref95].

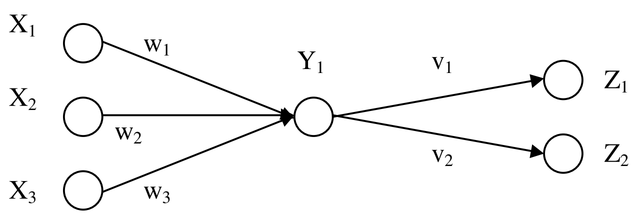
Although the processing of information in human brain may be carried out slightly differently from the manner just described, this model of behaviour of human brain cells works well in artificial intelligence. Currently Artificial Neural Nets are used in many areas of engineering, finance, business, linguistics, medicine, speech production, pattern recognition, control, etc. due to their flexibility. The beginning of research in the area of neural networks started in the 40's. Warren McCulloch and Walter Pitts designed what are generally regarded as the first neural networks. The following years in 50's and 60's brought a lot of enthusiasm to the area. However, by the 70's it became clear that single-layer networks, consisting of one input layer of neurons and one output layer has limitations, making such nets impractical in applications.

One of the uses of neural networks is to approximate a continuous mapping *f*. Since a single layer net cannot represent even quite simple ones, it is natural to ask how well a multilayer net can do. The answer is the "Kolmogorov mapping neural network existence theorem", which states that a feedforward neural network with three layers of neurons (input units, hidden units, and output units) can represent any continuous function exactly [Kolmogorov, 1957]. The new era of Neural Networks started to take off in the mid 80's when the 'backpropagation' method of training multilayer Neural Networks became popular.

The following example shows how the feedforward multilayer neural network can be trained to recognise patterns, e.g. poor performance of logistics system.

The feedforward multilayer Neural Networks has one input and one output layer, and one hidden layer between them (figure 4). Input layer *X* is activated by input signals. The weighted sum of these inputs with weights *w* is applied to the hidden layer *Y*. The threshold function at *Y* changes the signals and sends the weighted sum of signals with weights *v* from *Y* to output layer *Z*. A threshold function is again applied to the signals at the layer *Z* to produce the final outcome of the network calculation.

Figure 4. Simple Multilayer ANN



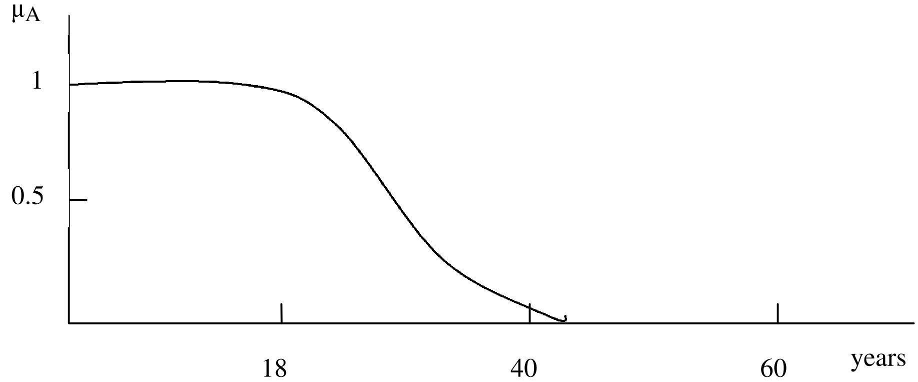
The result of the calculation is then compared with the actual and weights *w* and *v* are updated. This process is called the training of the network by the method of backpropagation (of errors). It is simply a gradient descent method to minimise the total squared error of the output computed by the net. Using gradient descent method or the method of updating the weights in the direction of the fastest reduction of the error allows trainability of the network [Fau94]. It means that after some number of training cycles the network may perform the function of pattern recognition quite reasonably.

Fuzzy Logic

Fuzzy Logic enables us to easily translate our qualitative knowledge about the problem to be solved, such as resource allocation strategies, performance evaluation, and performance control, into an executable rule set [Bon98]. In many situations, using the fuzzy variables is justified by the limitation of our knowledge about the phenomena or low level of precision in the behaviour of a system. Application of conventional operational optimisation to such systems can lead to incorrect planning decisions [Kick78].

Fuzzy sets and fuzzy logic were developed by L. A. Zadeh in 1965 as a mathematical theory of vagueness. In ordinary set theory, by definition, a set consists of the finite or infinite number of elements. The elements may either belong to the set or not belong at all. This is denoted by the characteristic function μ_A of the set A. This function can take the value 0 or 1. Zadeh introduced the concept of fuzziness in set theory by generalising the characteristic function [Zd74]. The function is allowed to assume an infinite number of different values in the closed interval [0,1]. Elements belong to a fuzzy set with different grades of membership (figure 5).

Figure 5. Membership function of the set "young"



Set "young" is a fuzzy set because it is impossible to draw a line between 'young' and 'not young' exactly. 10-year old belong to the set with membership $\mu_A = 1$. It means that he does not belong to the set "not young" at all. 30-year old will have a degree of membership in the set "young" less than 1, that is may be considered as both 'young' and 'not young'.

It is widely felt that the framework of formal logic is not particularly suitable for imprecise real-world problems. The rejection of the opinion that human reasoning could be specified and refined to fit exact formal logic, and the assumption that the power of human reasoning contrarily lies in its ability to handle inexact concepts directly led to the introduction of fuzzy reasoning, which is based of fuzzy logic.

For illustration of what is meant by fuzzy reasoning, compared with formal reasoning, consider the following two examples [Kick78]:

Socrates is a man.
All men are mortal
=>Socrates is mortal

and

Socrates is *very healthy*
Healthy men live *a long life*
=>Socrates will live *a very long life*

Obviously in the second example the italicised words are imprecise concepts; in fuzzy logic these are represented by fuzzy sets.

Neural Networks and Fuzzy Logic in Logistics Control

Neural nets and fuzzy logic are advanced techniques. Application of these techniques is not straightforward. A range of questions should be addressed in the research about applicability of Fuzzy-Neural Systems (FNS) to logistics control.

The first question is whether a company can achieve better control of its logistics operations if it uses fuzzy-neural control systems. A second important question is: what amount of effort should a company apply to build a new system and is this effort justifiable in terms of administrative and capital costs? The third question is what kind of training and education will be required for the people who work with Fuzzy-Neural Logistics Control Systems (FN-LCS).

As mentioned earlier, a logistics control system has three major components: goals in the form of budgets, a performance measurement framework, and a decision-making interface, which allows us to find the course of action to bring the performance in line with budgets. The major area of application of fuzzy logic and neural networks among those three is decision-making.

The corrective action is not necessarily taken just because the level of service is lower or costs are higher than planned. The error may be a result of some random events. Corrective actions consume managerial time and increase administrative costs. In addition, a control system, which follows every slight performance error, can be characterised as being “nervous”. In general, a control system should not be designed to respond to random errors. The problem of “nervousness” of a control system can be managed by application of fuzzy rules. The degree of the error as well as the amount of corrective action can be described in fuzzy terms. Errors can be described by the terms “high”, “low”, “insignificant” and responding corrective action can be “very strong”, “more or less moderate”, etc.

In many situations application of fuzzy rules is justified by the fact that the relationship between the error and amount of corrective action is not known exactly or there is no adequate measurement system to calculate the amount of corrective action.

On the other hand, some small errors may become a result of some fundamental changes in logistics system. If corrective action is not applied in time the error can grow. In such situations the system can hit the point where minor adjustments will not be able to solve a problem. Drastic measures, even alteration of logistics system, will have to be undertaken, which is both costly and requires some time to find and implement a solution. To avoid such troubles with logistics control a manager or an automated control system should be able to recognise when fundamental changes has occurred. Neural networks have proved themselves as very good and reliable tools of pattern recognition, and could potentially be used here.

The ability of neural networks to recognise patterns makes them very useful tools in financial and commodity markets forecasting [Zimm98]. There are generally two ways in which neural networks recognise different patterns. The first way is supervised learning. During the supervised learning process a set of data is presented to a network for calculation and a solution for training. For example, level of demand and supply, and different economic indicators are presented to a network for recognition of trend in the future price of copper. If the net predicted growth of the price, but it did not occur, the weights in the net are updated to reflect new information. The other way is unsupervised learning. Unsupervised network creates clusters based on similarities between the data [Wil96]. Each of the clusters can be considered as a different pattern. After labelling of the patterns the net performs a pattern recognition function quite reasonably.

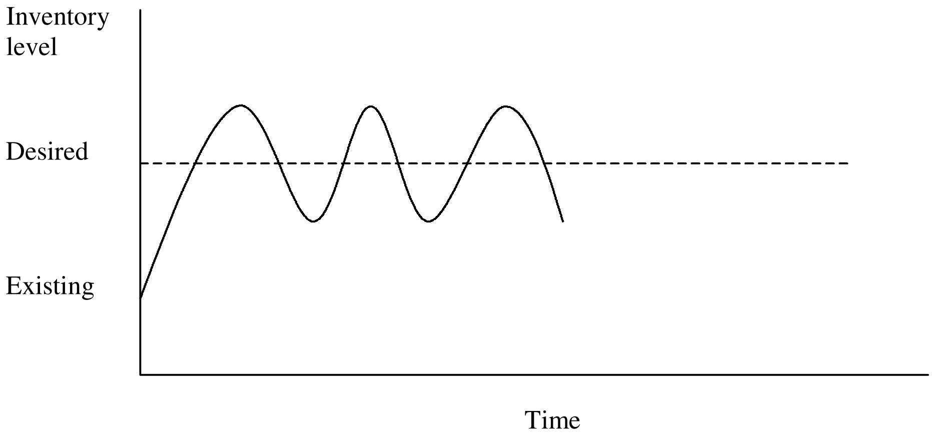
So, if a supervised or unsupervised network is built into a logistics control system it possibly will be able to find the difference between performance parameters patterns and signal the necessity of corrective action if some fundamental changes has occurred.

The idea of the current research has been based on engineering applications. Despite many differences, engineering and logistics systems have a lot of similarities too. One of the characteristics common for both systems is inertia. The other is a time lag between when a change in logistics processes occurs and when that change is detected. If information lag and mass of the logistics system are big the system will tend to “hunt” [Bal92]. This means that the system will never stabilise at the desired level (Figure 6). To overcome this problem, along with many others, companies tend to create leaner and more responsive logistics and information systems. Again, as in the previous examples, fuzzy-neural systems can offer a reasonable solution.

Firstly, the speed of response can be increased by eliminating a good share of human factor from the fuzzy-neural controlled logistics system. Secondly, neural networks can learn new strategies of balancing logistics system.

Implementation of FN-LCS in companies is not a straightforward process. It requires a lot of preparation. The most important piece of work is to develop understanding of what the logistics system of a company is. Not every company clearly understands its own logistics system. One of the reasons is existence of functional borders and dispersion of responsibility for logistics activities among different departments. In such situations it is not always quite clear where the borders of responsibility for logistics processes are. On the other hand defining the elements and the borders of logistics systems allows pinpointing of the “white spaces”, the crossovers from one function to another within the process. These spaces are normally not managed and therefore problems occur.

Figure 6. Control System 'Hunting' caused by Inertia and Time Lag



The next step is the development of an integrated performance measures framework [Shar95], which establishes direct linkages between the top-level measures and the cascade of action plans through the entire logistics system. These collectively add up to the achievement of established goals.

The most difficult part is the analysis of performance gaps. During this stage human experts should decide what scope of controlling activities can be trusted to computerised system. Performance gaps can be improved by different techniques, which require different levels of human involvement. If re-engineering is required, processes may not be controlled by FN-LCS until the re-engineering is successfully completed.

Although all these preparations are costly, the benefit to the organisation can be significant even as a result of process and organisational re-engineering. Better control of leaner logistics system without "white spaces" can outweigh the costs of preparation for the implementation of NF-LCS.

The last step is implementation of FN-LCS. After all previous steps, this stage may not be very difficult. Of course, management should be ready to trust a good piece of vital controlling function to a machine. But in terms of training and education requirements this process is not very dramatic. Current management used to work hand in hand with complicated DSS, which use many techniques of Artificial Intelligence. As in the case of contemporary DSS, the manager does not have to know what is inside, (s)he works with a user-friendly interface, which mimics the way of communication between humans. In [Eder98] a team of computer specialists shows that the neural network can be easily hidden in a computer application. Indeed, a user is often not at all interested in the underlying principles and the application architecture, but in how the application performs its tasks.

Summary

Logistics control ensures that logistics goals, around which the logistics plans were developed, are achieved. Perfect implementation of plans does not require control. Real world logistics systems do not work under perfect conditions, however. Many internal and external factors affect the logistics performance, making impossible the perfect implementation of logistics plans, expressed in the form of cost budgets and service plans. Tracing of performance gaps and their analysis help to pinpoint the cause of the problem and to bring the process under control.

Performance measurement plays an important role in logistics control. Logistics parameters allow pinpointing the gaps in productivity, logistics costs, quality, and speed of logistics processes. Adequate accounting system and information technology help to collect and analyse performance measures.

Analysis of logistics gaps is a prerequisite to finding the causes of errors and initiation of corrective actions. The complexity of logistics systems requires very high professionalism from the people carrying out these tasks. Recent developments in the field of computer technology give a logistics manager a hand in the form of Decision Support Systems. Techniques of artificial intelligence and knowledge of human experts about logistics systems used in construction of Decision Support Systems help to reduce administrative costs and increase the reliability of decisions.

The most recent techniques of Artificial Intelligence are still waiting their turn to be used in logistics control. Fuzzy Logic and Neural Nets find their way into the control of industrial operations. Merged together, these two techniques create a powerful tool, which has the ability to learn and work with insufficient, vague information.

The power of this tool requires a careful preparation for implementing of Fuzzy-Neural Logistics Control System (FN-LCS). Human managers have to trust a good share of their control responsibilities to a machine. It requires a thorough understanding of logistics control process, audit and reconfiguration of logistics system. Scrutinising the logistics system allows the pinpointing of the areas which are poorly managed or not managed at all, which is always good even without the implementation of FN-LCS.

In its final shape the FN-LCS is an information system with a high level of interactivity, enabling better logistics control due to both the learnability of neural networks and the expert knowledge of human managers in the form of a fuzzy rule base.

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