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2 Neural Networks: An Overview and Applications in the Space Economy

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2.1 Introduction

In the past decade a great deal of attention has been paid in the scientific literature to Neural Networks (NN) as alternative models of information processing. The principal inspiration of NN is the human brain whose structure is constituted by a large number of connected neurons. Every neuron is a cell body which receives electrochemical input signals through the dendrites¹ and transmits the resulting electrochemical output signal through the axon;² information transmission (electrochemical signals) is then spread by means of spatial connections, so called 'synapses', between axons and dendrites of different neurons. In particular, when the combined signals are strong enough, the neuron is 'activated' and will produce an output signal.

The structure of NN is generally represented by logical units (neurons) connected by channels of communication (synapses) which intercompute independently, since each neuron cooperates in the transmission of information by means of a different 'weight'.³ This differentiation in the weights thus corresponds to different values in the synapses. The above phenomenon happens in particular during the phase of 'learning' in order to allow adaptation to new conditions. In fact, like cerebral behaviour, NN are also able to recognize patterns which they have never observed before. This characteristic, by allowing systems of 'generalizing',⁴ identifies the behaviour of the system as 'intelligent'. In other words, since 'real' events never repeat themselves in the same manner, intelligent systems are able to observe, by means of past experience, continuity and similarity of such events, by offering the possibility of correctly predicting future events.

Compared to Artificial Intelligence, NN distinguish themselves in their ability to elaborate and create information by means of Parallel Distributed Processing systems. This is an important aspect of NN, since massive parallelism provides, on the one hand, the possibility of significantly increasing computer speed (see Kosko 1992) and, on the other hand, provides a great 'fault tolerance' (since interconnection between neurons is essentially local).

It is difficult to define NN in formal terms: in principle they can be considered as nonlinear dynamic systems with many degrees of freedom (see Terna 1992) as well as 'free' models of estimation (see Kosko 1992). Consequently, the common element in the above definitions is the concept of 'freedom'; in other words, there is a 'free biological behaviour' of NN which cannot be subjected to any mathematical model (usually creating logical bounds between output and input). Thus, in contrast to the necessity of computers to be programmed (requiring that knowledge of the mathematical model which represents the reality concerned is necessary), NN are trained; that is, they learn from a set of 'examples' with input and output⁵. In other words, *NN can be defined as connected systems* by means of which a wide range of complex problems, 'not formalizeable' by logical mathematical models, can be solved.

In the next section a concise historical overview of NN will be given. Then in Section 2.3, the general architecture of NN will be described and illustrated with some examples of different structures. In Section 2.4 the learning phase of a network, with reference to the two different methodologies ('supervisor' and 'unsupervisor'), will be illustrated. Next, in Section 2.5, some recent applications of NN in the field of urban and regional economics will be considered. Finally, Section 2.6 will conclude with a concise evaluation of the NN potential.

2.2 A Brief History

More than fifty years have elapsed since an NN model based on simple logical/mathematical relationships, was formulated for the first time (see for a historical review, NeuralWare 1987-1989). In 1943, McCullough and Pitts (see McCullough and Pitts 1943, NeuralWare 1987-1989) published a watershed paper titled 'A Logical Calculus of Ideas Imminent in Nervous Activity', in which they proposed a formal model of neurons, drawing inspiration from the human brain. In their work they emphasized the equivalence of the functions calculated by the Turing machine (on which the actual computer is based) to a neural network.

In 1949 Hebb (see Hebb 1949, NeuralWare Inc. 1987-1989) showed a mathematical relationship as a learning rule, inspired by biological learning as a synaptic phenomenon, in the following form:

$$\Delta W_{ij} = \epsilon 0_i 0_j \quad i, j = 1, \dots, N \quad (2.1)$$

where ΔW_{ij} is the difference (before and after a cycle of the learning rule, i.e. after the adjustment process; see Endnote 5) of the weights of connection between the neuron i and j ; it increases proportionally with the activations 0_i and 0_j of the neurons i and j . Finally, ϵ is a constant of proportionality. Such a rule plays a key role in learning mechanisms.

About ten years later Rosenblatt presented the first major results of a research project in neural computing: the development of an element called a 'perceptron'. The perceptron is a pattern classification system, identifying both abstract and geometric patterns. It represents the highest simplification of the central nervous system simulated by a neural network with two layers (input and output layer) (see NeuralWare Inc. 1987–1989; Rosenblatt 1962). The perceptron is able to compute only the class of 'linearly separable' functions. It means that, given the space of all inputs, all of those in one set must be located as one side of a hyperplane.⁶

In this framework, Minsky and Papert (1969) published later on the book 'Perceptron', in which they emphasized the limits of the perceptron to solve some simple function (like the non-linear separable one; see, for example, the or-exclusive (XOR)⁷ problem). Due to these limitations, a period of scepticism concerning NN followed after this publication, which lasted for more than ten years (see Neuralware, 1987–1989).

Then, only in the 1980s Kohonen and Rumelhart in their work on multilayer perceptron and backpropagation learning algorithms (see subsequent sections), succeeded in overcoming the limits of the Rosenblatt perceptron. Then, the interest in NN grew significantly, and they were used for various applications, particularly for pattern classification; even nowadays much attention is centred around backpropagation and its extensions. A further extension was the principle of competitive learning⁸ (see Kohonen 1982; NeuralWare 1987–1989).

A relevant contribution in this context was the work by Hopfield (see Hopfield 1982; NeuralWare Inc. 1987–1989), where the author conceptualized the network in terms of energy, emphasizing the notion of memories as dynamically stable attractors (see Hertz et al. 1991). In particular, the basic Hopfield paradigm consists of a set of processing elements which compute the weighted sum of the inputs, and assume that the output must be zero or one (see formulation (2.4)). Hopfield showed that an energy function exists for the network, and that processing elements are guaranteed to converge to a stable local energy minimum. Thus the Hopfield model can solve the class of associative memory model problems as well as the class of optimization problems where the energy function corresponds to the cost function or objective function.⁹

Starting from these basic results, the intensity of research on NN greatly increased not only in the fields of engineering and biology, but also in other fields such as economics, technological innovations, telecommunications and transport systems. For this reason, it may be helpful to highlight the basic elements (structure and behaviour) of NN in order to investigate the potential and applicability of NN in economics and regional science in general. This will be the subject matter of the next sections.

2.3 The Structure of a Neural Network

A generic NN can be set up according to three different structures (see e.g. Maren 1991):

- micro structure: it determines the activity of a single neuron.
- meso structure: it creates the physical organization of the neurons.
- macro structure: it is a union of different meso structures to solve complicated problems.

2.3.1 Micro Structure

The NN micro structure is the smallest component of the network, that is the j -th neuron (see Figure 2.1).

Figure 2.1 Micro structure of NN

The symbols in Figure 2.1 are defined as follows:

- $W_{ij}(i=1,...,n ; j=1,...,m)$ are the weights of synaptic connections between the j -th neuron and the neurons linked to it.
- $\Delta_j(j=1,...,n)$ are the activations of neurons. Each neuron has its own 'activation state' determined by the activity of the neurons linked to it, based on the following relationship:

$$A_j = f\left(\sum_{j=1}^n (W_{ij} A_j + \theta_j)\right) \quad (2.2)$$

- the expression 'f[]' denotes the 'activation' function (the so-called transfer function) which allows the transmission of the signals only when the activation of a neuron exceeds a particular threshold value.
- the symbol θ_j in f is the 'bias', which determines the threshold value of the j -th neuron activation. Such a value is different for each neuron and can be considered as the weight of a 'fictitious'

connection, between an imaginary neuron and the j -th neuron. It provides a means of adding a constant value to the summed input, which can be useful to scale the overage input into a useful range.

The transfer functions can assume different configurations (see Figure 2.2). In particular, in Figure 2.2 four types of transfer function are displayed, where y and x are – with reference to formulation (2.2) – defined as follows:

$$y = A_j \quad x = \sum_{j=1}^n (W_{ij}A_j + \mathfrak{I}_j) \quad (2.3)$$

Figure 2.2 Neural networks transfer functions

Source: Maren 1990

In a standard NN framework we have four types of basic functions for y and x :

- a A threshold-logic function: The activation of the neuron is binary $[0,1]$:

$$y = f(x) \begin{cases} y = 1 & \text{if } x > 0 \\ y = 0 & \text{if } x < 0 \end{cases} \quad (2.4)$$

In other words, if the summed input is greater than or equal to the neuron's threshold, the activation is assumed to be equal to 1; otherwise, the activation is assumed to be 0.

- b A hard-limit function: A superior and an inferior limit exists for the x variable, so that:

$$y = f(x) \begin{cases} y = 0 & \text{for } x \leq -\alpha \\ y = \frac{x}{2} + \frac{1}{2} & \text{for } -\alpha \leq x \leq \alpha \\ y = 1 & \text{for } x \geq \alpha \end{cases} \quad (2.5)$$

where α is a constant. In other words, if the summed input (from other neurons) is less than or equal to the inferior limit, y (the activation) is equal to 0; if the summed input reaches a value between the inferior and superior limit, then y is assumed to be a linear function; finally, if this sum is greater than or equal to the superior limit, y is considered equal to 1. It should be noted that only a few applications exist which use this function, since it cannot be derivable for $x = -\alpha$ and $x = \alpha$; consequently, its learning algorithms are complicated.

- c A continuous function: In order to overcome the limit of the previous function, Werbos (1974) proposed the sigmoid or 'logistic' function:

$$y = \frac{1}{1 + e^{-\alpha x}} \quad (2.6)$$

which is continuous, smoothly defined over the interval, monotonically increasing and differentiable (see Figure 2.2(c)). This last characteristic allows to formulate back-propagation learning algorithms (see the next section). Almost all applications are based on this function (see Table 2.1) due to the simplicity of the related learning algorithms. Obviously, it is possible to use also any growing monotonous function which has a superior and inferior limit.

- d Radial basis function: This is a Gaussian function with variable width. These types of function are particularly useful for feedforward networks focussing on continuous mapping (for example, parity problems are not continuous and are hence not good radial basic function applications).

There are some studies which have obtained better results using these NN than a two layer back-propagation (sigmoid function) for phoneme recognition (see Maren 1992).

2.3.2 Meso Structure

The meso structure is the architecture formed by all neurons; it is subdivided into layers and each layer contains a different number of neurons. Substantially, neurons are linked in three ways: a) 'forward', when the direction of the neuron's connection is from the lower layer to the upper layer; b) 'backward', when the direction is inverse with respect to the forward direction; and c) 'lateral', when the neurons of a layer are connected. Some examples of a classical meso-structure are succinctly summarized in Figure 2.3:

Multilayered Feedforward NN Each layer is entirely linked to the upper level. In this topology of NN there are no self, lateral or back connections; it is then certain that the network will converge to a solution, given an input pattern. For these reasons, it is widely used in several applications (see Table 2.1). Feedforward networks are typically chosen for pattern classification applications. Their ability to do this depends on the learning algorithm (see the next section).

Single layer, laterally-connected networks This architecture uses a single layer of laterally-connected neurons. Consequently, when a pattern is activated, different configurations appear in the single layer for each cycle of the operation, until a stability is reached. These NN are named dynamic networks and thus it is important to identify their stability conditions. In this context, the Lyapunov Theorem is very useful (see Maren 1992). Laterally connected networks are typically used for pattern autoassociation. They are appropriate for regenerating a clean version of noisy or incomplete pattern.

Bilayer feedforward (feedback networks) This type of NN has feedback and feedforward connections; then information pass through the layers, using two different sets of connection weights. This means that also these NN are dynamic; they are called 'heteroassociative networks', because they can associate a pattern in the first layer with another pattern in the second layer. Another dynamic network of this type is 'Resonating Network', where the patterns in the first and second layers repeatedly stimulate each other until the pattern in each layer settles to a stable state.

Multilayer cooperative-competitive networks This category of NN has lateral connections (plus feedforward/feedback) which generate a cooperation (if the connection is positive) or a competition (if the connection is negative) among the neurons of the same layer.

The choice of an architecture and also of the way a network operates, depends on some considerations about the design of input and output representations. For example, some networks can work only with binary signals, others with real valued signals (type of input). Moreover, some

can handle only static inputs, others can work with time varying sequences of information. Regards the type of output, some networks produce only a classification of input data, others may produce connections or adjustments in a process. All these distinctions can affect the designer's choice of a network, it is important to know the internet relations between input and output.

Figure 2.3 Six basic topologies of NN meso structures

Source: Maren 1990, p.53

2.3.3 Macro Structure

The NN macro structure is completely described by the connection of different meso structures. When no previously described single network can solve a problem, then it is useful to design a system of NN, where each NN ‘later’ performs a specific task, interacting with the others.

When an application has to be solved by means of NN, it is important to choose an appropriate NN design for its representation, in terms of its meso structure and considering the characteristics of individual neurons (micro structure). Once the architecture of NN is defined, the

subsequent phase concerns the learning process of NN. This learning possibility will be discussed in the next section.

2.4 Learning

The behaviour of NN depends mainly on the learning algorithm, since this phase provides the basic information on the environment at hand, by preparing the neural network to recognize and classify the patterns.

In particular, during the learning phase, an NN system may adapt or organize itself each time it examines a new sample, by changing the synaptic weights of each connection (the adjustment process; see Endnotes 4 and 5). Consequently, since NN only learn a part of the possible samples (which can be infinite), the choice of the samples is very important (since the samples have to reflect the whole environmental pattern). Indeed, during the learning phase, 'internal representations'¹⁰ of the samples take shape and define a 'quantization'¹¹ of the patterns by means of vectors of real numbers,¹² which can be modified in order to minimize the estimated error of the sample according to different criteria of numerical calculus (e.g., the 'mean squared error').

In this context two different standard classes of methodologies of learning processes have been developed in the literature:

- Supervisor;
- Unsupervisor.

They will be concisely discussed in the next two subsections.

2.4.1 Supervisor Learning

The perceptron network This kind of learning implies that a network learns by examples, providing – for every input configuration – the respective output.

The first network which made use of such an algorithm was the Rosenblatt perceptron (see Section 2.2). It was made up of two layers: an input and an output layer (see Figure 2.4):

In Figure 2.4, p is the p -th configuration of the training set. This type of NN, as already mentioned, presented serious limits, since it is only able to solve problems belonging to the class of 'linearly separable' functions. This can be shown by analysing the so-called XOR problem (the Exclusive-or problem, a Boolean logic problem; see Figure 2.5, where X_1 and X_2 are the input states and t the output states).

Figure 2.4 Perceptron architecture

Figure 2.5 The XOR problem

From Figure 2.5 it is clear that, if the training set is represented in the space of the input states X_1 and X_2 (which is bidimensional since there are only two input neurons), the two classes $t=1$ and $t=0$ cannot be separated by a single line. This is a 'linearly non separable' problem. Thus, in order to solve the above mentioned class of problem, the network needs other layers between the input and output layers, since only in this way the network is able to map some internal representations that are necessary to associate input and output configurations. This gives rise to the model of a multilayer perceptron network, often called *backpropagation network*. This will be illustrated in the next subsection.

The back propagation network The back propagation network is an extension of the perceptron network in which at least one hidden layer is defined.

The transfer function assigned to each single neuron is a sigmoid function. The training algorithm utilized is the 'generalized delta rule'. It is based on the minimization of the error between the output provided by the network and the expected one. In general, the generalized delta rule can be formulated as follows:

$$\Delta W_{ij} = -\varepsilon \frac{\partial E}{\partial W_{ij}} \quad (2.7)$$

where ΔW_{ij} has the same meaning as explained in formulation (2.1) and Section 2.3.1; the error term E is equal to:

$$E = \frac{1}{2} \sum_{j=1}^N (o_j^i - o_j)^2 \quad (2.8)$$

In other words, the total error E is determined by the difference between o_j^i (expected output) and o_j (resulting output); moreover, it is propagated by the connections among neurons in order to recalculate the new weights W_{ij} .¹³

Figure 2.6 The backpropagation network

Source: Maren 1990, p. 95

The error varies according to the changes in all weights of the connections forming the network, so that the error function has to be represented in the N -dimensional space (where N is equal to the number of the weights). Thus the problem is to find the minimum of a function in an N -dimensional space. This problem can be solved by means of the 'descent of gradient' technique: it consists of reaching the minimum point by increasing from one initial random point the value of the weight of the connections with values inversely proportional to the derivative in that point. Generally, the supervisor learning algorithms use the error information to reinforce the learning process, rewarding accurate classifications of patterns and punishing misclassifications. In fact, the supervisor learning process uses the information of the training

sample to define a numerical error signal (or vector), which guides the estimated gradient descent.

2.4.2 Unsupervisor Learning

Unsupervisor algorithms distinguish themselves from the previous ones because they do not use a training set. As a consequence, they show both a computational complexity and an inferior accuracy compared to the supervisor algorithms; therefore, they are mainly useful in real time environments where a high execution speed is needed or whenever there is lack of information.

Unsupervisor training computes synaptic weights by examining how these modify their values according to the local information received from the neural signals. Local information, available at time t , regard weights and neural activities.

In general, unsupervisor algorithms adaptively cluster the pattern groups in decision classes. As regards the 'competitive learning' algorithms, these groups evolve by producing winner neurons by means of both inhibiting processes and random induced activations from the examples; in this context the evolution of synaptic weights tend to estimate the centroid of the decision classes (see Kosko 1992). Other algorithms evolve towards basins of attractors of the space examined.

As previously mentioned, the synaptic weights modify their values with reference to the local information, for example, by associating neural signals. The easiest case is the product $A_i(x_i)A_j(y_j)$ (activation of the i -th neuron to the j -th neuron) which guides the learning equations (see Kosko 1992). In this context it is interesting to mention the rules governing the algorithms, like, for example, the following main classes of rules:

- a Signal Hebbian law
- b Competitive learning law
- c Differential Hebbian law
- d Differential Competitive law

These will briefly be described now.

a Signal Hebbian learning law This rule (see Kosko 1992) correlates local neural signals by means of the following differential deterministic equation:

$$\frac{dW_{ij}}{dt} = -W_{ij} + A_i(x_i) A_j(y_i) \quad (2.9)$$

where W_{ij} is the synaptic weight assigned to the connection between the i -th and the j -th neuron and where the connection between i and j is stimulated if $W_{ij} > 0$, and inhibited if $W_{ij} < 0$. This shows how the

activities of the neurons' signals interact proportionally with the variation of a synaptic weight.

b Competitive learning law The deterministic competitive rule (see Grossberg 1969 and Kosko 1992) creates a relationship between the synaptic signal resulting from the differences $A_i(x_i) - W_{ij}$ and the competitive signal $[0,1] A_{ij}(y_i)$:

$$\frac{dW_{ij}}{dt} = A_j(y_j) [A_i(x_i) - W_{ij}] \quad (2.10)$$

This expression indicates that the synaptic weights change their value at time t only if the output neurons are winners, that is if $A_j(y_i(t))=1$. The result is a retroactive competition among the neurons of the output field, where some neurons get stimulated at the same time and inhibit the closest ones.

This situation can also be evaluated from a metric point of view, where the winning neurons are those with the minimum distance between the vector of the input signals $A(x) = (A_1(x_1), A_2(x_2), \dots, A_n(x_n))$ and the row vector of the synaptic weights $W_j = (W_{1j}, W_{2j}, \dots, W_{nj})$. This can formally be expressed as follows:

$$A_j(y_j) = \begin{cases} 1 & \text{if } d(A(x), W_j) = \min d(A(x), W_k) \\ 0 & \text{if } d(A(x), W_j) > \min d(A(x), W_k) \end{cases} \quad (2.11)$$

c Differential Hebbian law The Hebbian learning differential rule (see Kosko 1988, 1992) states a relationship between the signal speed and the signal itself:

$$\frac{dW_{ij}}{dt} = -W_{ij} + A_i(x_i) A_j(y_j) + \frac{dA_i(x_i)}{dt} \frac{dA_j(y_j)}{dt} \quad (2.12)$$

where:

$$\frac{dA_i(x_i)}{dt} = \frac{dA_i}{dx_i} \frac{dx_i}{dt} = A'_i \frac{dx_i}{dt} \quad (2.13)$$

It is evident from (2.13) that a time vector is added to the Hebbian learning law which can influence both positively and negatively the modifications of the synaptic weights. Intuitively, the synapses learn more when the neurons' signals often change (i.e., when neurons are intensively simulated).

d Differential competitive law Finally, the differential competitive learning rule (see Kosko 1988, 1992) creates a combination between the competitive law (2.12) and the differential Hebbian rule (2.13) as follows:

$$\frac{dW_{ij}}{dt} = \frac{dA_j(y_j)}{dt} [A_i(x_i) - W_{ij}] \quad (2.14)$$

From expression (2.14) it is evident that the synaptic weights modify themselves only 'if there are modifications'. In other words, the synapses learn only when their post synaptic neurons change: the neuron wins the competition when it is continually simulated; however, if there are no modifications, the neuron loses. This local reinforcement or punishment is expressed by the speed of signal $dA_j(y_j)/dt$.

In conclusion, since in the unsupervisor process the synapses learn locally (without supervision), the emerging NN behaviour is the global output of adaptive local processes. For example, economic agents change their behaviour locally, and although each agent does not have a global view on the whole economic system, the local behaviour of an agent has a resonance with respect to global behaviour. This suggests that the use of unsupervisor NN in economics may be an innovative instrument for defining micro economic platforms indispensable for macro economic models. For this purpose, it is interesting to turn attention to unsupervisor learning algorithms (like for example, genetic algorithms) which, instead of acquired rules, 'reveal' new rules and new strategies of behaviour. Until now there have been few applications regarding this argument, but it is interesting to investigate the possibility connecting genetic algorithms with NN. In this context an important example is an application for building an economist operator's decision support system (DSS) (see Margarita 1992).

2.5 Application of Neural Networks to Spatial Economics and Transportation Science

NN, which have initially originated as mathematical models of the human brain, have later on successfully been applied in different scientific fields, such as engineering, biology, and recently in economics and transportation science (see Table 2.1). Their success was mainly based on the following two main methodological research directions (see Fabbri and Orsini 1993):

- statistical analysis and identification of rules underlying economic systems;
- simulation and forecasting of micro and macro behaviour.

We will focus here mainly on spatial economics and transportation science, although the above issues are common to all applications. In the following overview, recent NN applications in spatial economic systems as well as in transport engineering systems are considered, as these offer interesting examples of network behaviour.

First, we will discuss in a concise way interesting NN research concerned with spatial economic systems; a compact overview can be found in Table 2.1. As previously noticed, NN are based on a methodological approach which is useful for problems in which it is difficult to decide a priori on the exact relationship between different variables. In summary, NN aims at learning by example so as to reproduce observed behaviour, and are able to approximate very complex functions.

For example White (1989) has tried – by means of a NN approach – to capture the process of change and evolution in an urban structure. IN his work, White examines the distribution of consumers around shopping centres, by considering as an input a linear region divided into five areas with only two shopping centres in two separate areas and a given number of consumers distributed in these areas. In particular, White shows that the architecture of NN is a self-organizing systems, that is able to start from an arbitrary set of conditions and to evolve towards a desired result. There is a peculiarity worth pointing out in the structure of the network adopted by White: the input level is composed of five neurons of the areas (whose value is 1 or 0 depending on whether they have a shopping centre) representing five locations of the consumers plus a bias,¹⁴ the second hidden level has only five areas and a total connection for the location of the consumers. Seven cases are given as a ‘training set’,¹⁵ and a learning supervised algorithm, based on the descending gradient method (see Section 2.4.1.2), is used. The results then point out that first the final values are correct and close to the desired ones; secondly, by observing the final structure of the network and in particular the weights of the connections, the network did ‘study’ and learned to identify and to solve an implicit problem. Therefore, in White’s work neural networks are used as systems able to model evolutionary processes and to represent – through more or less complex inner configurations – functional relationships among the variables.

Starting from White’s results, Openshaw (1992) extends the above application by still using a network of the backpropagation feedforward type, but by adding further input neurons in order to better analyse the NN behaviour of the case of a great number of urban areas. The results are then compared with both the real ones and those derived from the applications of conventional models. The above comparative analysis seems then to favour the NN approach, despite the considerable amount of computer time involved. Moreover, Openshaw underlines the necessity of a computational model able to offer solutions to problems regarding the analysis of spatial geographical data, since the actual conventional tools (like Geographical Information Systems, GIS) – even though they can reach a high level of sophistication – may collapse in the presence of a continuously increasing number of geographical attributes. In this context, NN seems to offer a new methodological tool which does not depend on quantities and precision of the data and attributes, since NN can be freely expanded (by adding new attributes or

data) without being forced to determine in advance their functional impact on both the final results and the other attributes. Furthermore, NN can filter and then utilize imprecise or disturbed information.

Referring to the GIS diels, Leung (1994) offers an interesting contribution by proposing NN as a new tool for analysing spatial inference. In this framework, different architectures of NN (feedforward, Hopfield, ABAM,¹⁶ BAM,¹⁷ IBAM,¹⁸) are compared in order to identify the right methodology for representing spatial knowledge and inference.

By considering a statistical framework, NN appear to perform quite well, mostly in the sphere of linear and nonlinear regression. For example, Roson (1992) tries to find a functional relationship between consumption and income by using – as data – the training set of 15 Italian regions (out of 20) (from ISTAT data referred to 1988) and by giving values to a dummy variable in order to distinguish the southern regions from the rest of the nation. A three level architecture is used (Multilayered Perception), where the sigmoid function is the activator of the single neuron. The obtained 'fitting' shows better results than a classical linear regression. Roson also suggests a theoretical solution – by means of NN – for the optimization of the problems. The example analysed is the assignment of employment – to a certain number of people – by the following set of rules and presetting constraints. The structure of the network is a Hopfield Associative Memory) with $n \times n$ neurons) with a 'Threshold Logic' as neuron activation function. The stable configuration of the network is then reached through the minimization of the function 'Energy'.

With reference to the theoretical economic underpinning of NN, the work of Terna (1992) is very interesting. This author analyses in particular the class of dynamic systems characterized by many degrees of freedom. He deals with prediction problems in an economic and social context, where a behaviour is apparently easy, if represented by a unique person, but becomes complex if derived from the interaction with many different individuals acting according to their 'bounded rationality'¹⁹ (see also Parisi 1992). Then, the problem is how to utilize mathematical models which take into account bounded rationality by emphasizing the intuitive aspect²⁰ (which in this case is even more complex, since it stems from the behaviour of group of single individuals). This is the reason why economists are recently getting interested in NN. In particular, Terna observes that by using supervisor networks and building a training set on the basis of conventional models, a methodological improvement is not reached. In fact, in this way NN imitate the effect of conventional theories, gaining 'useless circular results' (see Terna 1992). A possible solution can be the construction of connectivity models, able to learn from the results of their actions, by considering their impact on the external environment. For this purpose Terna suggests three different techniques: Econet (see Parisi et al. 1990) and Cross-target (see Terna 1991), both characterized

by multiacting interactive models based on a plurality of Artificial Neural Networks, and finally genetic algorithms²¹ (see Margarita 1992).

The potential of NN is broad. Certainly, much work has still to be done in many research directions. So far, the results are encouraging, even though several limitations still exist. For example, the determination of the optimal configuration is a problem underlined in the work of Malliaris and Salchenberger (see Malliaris and Salchenberger 1992) as well as in the work of Fischer and Gopal (see Fischer and Gopal 1992, 1994). Malliaris and Salchenberger compare the ability of the NN approach and the Black-Scholes Model (see Black and Scholes 1973) in estimating the choice of market prices. The comparison shows that NN outperform the model of Black-Scholes in almost half of the examined cases. Next, these authors point out interesting limitations on the use of NN with respect to the difficulty caused by the lack of a formal theory related to the identification of an optimal network (the number of hidden levels, the number of neurons on this level, etc.). Thus the use of NN requires an effort from the analyst who has to accurately select the parameters, the activation function, the set of data and the type of network, for obtaining an adequate configuration of the model. Despite this, Malliaris and Salchenberger underline the validity of NN as an alternative tool to traditional models.

In management science, a further research direction using NN is worth mentioning, viz. the prediction of business failure. In the past years a number of artificial NN models has been developed to predict corporate bankruptcy with both promising and disappointing results (see for a review Boritz and Kennedy 1994).

A further study in this context – in which NN has been compared with traditional prediction techniques such as discriminant analysis, and logit and probit models – shows the relevance of the learning sample for all techniques, with particular emphasis on the types of NN used in the analysis (mainly based on backpropagation procedures (see again Boritz and Kennedy 1994). The need for extending research on NN is also underlined here, by focusing attention on the number of hidden processing elements as well as on the change in the set of explanatory variables.

Finally, Fischer and Gopal have analysed NN as a possible prediction tool, compared with the conventional model of spatial interaction (see also Fischer et al. 1992); in particular they use both techniques for forecasting the interregional telephonic traffic between 32 Austrian regions. As concerns the application of NN, the authors utilize a feedforward network with supervised learning (backpropagation rule) on the basis of an interesting training set.²² In this way, Fischer and Gopal emphasized the potential of NN as an estimation tool (since it learns from experience), even in the case of incomplete, imprecise and disturbed data. The results of their experiments show extremely precise values compared with the ones emerging from the conventional spatial interaction model. In a further paper, Fischer and Gopal (see Fischer and Gopal 1994) have carried out different experiments in order to find

the most exact parameters of the network with reference to the learning phase, which depends on the variables (number of layers, number of neurons) of the network, as well as on the related parameters.

We may conclude that there is a rich field of research in the NN approach to spatial economic systems. We are only at the beginning and most potentials are still largely unexplored.

2.5.2 Neural Networks in Transport Systems

NN are also offering an interesting contribution to the solution of transport systems problems, such as traffic control problems (see Table 2.1, lower part). For example, Belgaroui and Blosseville (1993) examine the use of NN in the automatic measurement of road traffic. In particular, they utilize NN to recognize the pattern of a road traffic scene. This kind of problem is the so called 'Automatic Vehicle Monitoring'. The network used for the experiments is constituted by 18 neurons in the input layer (corresponding to the 18 parameters of the image selected from discriminant analysis), two hidden layers and four neurons in the output layer, corresponding to the four classes which have to be classified. The results were compared with those emerging from a parallel discriminant analysis; in particular, the ability of NN to recognize and classify patterns (pattern recognition and classification) is underlined.

Another example is offered by the work of Huang and Pant (1994), where a new simulation model interfaced with a neural model is developed. This NN model is able to respect in a dynamic setting the elements of the traffic control system in order to examine the problems arising in the so called dilemma zones. Generally, it appears possible to improve the traffic control by using NN together with simulation models.

In the context of transportation problems connected with a spatial interaction analysis, it is interesting to mention the recent work by Chin et al. (1994) in which NN are used in order to synthesize origin-destination (O/D) flows in a circle. The authors carried out different experiments by varying the typesetting of the training set, on the basis of data extracted from an O/D license plate survey conducted in three different daily time bands. In this work the ability of NN to elaborate subtle or contradictory information, by capturing complex relationships, is emphasized. Nevertheless, the authors notice the inability of NN to recognize (in the test phase) 'never seen' surveys; in other words, the results are much better as soon as the training set contains different patterns.

Table 2.1 Main applications of NN in spatial economic systems and in transport systems

APPLICATIONS OF NEURAL NETWORKS TO SPATIAL ECONOMIC SYSTEMS						
Authors	Fields of application	Architecture of the network	n° of neurons on the layers	Comparison with other models	Results	Emerging problems
Boritz and Kennedy (1994)	Prediction of business failure	Back-Propagation feed-forward	/	Discriminant Analysis Logit Probit	X	* Achievement of better configuration
Flischer and Gopal (1994)	Interregional telecomm. flows	Back-Propagation feed-forward	3 / 28 / 1	Unconstrained spatial interaction model	XX	* Time involved * Achievement of configuration
Leung (1994)	Inference with spatial knowledge	Feed-forward Hopfield, IBAM ABAM, BAM	/	Comparison among the different architectures of NN	ABAM model is better than other models	/
Malliaris and Salchenberger (1992)	Market prices	Back-Propagation feed-forward	7 / 4 / 1	Black Scholes model	X	* Achievement of configuration
Openshaw (1992)	Spatial interaction in urban structure	Back-Propagation feed-forward	4 / x / y / 1 x=4,...,16 y=2,...,16	Unconstrained spatial interaction model	XX	* Time involved
Rosen (1992)	Regional economics	Back-Propagation feed-forward	3 / 2 / 1	Linear regression	XX	/
White (1989)	Evolution of urban structure	Back-Propagation feed-forward	10 / 5 / 5	/	XX	/
APPLICATIONS OF NEURAL NETWORKS TO TRANSPORT SYSTEMS						
Authors	Fields of application	Architecture of the network	n° of neurons on the layers	Comparison with other models	Results	Emerging problems
Belgaroui and Blossville (1993)	Road traffic control	Back-Propagation feed-forward Gradual training	18 / 10 / 7 / 4	Discriminant analysis	=	/
Chin et al. (1994)	O/D flows in a traffic circle	Back-Propagation feed-forward	12 / 5 / 36	/	X	* Inability to generalize
Hwang and Pant (1994)	Traffic control problems	Back-Propagation feed-forward	27 / 27 / 27 / 1	/	X	/
Gerl et al. (1994)	Semaphoric control	Back-Propagation feed-forward	/	/	X	* Achieve a better training set
Mussone (1994)	Uninterrupted flow control	Back-Propagation feed-forward	4 / 2 / 1	/	X	* Precision of prediction depends on choice of training set

= : similar results as the reference model;

X : good;

XX : better than the reference model;

An interesting approach is also the sequential use of NN and Genetic Algorithms, like in the work by Geri et al. (1994) concerned with a study of traffic with a semaphoric control. Here, in particular, the examples of the training set are supplied by a genetic algorithm. In this context, recent work by Mussone (1994), in which different applications of NN in transportation systems are presented, is worth mentioning. In particular (see also Florio and Mussone 1994), the authors propose a theoretical application on uninterrupted flow control: the results show that NN are able to recognize traffic conditions as well as forecast the related stability/instability in space and time.

Finally, a new stream of research modelling travel behaviour by means of a combined 'fuzzy logic NN' approach is worth mentioning. Such an approach adopted, among others, by Lin and Lee (1991), Lotan and Koutsopoulous (1993a, 1993b) and Vythoulkas (1994), is considered to be one of the areas for further investigation, because of its capability of modelling travellers' perceptions and stochastic choices.

Thus we may conclude that NN offer great perspectives for transport systems studies.

In the Annex to the chapter we have listed a set of applications of NN for transport systems and transport control functions. Table 2.A.1 contains a broad concise overview and related references (including also Table 2.1); for the sake of brevity these applications will not be discussed here, but they illustrate once more the above conclusions.

2.6 Concluding Remarks

In this chapter, the theoretical foundations of NN as well as their applications have been considered in order to investigate the NN potential in the framework of (dynamic) spatial economic systems. First, it is interesting to note that NN have the possibility of constructing 'inner' configurations – depending on (formalized) connections among neurons – which allow applications in the context of complex systems, or in general in all cases where it appears difficult to handle or to formalize relationships between relevant variables.

Secondly, the NN potential of 'generalizing' and hence the ability of NN to forecast evolutionary processes in spatial economic systems has to be mentioned. A first remark is in order here. It concerns the choice of the 'training set' (viz. the quantity as well as the quality of the examples considered), since this choice is critical in the 'forecasting' phase. In other words, if the network is 'prepared' with a low number of examples, the error between real and estimated data will be reduced, but the data forecasts will turn out to be biased. On the other hand, if we increase the number of examples in the training set, the 'estimated' error will consequently increase; however the network will be able to recognize a larger number of cases and hence forecast more correctly.

For the purpose of a correct forecast it should also be noted that a 'correct' identification of the number of neurons in the hidden layers is

necessary, since the 'generalization potential' – owing to the so called overfitting problem – is inversely related to the number of established connections. On the other hand, by reducing the number of neurons, and hence the related connectivities, it is rather hard to obtain a convergence for all examples.

The above issues – together with the necessity to define a priori some parameters characterizing the network typology, such as activity functions, learning coefficients, etc. – point out in a concise way the main limitations inherent in NN approach, viz. the lack of precise rules for defining the network typology which is always established in an experimental way, for each case.

A final remark concerns the long time period involved in the data elaboration of the learning phase which is simulated according to a real parallel process. Thus it seems interesting to investigate indepth NN potential and their 'hidden' rules, as well as to look for new hardware technologies able to improve the speediness of execution.

In conclusion, NN appear to be a new computational tool offering interesting results in several research areas, as is witnessed by the increasing number of NN applications. In this context, a great deal of research has still to be carried out at both a theoretical and the empirical level, particularly in the field of 'unsupervised' models which are undoubtedly interesting for spatial economic research.

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Annex: A survey of NN applications to transport-regional systems and transport control functions.

The list contained in Table 2.A.1 is broad, but by no means exhausted. It illustrates the wealth of possibilities offered by NNs in spatial and transportation research.

Table 2.A.1 A survey of NN applications in the transport field

Art.	Application field	Description		Comparison with mathematical models		Performance/ Results		Particularity
		Type of network used	Special structure					
1	Traffic and transport planning	A parallel processing method for the transportation equilibrium assignment problem.						Neural interconnections and equations of neural dynamics are derived.
2	Transport: vehicle design and safety	Viability of replacing elements of a modern electronic engine control system with trained NNs.						
3	Road traffic control	NN are used to recognise the pattern of a road traffic scene.	Back-Propagation feed forward Graded training	Discriminant analysis		Similar results as the reference model		
4	Transport: vehicle design and safety	A NN based system to track the pathway in front of the robot driving system.						
5	Interregional telecomm. flows	NN are realised as a possible tool of prediction, compared to the conventional model of spatial interaction.	Back-Propagation feed forward	Unconstrained spatial interaction model		Better than the reference model		• Time involved • Achievements of configuration
6	Traffic control	New image based vehicle detection system	Simple back-propagation/feed forward	Pattern matching algorithms		NN vehicle tracking model can be used to reliably detect vehicles		System more adaptable.
7	Traffic control	NN models are applied to automated detection of non recurring congestion on urban freeways.				Encouraging results.		
8	O/D flows in a traffic circle	NN are used in order to synthesize origin-destination.	Back-Propagation feed forward			Good		Inability to generalize
9	Traffic theory	NN are applied to short term forecasts of traffic flow.		Statistical models: linear regression, discounted linear reg., ARIMA		Differences were slight		NN models can be easier to develop and incorporate in local code.
10	Traffic theory	NN technology is used to identify association in the collected data.						
11	Traffic and transport planning	NN pattern recognition techniques for traffic monitoring are described.						
12	Transport: traffic theory	Application to recognition problems: a) state of congestion of a road; b) short term forecasting				NN technology can provide a powerful method of analyzing, interpreting and predicting complex data sets		NN are trained via a simulation package to infer parameters that are not directly measurable.
13	Prediction of business failure	NN are compared against traditional prediction techniques.	Back-Propagation feed forward	Discriminant Analysis - Logit - Probit		Good		Achievements of better configuration
14	Seamorphic control	NN applied to the study of traffic with a seamorphic control.	Back-Propagation feed forward			Good		Achieve a better training set
15	Vehicle design and safety	Use of a NN for the purpose of modeling an automotive shock absorber.	Back-propagation					Comparisons are made between the simulation outputs and experimental test results.

Table 2.A.1 (continued)

Art	Application field	Description	Comparison with mathematical models			Peculiarity
			Type of network used	Performances/ Results		
16	Traffic control	NNs are used to predict congestion in heavy duty conditions.	-	-	-	
17	Traffic control problems	A new simulation model interfaced with a neural model.	Back-Propagation feed forward	Good	-	
18	Properties of road surface	Artificial NN models are used in image processing.	-	Results demonstrate the feasibility of this new approach for the detection, classification and quantification of highway pavement surface cracking	-	
19	Transport traffic theory	A method which identifies the trip origin-destination (O-D) matrix when many pair of values for the right hand side (B) column and the bottom row (A) of the matrix are given.	Back-propagation	-	The method is useful to problems that require identification of the cause- effect relationship when many set of data are available.	
20	Accidents and the human factor	Experiments were conducted to a) detect congestion b) make short term traffic forecast c) investigate multivariate relationships.	-	NN can be used effectively for such work	Advantages/ disadvantages of using NN are described	
21	Design of tunnels	A NN expert system is proposed to identify probable failure modes for underground openings from prior case history information.	Rule-based expert system	NN system allows input information to be incomplete and vague.	-	
22	Inference with spatial knowledge	NN are proposed as new tool for analyzing spatial inference	Feed-forward, Hopfield, IBAM, ABAM, BAM	Comparison among the different architecture of NN	-	
23	Market prices	NN are compared against Black-Scholes model in estimating the choiche of the market prices.	Back-Propagation feed forward	Black Scholes model	Achieve the configuration	
24	Transport traffic control	*Quasi real time* recognition of vertical road sign in a running vehicle	-	a) structured programming b) expert system approach	-	
25	Uninterrupted flow control	Application of NN in transportation systems are presented.	Back-Propagation feed forward	Good	Precision of prediction depends on choiche of training set	
26	Vehicle design and safety	A feed-forward NN is applied in an intelligent system for automatic car control.	feed-forward	-	-	
27	Traffic control	A multilayer NN model is introduced in order to realize a self- organizing traffic control system.	Back-propagation	Results were in good accordance with analytical ones.	Two process: a) training and b) optimization. a) by back propagation method b) stepwise meth. combining couchy machine (montecarlo) with feedback method	
28	Spatial interaction in urban structure	NN models are used as systems able to model evolutionary processes.	Back-Propagation feed forward	Unconstrained spatial interaction model	Better than the reference model	
					Time involved	

Table 2.A.1 (continued)

Art. Application field		Description	Comparison with mathematical models			Performance/ Results	Peculiarity
Art.	Application field	Description	Type of network used				
29	Vehicle design and safety	Individual networks are trained to developed single capabilities and a rule-based technique combine multiple artificial networks with map-based symbolic reasoning to achieve high-level, goal-directed behavior.	.	.	.	.	.
30	Transport: traffic and transport planning	A survey on NN models for solving the euclidean Traveling Salesman Problem. Hopfield-Tank model, elastic net and the self-organizing maps are introduced, as well as many variants.	.	.	.	.	Extensive bibliography
31	Vehicles	To represent system under uncertainty conditions, a controller that incorporates a NN self-tuning model is presented.	.	.	.	.	.
32	Traffic control	Spatial and temporal traffic pattern are recognized and classified by a NN trained with a simulation.	.	.	.	NN models have the potential to achieve significant improvements in incident-detection performance	.
33	Properties of road surfaces	A system that integrates three AI technologies: computer vision, NNs, and knowledge-based systems in addition to conventional algorithmic and modeling techniques is presented.	Back-propagation	.	.	Results demonstrate the feasibility of a NN approach.	.
34	Regional economics	NN applied in linear and non-linear regression.	Back-Propagation feed forward	Linear regression	.	Better than the reference model	.
35	Traffic and transport planning	NN are applied to image processing combined with artificial intelligence techniques.	.	.	.	.	.
36	Accident and the human factor	A NN system is applied to driver models.	Back-propagation	.	.	It's possible to investigate driving behavior from NN system model	.
37	Transport: traffic theory	System Identification (SI) and artificial NN (ANN) methods for short term forecasting of traffic conditions in urban road network are investigated	Back-propagation - new learning rule based on Kalman filtering	Linear models	.	Both methods are promising	.
38	Traffic and transport planning	Application of a system to a comp. vision process applied to traffic monitoring	Back-propagation	Conventional systems	.	NN based system can perform as well as conventional systems but have capability to carry out additional task.	Troubles with 'over-training'
39	Evolution of urban structure	The author shows that the architecture of NN is a self-organizing system evolving towards a desired result	Back-Propagation feed forward	.	.	Better than the reference model	.
40	Transport: traffic and transport planning	A NN is used to model the behavior of driver when they are to choose between freeway or side road	.	.	.	Prediction accuracy of the model, the acceptance rate of advice and the quality of advice are closely correlated.	.

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Notes

1. Dendrites are usually defined as 'tree-like networks of nerve fibre' (see Hertz et al. 1991).
2. An axon is a 'single long fibre' (see Hertz et al. 1991).
3. A weight is here a real number associated with a connection between two neurons.
4. Generalizing is the capacity of a system to create new patterns in accordance with previously studied examples events.
5. In particular during the learning-phase, the weights of connections are adjusted depending on the given input.
6. For two inputs, a hyperplane is just a line in a plane; for three inputs, a hyperplane is a plane in a three dimensional Euclidean space (see also next section).
7. For a definition of the XOR problem we refer to Section 4.1.1.
8. Such learning is unsupervised (see next sections); in other words, it is a formalization of the lateral interaction of neighbouring groups of neurons in the brain (see also Hertz et al. 1991).
9. A well-known application is given by the classical combinatorial Travelling Salesman Problem in which the salesman starts at a particular city and travels from one city to another one visiting each city exactly once. The objective is to choose an itinerary such that the total distance travelled is at a minimum.
10. Prototype of sampled patterns.
11. Quantization is the set of weights (real numbers) created by the prototypes.
12. The so-called 'Adaptive Vector Quantization' (AVQ); see Kosko 1992.
13. This rule is based on the Hebb rule (see formulation (2.1)) which strengthens the connections among the most active neurons.
14. See also Section 2.3.1.
15. The so called training set is a set of examples utilized for NN learning.

16. Asymmetric Bidirectional Associative Memory.
17. Bidirectional Associative Memory.
18. These are the variants of BAM.
19. In fact, according to Parisi (1992) men behave mostly in an irrational way.
20. Researchers have to find an approach which to be as similar as possible to the way human being act and behave (see Arthur 1991).
21. In this context it is interesting to refer to other recently developed tools, such as the Fuzzy Cognitive Approach, which are able to represent complex social/spatial systems (see e.g. Taber 1991).
22. In fact, since they needed a large set, they used some ISTAT data plus some statistical inputs, obtained in a random way, while the output data were calculated by applying the conventional spatial interaction model.